



Predictive Analytics for Roadway Maintenance: A Review of Current Models, Challenges, and Opportunities

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Abstract

With the pressing need to improve the poorly rated transportation infrastructure, asset managers leverage predictive maintenance strategies to lower the life cycle costs while maximizing or maintaining the performance of highways. Hence, the limitations of prediction models can highly impact prioritizing maintenance tasks and allocating budget. This study aims to investigate the potential of different predictive models in reaching an effective and efficient maintenance plan. This paper reviews the literature on predictive analytics for a set of highway assets. It also highlights the gaps and limitations of the current methodologies, such as subjective assumptions and simplifications applied in deterministic and probabilistic approaches. This article additionally discusses how these shortcomings impact the application and accuracy of the methods, and how advanced predictive analytics can mitigate the challenges. In this review, we discuss how advancements in technologies coupled with ever-increasing computing power are creating opportunities for a paradigm shift in predictive analytics. We also propose new research directions including the application of advanced machine learning to develop extensible and scalable prediction models and leveraging emerging sensing technologies for collecting, storing and analyzing the data. Finally, we addressed future directions of predictive analysis associated with the data-rich era that will potentially help transportation agencies to become information-rich.

Keywords: Roadway Maintenance; Predictive Maintenance; Asset Management; Roadway Asset; Deterioration Model.

1. Introduction

United States is globally ranked among the top two countries for its excellence in financial systems, business dynamism, and innovation capability by the global competitiveness report of world economic forum [1]. However, this report ranked the United States 11th for road quality. Maintenance, repair, and rehabilitation (MR&R) strategies, significantly influence the condition of our roadway infrastructure, which was scored D, consistent with WEF report, on 2017 infrastructure report card of American Society of Civil Engineers [2]. During past decades, the importance of transportation infrastructure maintenance has significantly grown due to its contribution to economic growth. Well-maintained transportation systems (a) better-connect geographical locations, (b) lower transportation and transaction costs—through decreased vehicle maintenance, reduced delays, and lowered fuel consumption, and (c) enhance the safety of transportation systems [1, 2].

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Among major maintenance strategies—predictive, preventive, and reactive—categorized by AASHTO (2011), predictive approaches have gained much importance in recent years. It is due to their potential in enhancing several aspects of maintenance objectives to lower cost over the life span of highways, increase the highway performance, provide optimal long-term planning capability, and integrate risk management into asset maintenance planning [3, 4]. In addition, advanced sensing technologies with lower price points and higher computing power coupled with emerging prediction models pave the way for accurate condition prediction of highway assets.

To this end, not only increased investment is necessary to close the \$543 billion capital investment gap for highways and bridges maintenance [2], but also smart investment is critical to take the optimal advantage of allocated budgets. Several state and federal level legislations such as MAP-21 [5], and FAST Act [6] were signed into law to increase investment and provide guidelines to enhance asset management. For example, state DOTs are required by FHWA to establish a process for conducting a network level Life Cycle Planning (LCP) for the National Highway System (NHS) pavements and bridges. FHWA defines LCP as the process of cost estimation for managing assets over their life span with consideration for minimizing cost while maximizing or preserving the condition. Identification of deterioration models that support predictive maintenance is one of the required elements of the LCP process as stated by FHWA. Life cycle planning will support prioritizing the improvement of various assets with minimum possible costs to achieve maximum possible return on investments on the roadway infrastructure [7-9]. While the current focus of most state DOTs is on project-level life cycle cost analysis, planning towards a network-level analysis is required to increase the return on maintenance investment. That is why data-driven predictive analytics of multiple highway asset classes is critical to LCP planning.

To investigate the potential of different predictive techniques in tackling the challenge of efficient and effective MR&R planning, we reviewed prediction models in the literature for a range of highway assets. We reviewed several methodologies, from simple subjective assessments based on experts' opinions to parsimonious probabilistic and deterministic approaches. We also discussed the limitations of reviewed techniques and how these shortcomings might impact the application and accuracy of the models. Furthermore, we explored the factors influencing the accuracy of predictive analytics and identified opportunities for future studies to take advantage of advanced sensing technologies, emerging predictive analytics paradigm, and computing power.

To obtain the objective of this study, in the next section, we will introduce the structure of our methodology. Next, we will explain the key terms in asset management used in this paper. Then, the categorized literature of the prediction methods will be reviewed along with the limitations and shortcomings of the methods. Finally, we will discuss our findings, opportunities for future studies.

2. Review Methodology

The review methodology includes selection of relevant papers, classification of the utilized prediction methods, and assessment of limitations and shortcomings of each class. To this end, we classified prediction methods for each asset types into two groups: deterioration and life expectancy. Deterioration models estimate the future condition, performance or level of service of an asset item. However, life expectancy models primarily deal with the prediction of time-based terms such as time of failures, time of required maintenances or treatment intervals. Next, we reviewed the papers based on the utilized algorithms for developing prediction models in three sub-categories: deterministic, probabilistic, and machine learning. Then, we provided a summary of the shortcomings and limitations in each sub-category. The framework of the methodology is illustrated in Figure 1.

In classifying highway asset items, it should be noted that state agencies have different classification. For example, California Department of Transportation (CalTrans) categorizes transportation assets in primary classes of pavements, bridges, culverts, and Intelligent Transportation Systems (ITS) [4]. However, North Carolina DOT classifies assets into seven primary groups of pavements, bridges, tunnels, roadside features, pavement markings, rest areas, and maintenance yards [10]. Among these categories, that are different from state to state, we reviewed prediction methods for a subset of assets, including pavements, pavement markings, traffic signs, barriers, and culverts.

We focused mostly on recent papers published in the past 20 years. To the best of our knowledge, we included most of the significant research studies reporting the application of predictive analytics. The total number of the investigated papers versus years of publication is shown in Figure 2.

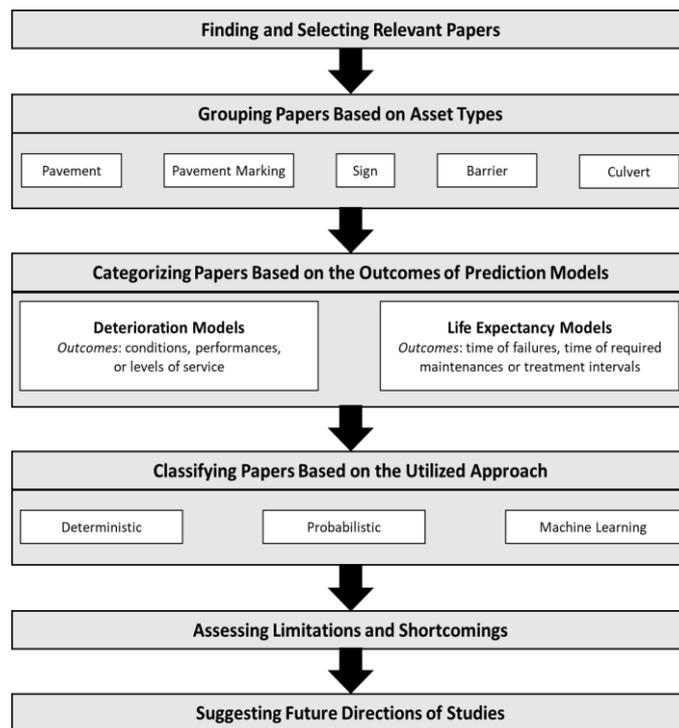


Figure 1. Methodology framework

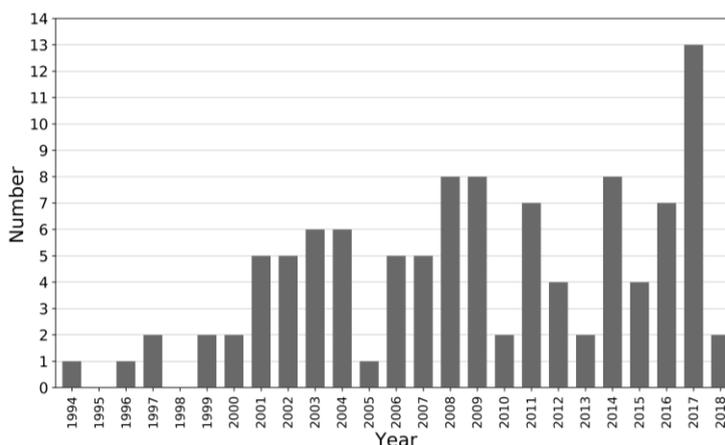


Figure 2. Number of investigated papers versus publication year

3. Key Terms in Asset Maintenance

Throughout this paper, the following terms are widely used. While a variety of definitions can be found in the literature, the authors comply with the following definitions and considerations.

Condition: The generally accepted use of the term “condition” refers to the physical characteristics of an asset which may affect its performance. The condition is assessed using physical factors.

Performance: To provide a satisfactory service, all transportation assets should work in an acceptable range of functional requirements. The performance of an asset denotes the degree to which these requirements are met, based on the expectations of users or owners [11, 12].

Condition and performance are highly correlated and they have been interchangeably used in the literature. Since the focus of this paper is on the process of prediction, we also used these two terms interchangeably.

Levels of Service: The condition of an asset or services provided by the owner, which is evaluated according to the user’s perception, is usually referred to its level of service. Levels of service are utilized to identify time and type of maintenance activities. This concept incorporates condition and performance into an easy to use indicator [13]. The NCHRP report provided a framework to measure levels of service based on quantitative grades using a letter-format classification [14].

Service Life: The period over which the performance of an asset is within an acceptable range is defined as its service life [11].

Remaining Service Interval: Because of different interpretations of Remaining Service Life (RSL) among stakeholders, and uncertain use of term “life” to represent various events of construction treatments in an asset’s history, another term, Remaining Service Intervals (RSI) was recently introduced. This term defines the remaining time until a specific required MR&R event. RSI focuses on two questions: when a treatment is needed and what kind of treatment should be used. This process is created by taking into consideration the Life-Cycle Cost Analysis (LCCA) and prioritization of maintenance activities, in accordance with future construction events and user’s benefits [15, 16].

Reactive, Preventive and Predictive Maintenance: AASHTO (2011) categorized transportation asset maintenance into: (1) reactive or unplanned and (2) proactive or planned [3]. Reactive maintenance refers to activities performed after a failure occurs in a system [17]. But proactive maintenance is a strategy that is accomplished to prevent or postpone a failure from taking place [18]. Preventive and predictive are two types of proactive maintenance. The preventive techniques refer to a series of scheduled activities to prolong the life of an asset. However, the predictive methods are based on an inspection analysis to forecast the time of failures in a system. This type of maintenance also schedules necessary maintenance actions to prevent those failures [19]. A schematic representation of maintenance strategies including reactive, preventive and predictive is shown in Figure 3.

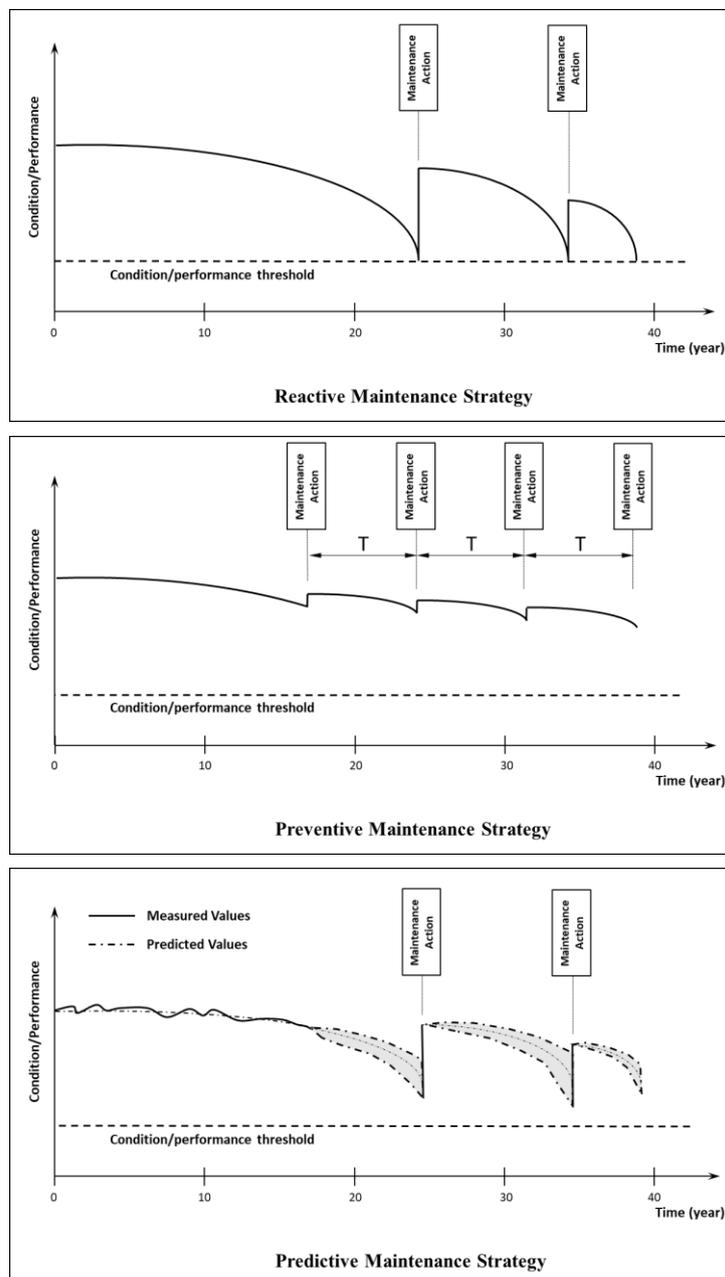


Figure 3. Schematic representation of maintenance strategies

Forecasting the future condition of assets is the most important aspect of the predictive strategy. Therefore, in the next section, we reviewed prediction models for a range of highway assets.

4. Prediction Models

Information about time, location and extent of foreseen failures, help agencies to be prepared for accomplishing associated treatments to those failures. One of the major drawbacks of using reactive maintenance is the lack of such information. Hence, the maintenance activities of the reactive method might be longer than expected and are relatively expensive. Unexpected failures result in unexpected times and costs of repairs. Therefore, budget allocation and coordination of maintenance teams in reactive strategy are poor. In contrast, proactive maintenance prevents most of the failures before happening and enables agencies to manage maintenance actions. In addition, the proactive strategy improves the reliability of the performance of highway assets by avoiding failures.

Preventive and predictive strategies, that are two types of proactive maintenance, perform maintenance works in two different ways that influence the efficiency of the maintenance plan differently. Since a preventive procedure implements a series of regular periodic actions with specified time intervals, sometimes it results in unnecessary maintenance works. But predictive procedures propose maintenance actions based on the forecasted condition of assets. Therefore, decision-making is relied on maintenance needs instead of predefined times of periodic actions. Consequently, in a predictive procedure the budget allocated to maintenance works is spent more efficiently.

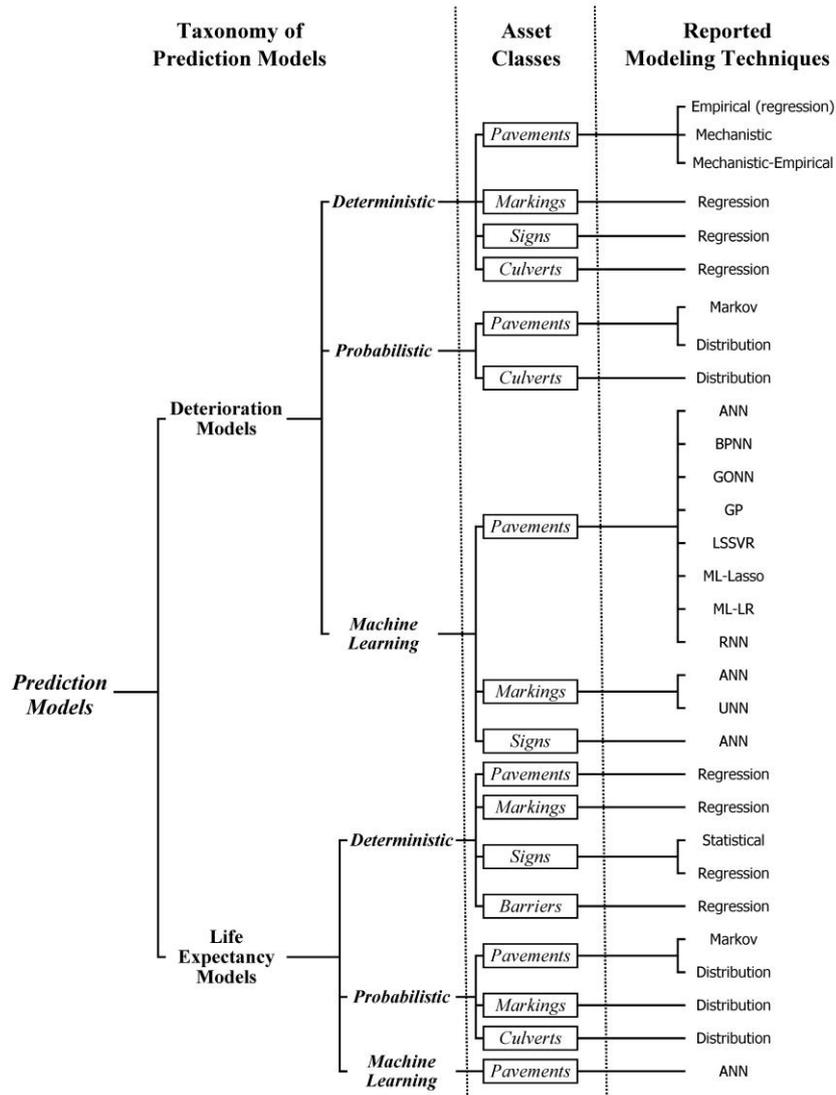
Agencies rely on prediction models to coordinate maintenance teams, allocate required budget, assign resources, and prioritize and schedule maintenance works. Predictive analytics provide valuable information about location, time and type of failures that are likely to happen. Based on the outcomes of the utilized models, we investigated the selected papers in two groups: deterioration and life expectancy. In the next section, a summary of the investigation is provided.

4.1. Deterioration and Life Expectancy Models

Models that forecast the future condition, performance or level of service of an asset item are known as deterioration models. In contrast, predictive modeling that primarily deals with forecasting the time of failures, time of required maintenances or time between treatments are referred to as life expectancy models.

Methodologies that are used to forecast the life expectancy are classified in condition-based and interval-based classes. In a condition-based technique, the timings of necessary maintenance interventions are evaluated by considering trigger levels. Trigger levels are adequate values of condition, under which the asset is unable to provide its required service quality, and maintenance activities should be carried out. Interval-based techniques use times of previous maintenance interventions to evaluate the time of the required maintenance, without direct consideration of the condition value. Incorporating condition-based and interval-based methods, which is called condition-interval hybrid, increases the potential of accurate outcomes [20].

Based on the algorithms used in developing a prediction model, deterioration and life expectancy groups can be classified into deterministic, probabilistic and machine learning classes. Deterministic models are in the form of mathematical functions. Probabilistic models use probability distributions to forecast a range of possible conditions or the probability of a particular condition in the future [21-23]. However, in a machine learning model, Artificial Intelligence (AI) is leveraged to find relationships between contributing factors and the condition/life expectancy of assets, based on the learning process from historically recorded data. Figure 4 unveils the classification of reviewed prediction models.



Note: ANN: Artificial Neural Network, BPNN: Back Propagation Neural Network, GONN: Genetically Optimized Neural Network, GP: Genetic Programming, LSSVR: Least Squares Support Vector Regression, ML-Lasso: Machine Learning regularized regression with Lasso, ML-LR: Machine Learning Linear Regression, RNN: Recurrent Neural Network, UNN: Unsupervised Neural Network

Figure 4. Classification of reviewed prediction models

Furthermore, Figure 5(a) shows the total number of reviewed papers classified in two groups of deterioration and life expectancy methods. Figure 5(b) reveals the total number of investigated papers in three sub-categories: deterministic, probabilistic and machine learning.

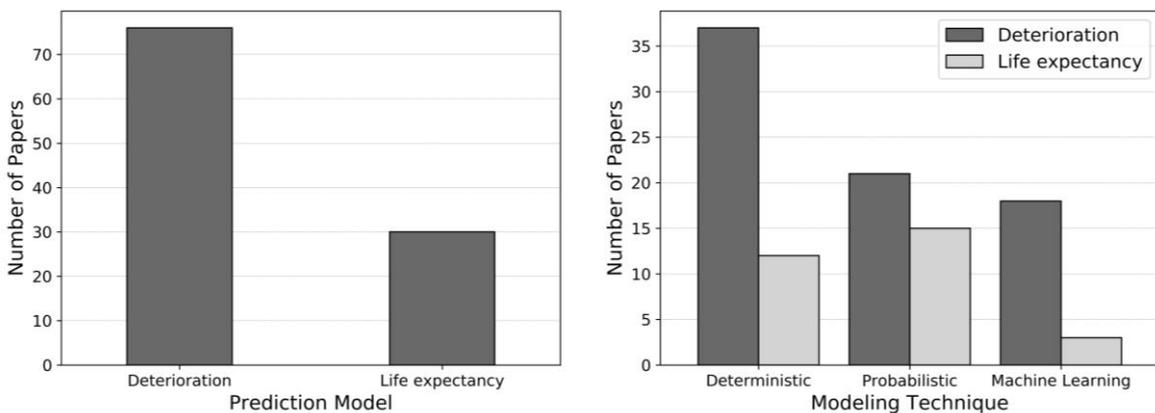


Figure 5. (a) Categories of reviewed deterioration and life expectancy models; (b) Categories of reviewed modeling techniques: deterministic, probabilistic and machine learning

4.2. Deterministic Models

Several parameters affect the condition of an asset. For example, pavement roughness, an index for the assessment of the pavement condition, is affected by initial roughness, age of pavement, climatic variables, structural characteristics of pavement, traffic load, subgrade specification, drainage type, drainage condition, and all historical treatment and maintenance activities [24-31]. Deterministic models introduce a relationship between the condition and factors that contribute to the deterioration. These models are vastly used by transportation agencies, because they are easy to understand and simple to use.

Reviewing the studies that developed deterministic models, revealed that they have focused only on a few factors that contribute to the degradation of assets. This has been due to the limitation of available data and insufficient knowledge about all factors that contribute to the deterioration. Consequently, considering a few numbers of contributors might limit the applicability, scalability, and extensibility of the models. Furthermore, in deterministic techniques, expert-based subjective assessments play a major role in the recognition of patterns in the data, which might impact the accuracy of the outcomes. Hence, to increase the reliability of the models, several studies reported the use of a combination of subjective engineering evaluation and statistical testing to find the relationships [32-34]. However, the subjectivity in making assumptions and simplifications are challenges of deterministic techniques.

4.3. Probabilistic Models

These models forecast the probability of the future condition/life expectancy of an asset or a range of possible condition/life expectancy by using the probability concept [35, 36]. These models represent a better view of risks. Therefore, they may help asset managers to reduce the risks of their decision makings [23, 37]. In this paper, reviewed probabilistic approaches are classified into Markov chain and distribution models.

Markov chain algorithms use the stochastic concept of the Markov process, in which the sequence of possible events is specified based on the probability of each event. This probability only depends on the state of the previous event. Transitions of the condition of an asset item, from one inspection time to the next one, create a transition matrix which is used to predict future condition values [38]. Markov chain is widely used to predict condition values, especially when there is not enough information on all contributing factors. The main focus of this model is on transition probabilities, and the cause of this transition, instead of factors that lead to the condition degradation. The analysis is merely based on the historical operation and maintenance data of roadways. A review of the literature on Markov chain approaches revealed they can be categorized into two types: homogenous and non-homogenous. Homogenous models assume that the condition of an asset item at a specified time is only related to its previous condition. Moreover, these models assume that transition probabilities are constant over time. The inaccuracy of outcomes may be resulted from such assumptions. Non-homogenous models use different transition probabilities at different times. Thus, these models consider all previous stages to predict the future condition of an asset. However, some studies reported inaccuracies of the results of non-homogenous models [39].

Distribution models use a specified probability distribution for the prediction purposes. The future condition and its probability are affected by a variety of factors, which remain unknown when available data are insufficient. Hence, using simplifications and selecting a probability distribution to specify condition probabilities during the lifetime of an asset help to forecast its future condition. However, the utilized probability distribution might not completely fit the actual observations and consequently leads to inaccuracies. Commonly probability distribution models that are addressed in the literature, are Weibull, Markov-Weibull, Cox, Kaplan-Meier, ordered-probit and Bayesian.

In a Weibull-based analysis, the survival time distribution of an asset item is assumed to follow the Weibull probability distribution. In the Markov-Weibull procedure, the Markov transition matrix and the Weibull survival distribution are incorporated to predict condition possibilities in the future. In this model, the Weibull distribution is used to find an age-based probability of failures. Cox is a well-recognized proportional hazard model. In the Kaplan-Meier model, the survival function is estimated from recorded data. In Ordered-probit, the probability concept is used to forecast the condition of an asset in discrete ordinal levels. Finally, Bayesian analysis incorporates existing knowledge of condition measurements with the information from historical observations to provide a probabilistic prediction model [22, 23, 40].

4.4. Machine Learning Models

Arthur Samuel introduced the machine learning concept in 1959. The learning process of a computer when it is not explicitly programmed is referred to as machine learning [41]. In recent years, the use of machine learning has attracted the attention of researchers in the prediction of maintenance activities [42]. A machine learning technique investigates deep inter/intra-correlations and patterns in a dataset with minimal human intervention. By learning from data, instead of using subjective assumptions and simplifications, machine learning improves predictive analytics.

Artificial Neural Network (ANN) is one of the most commonly used machine learning algorithms in highway asset management. Time-consuming training process and instability in local minimum points during training were addressed in the literature as shortcomings of the ANN. Additionally, selecting the optimal architecture of neural nets and choosing proper training algorithms have been addressed as challenging issues in an ANN model [22].

A summary of the reviewed prediction approaches in the literature for a range of transportation assets is provided in the next sections.

4.5. Pavement Prediction Models

Because of the huge length of roadways, the budget allocated to maintenance activities on pavements is considerably high. Furthermore, the condition of pavements influences the traffic and safety. Consequently, pavement is considered as a high capital asset in the highway asset management. We reviewed prediction models for pavements under two categories: deterioration and life expectancy models.

4.5.1. Pavement Deterioration Models

In this section, pavement deterioration models are reviewed in three main groups: deterministic, probabilistic and machine learning.

4.5.1.1. Deterministic Models

Since these models are easy to understand and simple to use, they are widely used by transportation agencies. Deterministic models for pavements are classified into three groups: mechanistic, empirical and mechanistic-empirical.

In a mechanistic approach, the process of condition prediction is accomplished based on the mechanical and structural characteristics of pavements [21]. Mechanistic models define the condition of assets as a function of mechanistic responses, including stresses, strains, and deflections. For example, the load of vehicle wheels is utilized to estimate stresses and strains in a pavement layer. Then, these estimations are utilized in mechanistic functions to quantify condition values [35, 43]. Hence, these models provide a deep understanding of the relationships between mechanical responses and the condition. However, the accuracy of results is questionable due to the complexity of considering all parameters that potentially influence the condition [22].

Empirical methods deploy statistical analysis and consider main factors that contribute to the deterioration, such as traffic load and pavement age [21]. Literature review unveils widely use of empirical procedures to predict the future condition of pavements. However, shortages in the available data made these models be valid only in limited situations. Furthermore, a key problem with most of the empirical methods is that they consider only a few determinant factors in the degradation of assets due to the insufficient available data or the limitations of the utilized analysis algorithms. The complexity of equations that define the relationship between contributing factors and the condition is addressed as another challenge [25].

Linear and non-linear regression is commonly used in empirical methods. In contrast with linear regression, non-linear approaches have a better estimation because of their capability of testing multiple arrangements of condition curves [32]. When regression analysis is conducted with one variable, it is called the univariable regression method. If multiple variables are used, it is known as a multivariable regression technique. Due to a variety of factors that might impact the degradation of assets, univariable regression methods are usually unable to provide accurate outcomes.

Mechanistic-empirical procedures use mechanistic functions and historical observations to come up with a prediction model. These models determine functional forms and descriptive variables by leveraging mechanistic methods [21, 22]. These models are often applied at the project level and rarely at the network level. However, in contrast with empirical methods, these models can be used in more situations [44]. Nevertheless, calibration is a vital process to make the models be valid in various situations [21]. In addition, the main challenge of mechanistic-empirical models is the need for more structural data that are usually unavailable. Table 1 shows a summary of reviewed papers that developed deterministic models for the prediction of the pavement condition.

Table 1. Summary of deterministic prediction models for pavement deterioration in reviewed papers

Author(s)	Year	Application	Contribution	Approach
Norouzi and Kim [45]	2017	Asphalt	Developing a Layered Viscoelastic Critical Distresses (LVECD) model to predict the fatigue performance	Mechanistic
Al-Qadi, Elseifi [46]	2004	Hot-Mix Asphalt (HMA)	Developing a finite element model to predict pavement surface damage and its partial recovery after load application	

Kim, Won [47]	2001	Continuous reinforced concrete	Incorporating temperature and moisture variation of the concrete slab to expand the ability of previous mechanistic models	
Alaswadko, Hassan [48]	2017	Sealed granular pavements	Improving robustness of multilevel roughness progression prediction by considering traffic data, subgrade characteristics, climate and condition of drainage condition	
Hassan, Lin [49]	2017	Chip/spray seal (SS), Geotextile seal (GEO), Stone mastic asphalt (AC), Open graded asphalt (OGA), Ultra-thin asphalt (UTA)	Improving identification and prioritization of resurfacing needs by comparing deterioration models of five types of bituminous surfacing	
Sylvestre, Bilodeau [50]	2017	Flexible pavements	Taking into consideration the frost heave in long-term roughness performance prediction model	
Wang, Qin [22]	2017	Jointed plain concrete pavement (JPCP)	Comparing Multivariate Non-Linear Regression (MVLN) faulting-based pavement performance model with ANN and Markov Chain models and investigating their accuracy	
Sultana, Chai [51]	2016	Flexible pavements	Incorporating flooding impacts on a prediction model for short-term behavior of flexible pavements	Empirical
Ziari, Sobhani [52]	2016	Flexible pavements	Comparing capabilities of Group Method of Data Handling (GMDH) and Artificial Neural Network (ANN) for IRI prediction	
Anyala, Odoki [21]	2014	Asphalt	Incorporating climate change impacts in the deterioration model	
Chen and Zhang [53]	2011	Asphalt	Investigating the applicability of four IRI-based deterministic deterioration prediction models	
Prozzi and Madanat [54]	2004	General	Optimizing the use of available experimental and field data and improving statistical properties compared with techniques such as ordinary least squares	
Hoerner, Darter [44]	2000	Portland Cement Concrete (PCC)	Improving and increasing the accuracy of a performance prediction model	
Mohd Hasan, Hiller [55]	2016	Flexible pavements	Investigating the effects of mean annual precipitation & temperature on distresses	
Jung and Zollinger [56]	2011	Jointed plain concrete pavement (JPCP)	Considering subbase erosion, this was not included in the design-related analysis before	
Ker, Lee [57]	2008	Jointed plain concrete pavement (JPCP)	Tackling the challenge of the inadequate accuracy of previous prediction model in NCHRP Project 1-37 A	Mechanistic-Empirical
Sun, Hudson [58]	2003	Flexible pavements	Formulating the probability density distribution of fatigue damage of flexible pavements and increasing the accuracy of fatigue cracking forecasts	

4.5.1.2. Probabilistic Models

Table 2 reveals a summary of reviewed papers associated with probabilistic models for the prediction of the pavement condition. The review revealed that the Markov chain is the most commonly used probabilistic method to forecast the performance of pavements.

Table 2. Summary of probabilistic prediction models for pavement deterioration in reviewed papers

Author(s)	Year	Application	Contribution	Approach
Rose, Mathew [59]	2018	Low volume roads	Considering and incorporating uncertainties of low volume road pavement behavior in predictions that are not taken into account in deterministic models	Gamma, exponential & inverse-Gaussian
Soncim, de Oliveira [60]	2017	Asphalt	Introducing a procedure for IRI forecasting where there are no historical data of conditions	Markov chain
Saha, Ksaibati [61]	2017	General	Improving deterministic techniques used in Colorado DOT for deterioration prediction by considering uncertainties of degradation process	Markov chain
Abaza [62]	2017	Rehabilitated pavement	Proposing a model for the performance of rehabilitated pavements that was not adequately addressed in previous studies	Markov chain
Abaza [63]	2016	Flexible pavements	Considering the increase of deterioration transition probabilities over time due to increasing traffic loading and degradation	Markov chain

Chen, Cavalline [64]	2014	Flexible pavements	Developing a prediction model for transverse cracking condition with ordinal ratings by computing individual distress probabilities using ordinal logistic regression	Ordinal logistic
Khan, Mesbah [65]	2014	General	Enhancing decision making for appropriate treatments applicable to post-flooding rehabilitations by considering flooding effect	Markov chain
Anyala, Odoki [21]	2014	General	Using Bayesian and Monte Carlo sampling for multi-regression prediction model to investigate climate change impacts on the deterioration	Bayesian
Thomas and Sobanjo [66]	2013	Flexible pavements	Developing a semi-Markov model to mitigate the restriction of other Markov models due to their memoryless property	Markov chain
Gao, Aguiar-Moya [67]	2012	Flexible pavements	Considering unobserved heterogeneity by adding a random term to hazard function and removing inconsistent estimations of fatigue cracking	Bayesian
Chen and Zhang [53]	2011	General	Comparing a survival curve prediction model for pavement service life with pavement age and traffic loading approaches	Kaplan-Meier
Kobayashi, Do [68]	2010	General	Proposing a new approach for the estimation of the condition states transition probabilities for any arbitrary time intervals, which previous studies lacked	Markov chain & Weibull hazard
Pulugurta, Shao [69]	2009	General	Providing the capability of forecasting various distresses and improving pavement condition prediction for Ohio DOT	Markov chain
Golroo and Tighe [70]	2009	Concrete pavements	Tackling the challenges of subjective & limited data for developing prediction models in cold climates	Markov chain
Nakat and Madanat [71]	2008	Pavement overlays	Using new hazard function shape to develop a prediction model for crack initiation with more realistic maintenance prediction	Cox
Li and Zhang [72]	2007	General	Developing prediction models to capture the dynamic and stochastic nature of pavement deterioration processes by using a structural state space model	Ordered-probit
Pulugurta [73]	2007	General	Increasing the accuracy of the prediction by investigating pavements in three separated groups with low, medium and high performance	Kaplan-Meier
Ortiz-García, Costello [74]	2006	General	Developing new procedures for formulation of transition matrices to mitigate difficulties of transition determination from empirical data and observations	Markov chain
Hong and Prozzi [75]	2006	General	Providing a more realistic forecast by a fully accounting for the heterogeneity issue	Bayesian & Markov

4.5.1.3. Machine Learning Models

A review of the literature on machine learning prediction models for pavements unveiled that most studies used Artificial Neural Network (ANN) technique. Table 3 provides a summary of the reviewed papers.

Table 3. Summary of machine learning prediction models for pavement deterioration in reviewed papers

Author(s)	Year	Application	Contribution	Approach
Chopra, Parida [76]	2018	Flexible pavements	Increasing the accuracy of distress deterioration prediction	GP
Okuda, Suzuki [77]	2017	General	Improving algorithms to increase the rutting depth prediction accuracy, using RNN	RNN
Marcelino, de Lurdes Antunes [78]	2017	Asphalt	Comparing two machine learning approaches, one based on linear regression and another one on regularized regression with lasso, to predict the pavement friction	ML-LR & ML-Lasso
Hamdi, Hadiwardoyo [79]	2017	Flexible pavements	Developing an ANN model to predict Surface Distress Index (SDI)	ANN
Sanabria, Valentin [23]	2017	Flexible pavements	Comparing capabilities of ANN and ordered-probit models in forecasting the pavement distress rate	ANN
Amin and Amador-Jiménez [80]	2017	Flexible & rigid pavements	Reducing the measurement errors of pavement performance modelling	BPNN
Karlaftis and Badr [81]	2015	Asphalt	Increasing the accuracy of probability forecasts of alligator crack initiation following rehabilitation treatments	GONN
Kargah-Ostadi and Stoffels [33]	2015	Asphalt	Preparing a framework for comprehensive comparison of techniques used for pavement performance modeling, and improving the robustness of parameterization	ANN

Sirvio and Hollmén [82]	2014	General	Comparing three prediction model for road condition	LSSVR
Lee, Ker [83]	2014	Flexible pavements	Increasing the accuracy and decreasing training time of ANN by taking all dominating dimensionless parameters into account	ANN
Saghafi, Hassani [84]	2009	Jointed plain concrete pavement (JPCP)	Comparing ANN and Multivariate Linear Regression (MLR) prediction methods for transverse joint faulting	ANN
Tack [85]	2003	General	Considering both spatial and non-spatial variability in forecasting process	ANN
Yang, Lu [86]	2003	Asphalt	Increasing the accuracy of forecasts for crack, ride and rut ratings, compared with traditional regression procedures	ANN
Lou, Gunaratne [87]	2001	Asphalt	Using ANN for crack index prediction to avoid difficulties in the selection of appropriate formulations in mechanistic-empirical and empirical models	ANN
Attoh-Okine [88]	1994	Flexible pavements	Evaluating the capabilities of ANNs in predicting roughness progression in flexible pavement from structural deformation	ANN

Note: ANN: Artificial Neural Network, BPNN: Back Propagation Neural Network, GONN: Genetically Optimized Neural Network, GP: Genetic Programming, LSSVR: Least Squares Support Vector Regression, ML-Lasso: Machine Learning regularized regression with Lasso, ML-LR: Machine Learning Linear Regression, RNN: Recurrent Neural Network

4.5.2. Pavement Life Expectancy Models

A variety of factors affect the life of an asset: Pavement material, traffic, age, climatic parameters, subgrade specifications, maintenance, and operation history are some of these factors that are addressed for pavements [20]. All contributing factors to the deterioration of an asset influence the length of its life or remaining service intervals. Life expectancy models consider these factors to predict time-based terms, such as remaining time to failure or remaining time to the next maintenance need. These terms are usually achievable by using deterioration models. But, in this section, we reviewed life expectancy models separately because they specifically focus on the quantification of time-based terms. We reviewed life expectancy models in three groups of deterministic, probabilistic and machine learning.

4.5.2.1. Deterministic Models

The reviewed papers that leveraged deterministic approaches for the prediction of life expectancy of pavements, utilized linear and non-linear regression techniques for explaining the relationship between variables. Table 4 provides a summary of these papers.

4.5.2.2. Probabilistic Models

Probabilistic techniques are used to forecast the life expectancy of pavements. Table 5 shows a summary of the reviewed studies that developed probabilistic models.

Table 4. Summary of deterministic prediction models for pavement life expectancy in reviewed papers

Author(s)	Year	Application	Contribution	Approach
Gedafa, Hossain [90]	2010	Flexible pavements	Developing a model to forecast RSL from surface deflections	
Chou, Pulugurta [91]	2008	General	Comparing three methods to determine RSL of pavements based on their forecasted conditions	
Flom and Darter [92]	2005	Concrete pavements	Comparing three methods for predicting RSL	
Lee, Chatti [93]	2002	Flexible, rigid & composite pavements	Enabling highway agencies to determine when a particular pavement needs to be smoothed to obtain a given (desired) life extension	Regression
Labi [94]	2001	General	Investigating impacts of maintenance treatments in short-term and entire life of pavements, and examining the trade-off relationships between rehabilitation intervals and maintenance, traffic loading and weather to improve pavement management system	

Table 5. Summary of probabilistic prediction models for pavement life expectancy in reviewed papers

Author(s)	Year	Application	Contribution	Approach
Han and Lee [95]	2016	General	Investigating uncertainties in deterioration process and various maintenance criteria & developing a method to determine joint distribution of total maintenance demands	Bayesian Markov hazard
Irfan, Khurshid [96]	2009	Thin hot-mix asphalt overlay	Proposing a probabilistic approach to capture the stochastic nature of the post-overlay deterioration, and investigating the variability in the life of that treatment	Survival analysis

Anastasopoulos [97]	2009	General	Developing a model to evaluate the effectiveness of rehabilitation treatments on service life	Probability distribution
Yu, Chou [98]	2008	Asphalt overlays	Considering the structure thickness, climate, traffic loading, and pavement conditions prior to repair in the RSL prediction method	Cox
Chou, Pulugurta [91]	2008	General	Comparing three methods to determine RSL based on forecasted conditions	Markov chain
Yang [99]	2007	General	Comparing parametric duration models with nonparametric life table method	Duration
Bausano, Chatti [100]	2004	Asphalt	Preparing a decision support table to express the probability of reaching the performance of a particular pavement with a given preventive maintenance treatment to a specified threshold	Probability distribution
Chou, Tack [101]	2004	General	Investigating the variation of pavement performances among Ohio DOT districts to improve treatment strategies and allocation of associated funds	Kaplan-Meier
Gharaibeh and Darter [102]	2003	Flexible and rigid pavements	Developing RSL prediction model for Illinois DOT flexible and rigid pavements and overlays, and proposing a methodology to forecast the probability of failures	
Shekharan and Ostrom [103]	2002	Flexible & rigid pavements	Providing a methodology to forecast RSL based on the reliability and traffic loadings	
Romanoschi, Metcalf [104]	1999	Flexible pavements	Developing a model for RSL prediction of road lanes with several alternative base construction materials in semitropical climate	Survival analysis
Colucci, Ramírez-Beltrán [105]	1997	Flexible pavements	Considering different climatic regions with various subgrade conditions in RSL forecasts	
Vepa, George [106]	1996	Flexible pavements	Comparing models for RSL prediction	

4.5.2.3. Machine Learning Models

Some studies were carried out to implement machine learning to forecast life expectancy of pavements. ANN models were commonly used for this purpose. Table 6 reveals a summary of the reviewed papers that leveraged machine learning to predict the life expectancy of pavements.

Table 6. Summary of machine learning prediction models for pavement life expectancy in reviewed papers

Author(s)	Year	Application	Contribution	Approach
Miradi, Molenaar [107]	2009	Porous asphalt concrete	Investigating historical data of the porous asphalt concrete to provide better understanding of its behavior and predicting its service lifespan	ANN
Abdallah, Ferregut [108]	2000	Flexible pavements	Developing a software program for the remaining life forecasting without the necessity of back-calculation process for determining the moduli	ANN
Ferregut, Abdallah [109]	1999	Flexible and rigid pavements	Proposing a method for computation of remaining life of a section of road without the need for laboratory-derived properties data and back-calculation of the elastic moduli of each pavement layer	ANN

ANN: Artificial Neural Network

4.6. Markings Prediction Models

Pavement markings are generally used to convey messages to drivers. Markings provide helpful information such as which part of the road should be used, what conditions are ahead or where passing is allowed. There are various types of markings associated with their role. The expected roles of markings in a transportation system indicate their color, pattern, shape, and location. As markings are usually in contact with corrosive and destructive phenomena, they deteriorate over time. Some of the causal factors of deteriorations are weather and climatic parameters, debris and vehicle transit. In this paper, the review of markings prediction models was conducted in two groups: deterioration and life expectancy.

4.6.1. Markings Deterioration Models

Retroreflectivity is a general definition used to evaluate the performance of markings. Retroreflectivity is the capability of materials to reflect light back to its source [89]. For markings, the retroreflectivity reveals the ability of

which for reflecting light from vehicle headlights to the eye of drivers [40]. To predict the future condition of markings, most studies focused on the retroreflectivity forecasts. Deterministic methods are the most common procedure used in the reviewed studies. However, there were a few studies that developed machine learning models. A summary of the literature on the prediction modeling for the deterioration of markings is given in Table 7.

4.6.2. Markings Life Expectancy Models

Most research studies on the life expectancy of markings used deterministic approaches. A summary of the review of life expectancy models for markings is outlined in Table 8.

4.7. Signs Prediction Models

In this paper, signs prediction models were reviewed in deterioration and life expectancy classes.

4.7.1. Signs Deterioration Models

To measure the condition of a sign, retroreflectivity is the most common characteristic which is identified as a condition indicator [130]. The retroreflectivity identifies how a sign is distinguishable during day and night, and the measurement of this parameter has a main role in preparing maintenance plans. A review of the literature showed various contributing factors to the retroreflectivity degradation. Most of the previous studies used deterministic procedures to find a relationship between determinant parameters and the condition of a sign. There are a few research studies on other types of prediction models. For example, Swargam et al. (2004) utilized an ANN method to predict the sign retroreflectivity based on the Louisiana DOT database and compared its results with linear regression models [131]. The reviewed papers that used deterministic models for signs are addressed in Table 9.

4.7.2. Signs Life Expectancy Models

The review of previous studies showed that models developed for the prediction of life expectancies of signs are mainly deterministic. A summary of the reviewed research studies is shown in Table 10.

Table 7. Summary of prediction models for markings deterioration in reviewed papers

Author(s)	Year	Application	Contribution	Approach	Model class
Wang, Wang [110]	2016	Durable pavement markings	Improving degradation models by considering winter weather events in the prediction process	Piecewise multiple linear regression	
Malyuta [111]	2015	Pavement markings on asphalt	Investigating contributing factors to degradation and proposing a prediction model for Tennessee highways	Linear regression	
Robertson, Sarasua [112]	2013	High-build waterborne and conventional waterborne pavement markings	Developing a method for estimating and comparing lifecycles of pavement markings on non-interstate primary and secondary roads in South Carolina	Stepwise regression	
Sitzabee, White [113]	2012	Polyurea pavement markings	Proposing a performance model for North Carolina and investigating the effects of the type of glass bead in markings deterioration trend	Linear regression	
Fares, Shahata [114]	2012	General	Developing performance prediction models for different lateral locations and materials in various type of roads in cold weather	Regression	Deterministic
Hummer, Rasdorf [115]	2011	Markings in two-lane rural roads	Improving the accuracy of degradation modeling for North Carolina by using a longitudinal data analysis	Linear mixed-effects	
Sitzabee, Hummer [116]	2009	Thermoplastic pavement markings	Examining the relationships between retroreflectivity values and time, traffic volume, and marking color in North Carolina by considering lateral location of markings	Linear regression	
Fitch and Ahearn [117]	2007	Thermoplastic, polyurea & epoxy paint markings	Evaluating the retroreflectivity and resistance to wear of several types of durable markings	Logarithmic regression	
Bahar, Masliah [118]	2006	Longitudinal pavement markings and markers	Investigating the safety effect of retroreflectivity over time on non-intersection locations during non-daylight conditions	Polynomial regression	
Kopf [119]	2004	Waterborne and solvent-based paint markings	Preparing degradation curves for markings	Logarithmic & exponential regression	

Sarasua, Clarke [120]	2003	Interstate highway markings	Comparing devices for collecting retroreflectivity data, and developing retroreflectivity prediction models in South Carolina	Linear & non-linear regression	
Lindly and Wijesundera [121]	2003	Flat thermoplastic & profiled pavement markings	Comparing service life, life-cycle costs, crash rates, and wet-night retroreflectivity of two types of markings	Linear & exponential regression	
Migletz, Graham [122]	2001	Edge-lines, center-lines & lane-lines	Evaluating condition of different marking lines with different materials and types of roadways as a function of time & traffic	Linear & exponential regression	
Elwakil, Eweda [123]	2014	Alkyd paint markings	Modeling the effect of various factors on the condition	UNN	
Karwa and Donnell [89]	2011	Thermoplastic markings	Proposing a performance prediction model to consider nonlinear relationships between determinant factors and retroreflectivity	ANN	Machine learning

Note: ANN: Artificial Neural Network, UNN: Unsupervised Neural Network

4.8. Barriers and Culverts Prediction Models

To gain better perspective on prediction models that are used in various asset items we reviewed some of the studies on barriers and culverts. Whether deterioration or life expectancy models are considered, most studies utilized deterministic and probabilistic approaches for their prediction. A summary of the reviewed studies for culverts and barriers is shown in Table 11.

Table 8. Summary of prediction models for markings life expectancy in reviewed papers

Author(s)	Year	Application	Contribution	Approach	Model class
Pike and Songchitruksa [124]	2015	Longitudinal markings	Providing better understanding of the relationship between the accelerated wear area on a transverse marking and how it relates to typical wear on a longitudinal marking	Exponential decay regression	
Abboud and Bowman [125]	2002	Paint & thermoplastic Striping	Preparing a method for service life determination by considering striping age and average daily traffic (ADT)	Exponential regression	
Migletz and Graham [126]	2002	Markings and markers	Synthesizing and summarizing resources that addressed evaluation of service life	Regression	Deterministic
Andrady [127]	1997	Solvent-borne & water-based paints, thermoplastic markings, tapes and raised pavement markers installed using an adhesive	Proposing a material-selection method considering impacts of Volatile Organic Compounds (VOC) and Hazardous Air Pollutants (HAP) and engineering performance	Logarithmic regression	
Sathyanarayanan, Shankar [128]	2008	Water-based paints	Proposing a procedure to forecast service life	Weibull	Probabilistic
Zhang and Wu [129]	2006	Pavement markings	Developing a methodology for predicting service life	Time-series analysis	

Table 9. Summary of prediction models for signs deterioration in reviewed papers

Author(s)	Year	Application	Contribution	Approach	Model class
Immaneni, Hummer [132]	2009	Type I to type III	Developing a model to assess the decrease of the condition of signs over time	Linear non-linear regression	
Rasdorf, Hummer [133]	2006	Type I to type III	Providing a sign replacement decision system to enable NCDOT to optimize sign management activities	Linear regression	Deterministic
Kirk, Hunt [130]	2001	Type III	Establishing a relationship between the condition of signs and their age considering effects of physical orientation of signs	Linear regression	
Black [134]	1992	Type II & type III-A	Proposing time of replacements for signs based on their condition	Linear regression	
Swargam [131]	2004	Type I & type III	Comparing ANN condition prediction model with linear regression methods	ANN	Machine learning

Note: ANN: Artificial Neural Network

Table 10. Summary of prediction models for signs life expectancy in reviewed papers

Author(s)	Year	Application	Contribution	Approach	Model class
Ré, Miles [135]	2011	Type III	Proposing a model to estimate the service life of signs in Texas	Linear regression	
Markow [136]	2007	General	Synthesizing state of the practices for life prediction	Statistical analysis	Deterministic
Bischoff and Bullock [137]	2002	ASTM Type III	Assessing the service life of signs with different colors	Statistical analysis	

5. Discussion

Prediction algorithms are one of the key elements in making optimal life cycle decisions for maintenance management. Accurate predictions will help to develop decision support systems for improving the performance of assets while decreasing their life cycle maintenance costs. The authors of this paper investigated the literature of prediction models for transportation asset management and highlighted some of their shortcomings that might lead to inaccuracy of the outcomes. The level of inaccuracies is different across asset classes, and prediction methods. In addition, considering the amount of data, which has recently become available through new sensing technologies, the accuracy of some of these models still seems unsatisfactory.

Table 11. Summary of prediction models for barriers and culverts in reviewed papers

Author(s)	Year	Application	Contribution	Approach	Model class
O'Neil and Smith [138]	2016	W-beam & Wire-Rope barriers	Investigating the occurrence and maintenance costs of vehicle strikes on barriers	Linear and non-linear regression	
Chimba, Emaasit [139]	2014	Median cable barriers	Developing a model to forecast the frequency of median-crashes and needs for replacements	Poisson and negative binomial regression	Deterministic
Salem, Salman [140]	2012	Culverts	Examining significant factors that affect culvert performance and durability	Binary logistic regression	
Karim, Alam [141]	2011	Barriers	Examining factors that impact barrier maintenance costs and propose a method to estimate the number of repairs	Linear and Poisson regression	
Halmen, Trejo [142]	2008	Galvanized culverts	Investigating the corrosion performance of culvert embedded in different controlled low-strength materials	Probability distribution	Probabilistic
Meegoda, Juliano [143]	2008	Brick/Clay, Concrete, Cast Iron, Corrugated Steel and Corrugated Aluminium culverts	Proposing a method to forecast RSL of five different type of culverts including a reliability analysis	Weibull	

In this section, some of the important limitations and challenges of the reviewed prediction methods are discussed.

- In deterministic and probabilistic methods, some simplifications are made to define and formalize relationships between variables. In addition, the process for recognition of patterns is based on subjective assumptions and simplifications. For example, in the Weibull distribution models, it is assumed that the distribution of survival time for an asset follows Weibull probability distribution, which may not completely fit the actual historical observations. Therefore, these assumptions may lead to meaningful discrepancies between the forecasted and observed values.
- Since the 90s, ANN is a widely used machine learning algorithm in the prediction problems including condition or life expectancy of highway assets. In traditional ANNs, not only selection of training algorithms, and optimal architecture of the model are challenging; But also, time-consuming training process and instability of the model in local minimum points limit the performance of the models [22, 144]
- Most prediction models were built upon limited historical data. Costly data collection procedures in the past and limited available sensing technology to facilitate extensive data collection are some of the reasons for inadequate historical data. The robustness of data processing and developing a prediction model highly depends on the quantity and accuracy of the collected data. Sometimes, the inadequacy of the data is a major challenge. Consequently, most prediction models are not scalable and extensible, and the inaccuracy of outcomes is likely.
- Addressed predictive procedures considered limited factors that have a probable contribution to the deterioration. It was due to the limited available data and/or challenges of big-data analysis at the time of the previous studies.

- The condition of asset items might be affected by the condition of other assets. For example, pipe erosion of underway culverts has the potential of impacting the pavement condition. Most prediction models focused only on one asset item or analyzed the behavior of assets independently. Therefore, the interrelation between neighboring asset items and their mutual impacts has not been the focus of most studies.
- Advancements in material science and the utilization of new materials in the construction and maintenance of transportation assets will impact operation and maintenance decisions. For example, using lightweight structural materials, including foamed structures, magnesium-based components, and advanced aluminum alloys [145], self-healing concrete [146], nano-materials in concrete [147], and nano-modified asphalts [148]. Utilizing new materials in construction or production of highway assets results in a change of characteristics and the enhancement of their properties. There are limited studies on the deterioration pattern of these new materials to be used in prediction models.
- Most studies focus on primary roads and interstate highways, and there are a few studies on secondary and rural roadways. Hence, the accuracy of the prediction in these roadways is still a challenge.

6. Conclusions

Different deterministic, probabilistic, and machine learning models have been developed for pavements, however, developing prediction models for other assets has often been based on deterministic or probabilistic methods. The current review has raised several shortcomings of existing models that calls for further investigation. The critical issues and challenges, discussed in the previous section, suggest the following opportunities for the future research studies.

- By improving data modeling, state-of-the-art machine learning and deep learning approaches tackle challenges of subjective assumptions and simplifications in deterministic and probabilistic models. Machine learning methods, by minimal human intervention, use fewer assumptions about inter/intra correlations in data. Additionally, they provide insights into deep correlations and patterns that might not be apparent to a human. Furthermore, advanced machine learning algorithms and training methods mitigate several shortcomings and limitations of traditional ANNs and offers the potential for beneficial developments in prediction models. Therefore, it is recommended that future studies investigate the potential use of advanced machine learning and deep learning models in condition predictions.
- To overcome the challenge of limited available data, more frequent and extensive data collection are needed. Advanced sensing technologies facilitate inspection and data collection processes. For example, collecting 3D surface data by using Stereovision and Light Detection And Ranging (LIDAR) [149], utilizing Unmanned Aerial Vehicles (UAV), and robots such as Pioneer P3-AT and Pioneer 3-DX for inspection purposes [150]. Future studies should be conducted to investigate these technologies and their impacts on the cost, safety, and accuracy of data collection to identify high impact technologies. In addition, requirements for the implementation of a data management system for storing and processing the collected data should be investigated.
- The integration of big-data analytics and advanced sensing technologies delivers an enormous amount of data for developing a robust predictive analysis. To handle the huge volume of data a platform is required for connecting, securing and analyzing the data [151]. Research studies should be conducted to identify and propose the structure and application of the platform in TAM, including collecting, storing and manipulating the data.
- Recently, specialized hardware productions make the complex computation of massive data more possible than before. Furthermore, using state-of-the-art methods of data analysis provides more opportunities for researchers to examine big-data in their studies on predictive maintenance. Therefore, new investigations are recommended to examine the potential of various factors that have probable contributions to the deterioration but are not considered in the previous studies.
- To respond to the challenge of considering the mutual impacts of multiple nearby assets, further studies are needed to examine and consider interrelationships between conditions of multiple assets in neighboring locations. Consideration of the mutual impacts helps to improve the robustness of forecasting models.
- The effects of extreme climate events lead to situations that are not considered in the design of many infrastructures. Drought, extreme flood, warm weather, changing wind speed, hurricanes and intense freezing-thawing cycles are some of climate change consequences [145]. Climate change impacts roadway assets. For example, more frequent buckling might occur because of the rising temperature, unpaved shoulders might be washed-out due to increasing of intense precipitations, and intense freezing-thawing cycles lead to more cracks on pavements. Hence, MR&R plans based on the current prediction models should be reassessed to improve the

resiliency of assets to climate change. More studies are needed to consider climate change, examine its impacts on the long-term performance of assets, and develop new prediction models.

- The investigation of how advancements in treatment technologies and the use of new materials impact predictive maintenance is another challenge for future studies. New prediction models are needed to consider the impacts of new materials on the performance or useful life of asset items.
- There are many studies on new methods of commuting to make greener, safer and more efficient transportation systems. For example, innovations in transportation methods and state-of-the-art Autonomous Vehicle (AV) technologies are expected to make a revolution in the transit system. On one hand, this change has significant effects on traffic patterns and consequently on the condition and performance of asset items and their useful life. Hence, future studies should deal with the effects of new methods of commuting on the prediction of the deterioration and life expectancy. On the other hand, using AVs will change the extent of needs for some of assets. For example, the width of lanes and shoulders, using median barriers and guardrails are some of the issues that will be affected by the use of AVs. This emerging paradigm of transportation leads to a new and different viewpoint in the design, construction, operation, and maintenance of the transportation system. Therefore, further studies are recommended to examine the impacts of new commuting methods on long-term conditions of various highway assets.

7. Conflicts of Interest

The authors declare no conflict of interest.

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