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A Novel Methodology for Predicting Roadway Deterioration in Iraq

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ABSTRACT

The accurate prediction of roadway conditions is challenging for infrastructure services, especially when considering an increase in traffic volume. This is the first study conducted in Iraq that focuses on predicting roadway condition deterioration and its relation to yearly traffic volume, using surveying data collected between 2019 and 2021. The main purose of the conducted study was to inspect the accuracy, reliability, and ability of a combination of predictive techniques, this combination including Markovian Chains (MCs) and Artificial Neural Networks (ANNs), known as (MC-ANN), accurately to forecast mid-term to long-term (yearly) roadway condition. The principal findings of this research are as follows: a) MCs is a powerful method applied to predict future condition depending on previous one; b) ANNs modelling was performed that be able to produce a more reliable model of roadway condition based on selected road traffic volume change, climate circumstances and road age. The study reached a correlation coefficient of 0.94 between inspected and predicted roadway conditions using a valid collected dataset and a slight mean square error of 0.0195.

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NOMENCLATURE

MCs	Markovian chains	*PCR*	Pavement condition rating
ANNs	Artificial neural networks	n	Number of road segments
MC-ANN	Markovian chains- artificial neural networks	P_{ij}	Probability transition from i to j
RNN	Recurrent Neural Networks	*i*	Chosen segment number
IRI	International Roughness Index	*j*	Type of maintenance strategy options
CRI	Condition Rating Index	*m*	Total number of pavement maintenance options
PSI	Present Service Index	X_{ij}	Values between 0 and 1 represent the percent of a segment of the roadway under treatment.
VCI	Visible Condition Index	AI	Artificial intelligence
SVM	Support Vector Machine	ML	Machine learning
M&R	Maintenance and rehabilitation	MSE	Mean square error
MS	Maintenance strategy	MAE	Mean absolute error
DSS	Decision support system	R	Pearson's correlation
SDGs	Sustainable development goals	RMSE	Root mean square error

1. INTRODUCTION

The road maintenance management sector faces many obstacles, and the most important of these obstacles are the limited resources and budget. Therefore, developing an appropriate plan for distributing resources, allocating maintenance requirements and choosing the appropriate timing in order to determine the priority of maintenance and rehabilitation (M&R) programs are the most important success factors . In order to maintain the roads and avoid their deterioration then out of service due to an increase in frequency of traffic load or climatic factors, roads require continuous maintenance work. Especially, in the event that a limited budget is allocated to the road Maintenance and rehabilitation (M&R) works, it has become necessary to use the funding optimally in order to reach an efficient maintenance program that maintains the road as long as possible [1]. The maintenance strategy

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represents a plan for the actions or steps of conducting maintenance operations according to available resources at the appropriate time, which depends on defining the actions to be taken such as "identifying pavement defects and their extent and severity, defining the remedial actions for each defect and allocating the necessary resources for those procedures [2].

Based on Shafiee and Sørensen's [3] study, the maintenance strategy (MS) is defined as the decision support system taken to develop a plan for maintenance activities, in addition to a set of policies and procedures planned to be conducted in order to "maintain" or "restore" the pavement. While another (MS) definition states that it is an integrated administrative system for managing project activities by highlighting the types of maintenance work for each type of defect with its costs and schedule and determining the extent of the impact of these works and procedures on maintenance costs [4]. Maintaining roads within a good or acceptable service level requires an adequate maintenance management system and effective pavement maintenance management plans. While neglecting these measures leads to huge damages that follow by the collapse of the service and high costs of maintenance and rehabilitation alternatives [5].

The process of maintenance management and optimal decision-making requires the provision of integrated data that shows the nature of the infrastructure project understudy and sufficient information about the deterioration curve and the remedial actions taken based on identifying the problem as a key to decision-making. It also requires identifying the most important obstacles that may hinder the preparation of a comprehensive and effective maintenance program for the project under study [6].

In fact, the most important constraint to reaching the project of the effective decision support system (DSS) is identifying the past, current, and future state of the project [7]. Currently, it has become possible to improve the decision-making process by taking advantage of scientific innovation in the field of artificial intelligence and mathematical modeling and integrating them into the field of decision support systems and management sciences. This study will address the use of Markov chains and neural networks as an innovative model for predicting the state of future road projects as a means to help support and make the decision of pavement maintenance management.

2. LITERATURE REVIEW

Establishing a system to accurately predict the condition of pavement deterioration is essential and effective for road management. Pavement deterioration progresses continuously but relatively slowly and is caused by various physical and environmental factors, such as track loads, paving materials and pavement design, total rainfall, and average annual temperature [8, 9]. Most of the previous studies relied on visual inspection data to predict the deterioration of the pavement. The difference between the previous and current amounts of deterioration was compared to find the deterioration speeds [10]. Shin [11] predicted crack deterioration in pavement using a semi-parametric random duration model. Loizos and Karlaftis [12] also developed a model based on the principle of probabilistic duration to predict pavement surface. However, current statistical degradation models suffer from problems and are still in the initial stage [13, 14].

Extensive studies have been conducted using deep learning methodology as well as statistical analysis methods. They can be categorized into studies using Recurrent Neural Networks (RNN) and those using ANN algorithms. Attoh-Okine [15] developed an ANN-type backpropagation algorithm to develop a pavement degradation model. He used explanatory variables to train, such as deformation of track loads, rate of rips, road structure, surface tightness such as patching, and depth of bore in the previous year. A significant improvement was found in the performance of the ANN algorithm for the prediction of degradation when other factors such as life stages of pavement degradation and environmental factors were taken into additional consideration. Attoh-Okine [16] also analyzed the condition of the pavement and developed a degradation model using the ANN back-propagation of the International Roughness Index (IRI). The ANN algorithm and various input variables were used to predict the pit depth, pavement crack depth, Condition Rating Index (CRI), International Roughness Index, Present Service Index (PSI), and Visible Condition Index (VCI) [17]. Furthermore, more studies found that the performance of pavement condition prediction using the ANN algorithm was more accurate and reliable than those models calculated using traditional statistical analysis [18, 19].

In several studies conducted to predict the service life of the platform for analyzing time series data, the RNN algorithm was used, which is suitable for these conditions [20, 21]. Choi and Du [22] reported that prediction using the ANN algorithm improved its performance when overfitting was resolved. Tabatabaee et al. [23] developed a hybrid prediction model for PSI that uses a support vector machine (SVM) as the first stage to classify sections with structural similarity and from other independent variables produced an RNN algorithm to predict PSI in the following year, based on classification results from the first stage. The Minnesota Department of Transportation provided a dataset for a case study that revealed that a hybrid model using the SVM and RNN algorithm was superior, in terms of error rate and prediction performance, to the model that used the RNN algorithm only [23].

In this study, the innovation is to use Markov chains to determine the evolution in pavement degradation as a first stage and then include physical and environmental factors to use the ANN algorithm, to properly deal with time series data. In addition, obtaining an optimal model performance for each by performing an overlapping prediction according to the length of the chronology is a section of the road pavement.

3. METHODOLOGY

The proposed methodology is considered new through the combination of a number of techniques, the methodology used, includes:
1- Data collection in cooperation with the Wasit Roads and Bridges Directorate, south of Baghdad.
2- Markov chains were applied at different time intervals to reduce the error in measuring pavement performance according to weather variables on the time series.
3- ANN technique was used to choose the optimal approach to the model inputs.
4- The data were divided into three groups (input, training, and output).
5- Finally, the new methodology was developed to predict the deterioration of the pavement condition based on weather variables such as rain, temperature, and traffic loads calculated with the lowest error measure. And applying the developed methodology, measuring performance evaluation criteria and the reliability of the results. Figure 1 presents summary of the adopted methodology.

4. STUDY AREA DATA SET

A roadway in Iraq located in southern Baghdad city, This road is one of two main roadways that have been used to connect the capital with the south of Iraq's city. Historical semiannual road condition data of (320) sample variables were collected from the road and bridge department. This data comprised road condition (rating), temperature (°C), traffic load (number of the car), annual rainfall (mm), and road section age (year). Data collected from the road and bridges directorate of Wasit is described in Table 1.

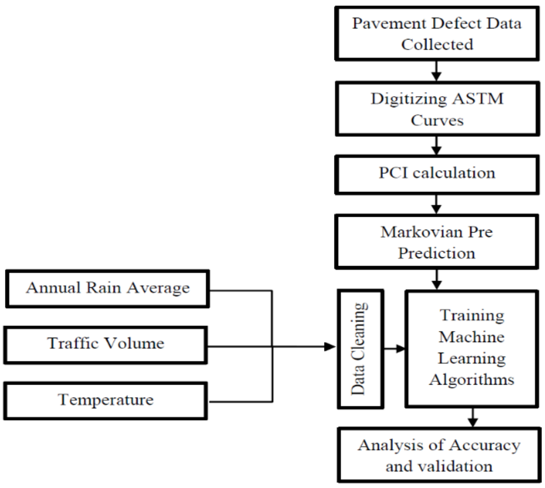

Figure 1. Summary of adopted methodology

5. HYBRID MARKOV CHAINS PREDICTION-ARTIFICIAL NEURAL NETWORK (MC-ANN)

Artificial intelligence (AI) is an important component in the field of civil engineering, especially in the direction of using digital data and intelligence, thus significantly increasing the reliance on automation to improve performance and reliability, in addition to creating efficient communication between physical conditions and digital data of construction [23, 24].

The construction industry can affect national economic sector growth and development [25, 26]. Moreover, governments in most countries around the world are taking more steps toward applying AI in the construction industry to obtain a competitive preference [27].

For example, of government procedure around the world, the U.K. government take serious steps to put the country at the primacy of AI science in order to make its projects creative and more innovative [28, 29]. In a similar way, France plans to spend huge resources on AI developers. Especially, at the national level, such investments can supply the economy with a competitive feature; although, these procedures can cause a negative impact on the globalization of services and production [30, 31]. Companies that fully depend on AI capabilities will not need to take into account outsourcing resources [32-34].

Artificial intelligence can be defined as a means of distribution, statistics, and coding that aims to find solutions by simulating human means through focusing on knowledge and continuous learning, leading to decision-making, and devoting efforts to collect previous data for training and modelling [35-37].
AI can immediately help us make superior improvements toward Sustainable Development Goals (SDGs) [38]. Furthermore, AI offers many opportunities for significant efficiency gains by quickly and accurately

TABLE 1. Data set sample

Segment NO.	1	2	3	4	5
PCI	31	61	62	57	36
Rainfall Intensity mm	204	207	198	211	205
Traffic Load	73512	68533	69726	72564	72145
Temperature °c	37	40	36	38	39

analyzing large amounts of data [39]. Moreover, AI systems and technologies can handle complex and non-linear functional problems and, once taught, can make predictions and generalizations at a high rate in digital architecture [40, 41].

Ultimately, AI aroused great interest in a variety of fields, including economics, medical, civil, and mechanical engineering, and especially in the field of forecasting, which attracted the attention of researchers [42, 43].

5. 1. Markovian Modelling Markov chain dealt with a series of random factors or variables, that match the state of a confirmed system [44]. In this approach that the pavement condition rating (PCR) at any time depends essentially on its status in a bygone time period [45].

However, if Xn= i, this shows that the element state is i, at n time. The deterioration will transition from state i to j and all that shows a constant probability Pij. In case of the probability of Pij is not dependent on the time. Therefore, Moreira et al. [46] assume that:

$$P= X_{(n+1)} = i, X_{(n)} = j, X_{(n-1)} = i^{n-1},\ldots\ X_{(0)} = i^{0} \quad (1)$$

Here, (I, j, in-1, i,… in) ∈ n.
Where,
Pij = the probability transition from i to j;
Xn = PCR for section ij .
Nij = pavement sections numbers those PCR change from state i to state j;
Noticeably one has [29]:

$$P_{ij} \geq 0, \sum_{i=0}^{n} P_{ij} = 1,\ j = 0,1, \ldots \ldots \quad (2)$$

where :
P= probability at time n.
i, j= status at any time, where i, j ∈ n
In another hand, the transition matrix of probability including Pij:

$$Pij = \begin{pmatrix} P_{00} & P_{10} & .. \\ P_{01} & P_{11} & .. \\ . & . & .. \end{pmatrix} \quad (3)$$

It is easy to express the probability matrix as:
Poo = 1− α, Plo = α, Pll = 1− β and Pol = β.
Then the one-next-step (in the next time period) transition matrix of probability as:

$$P = \begin{pmatrix} 1-\alpha & \beta \\ \alpha & 1-\beta \end{pmatrix} \quad (4)$$

where α and β presented are as possible values of probability.

5. 2. Artificial Neural Network (ANN) The expression Artificial Intelligence (AI) model denotes one that is obtained from past highway pavement documented data using an artificial intelligence algorithm. The field of (AI) includes diverse mechanisms that have been utilized in a variety of applications throughout the last past century. There are several models of AI techniques that have been known as influential tools to settle complex problems such as Machine learning (ML) and Artificial neural networks ANNs [47]. The study conducted by Cutore et al. [48] utilized AI tools to develop prediction models for adequacy ratings of bridges using current design, service life, load and density of traffic, and constitutional features. Figure 2 displays the ANN architecture.

MATLAB was used to apply the (MA-ANN) algorithm, Figure 3 shows the ANN model flow chart [49] applied to simplify predict roads deterioration accuracy.

6. MODEL PERFORMANCE AND RELIABILITY OF MEASUREMENTS

The assessment process of performance for the proposed model can be reached by utilizing different traditional statistical measures, as shown in Figure 4.

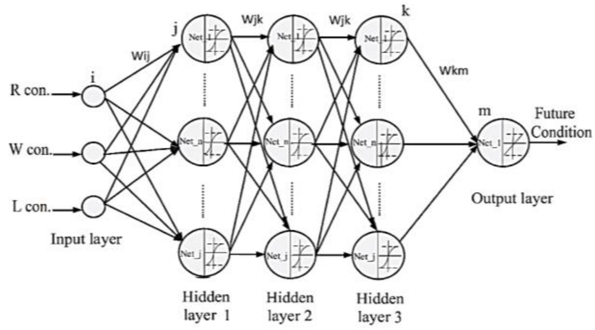

Figure 2. ANN architecture

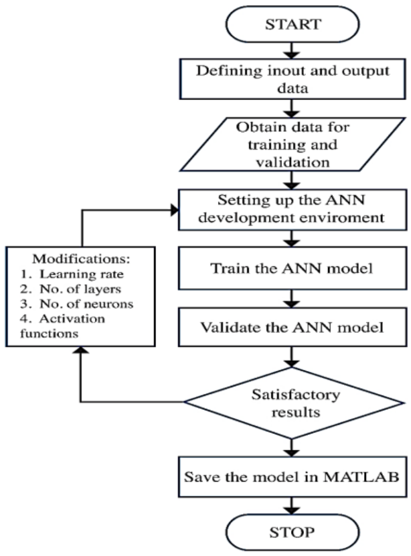

Figure 3. Flow chart of ANN algorithm

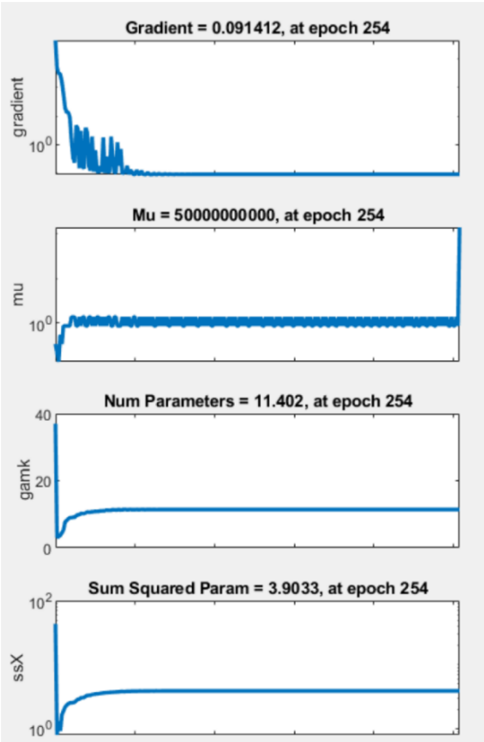

Figure 4. Data assessment

In this study, to examine prediction reliability five standards were used; (MSE) mean square error, (MAE) standard deviation, and (RMSE) root mean square error.

$$MAE = \frac{\sum_{m=1}^{N} |y_0 - y_p|^2}{N} \quad (5)$$

$$MSE = \frac{\sum_{m=1}^{N} (y_0 - y_p)^2}{N} \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{m=1}^{N} (y_0 - y_p)^2}{N}} \quad (7)$$

$$R = \left[\frac{\sum_{m=1}^{N} (y_0 - y_0)(y_p - y_p)}{\sqrt{\sqrt{\Sigma(y_0 - y_0)^2 - \Sigma(y_p - y_p)^2}}} \right] \quad (8)$$

where y_o: the observed road condition; y_p: predicted road condition; N: population size; y_o, mean of observed road condition and y_p, mean of predicted road condition.

7. RESULTS AND DISCUSSION

7. 1. Development Model Input It is necessary for normalizing data by applying the normal distribution, the time series data of road conditions rating without noise was obtained by employing the pretreatment signal technique [50].

Pre-processing of collected data increases the correlation coefficients (cc) among independents and dependent variables for a different rating of road conditions, e.g., the cc of raw data of rating increased significantly from 0.72 to 0.94, 0.92, 0.89, and 0.83, respectively, for the three-time series.

Fidell [34] indicated that the relationship between the independent variables and the size sample (N) should be confirmed with Equation (9).

$$N = 50 + 8\,m \quad (9)$$

m = predictor variables number.
In this study, the data size needed is 90 less than the case number N = 116, compliance with the proposition limited by Mardani et al. [34].

7. 2. Application of Hybrid Ma-Ann Techniques After performing data pre-processing methods, data must be divided into three different datasets, training, testing, and validation, as shown in Table 2. This table classifies all datasets into four statistical standards including maximum pavement condition rating (PCRmax), minimum pavement condition rating (PCRmin), mean pavement condition rating (PCRmean), standard deviation (PCRstd), and sample size for each dataset (S). The results present that all sets have the same pattern.

The determination coefficient (R2) was calculated between the observed and predicted road rating for training, testing, and validation sets, to examine the proposed model accuracy for generalization, as shown in Figure 6. The measured pavement condition rating is plotted on the x-axis against the No. of sample on the y-axis. The results were calculated by applying the hybrid(MA-ANN) in comparison with those collected from visual inspection to validate the proposed model.

TABLE 2. Statistical parameters for datasets

Pavement Condition Rating (PCR)	PCRmax	PCRmin	PCRmean	PCRstd	n
Training set	79	61	70	0.055	60
Testing set	80	62	71	0.054	15
Validation set	78	61	70	0.058	15

The resulting deterioration model obtained when applying (MA-ANN), has a small value of root mean square error (RMSE). To explore the performance quality of the proposed prediction methodology for the hybrid model, a regression coefficient (R) was set between the computed and predicted road condition, as shown in Figure 5. The composite model was significant R = 0.981 for the data collected for the road under study, in the validation phase of the results these figures confirm the ability of the hybrid (MA-ANN) technique to forecast precisely road deterioration and indicate its future condition. In addition, various statistical indicators such as CE, MAE, RMSE, and MARE for examining the performance of training, testing, and validation datasets for the (MA-ANN) model, as presented in Table 3.

The error value was calculated to ascertain the reliability of the model. Figure 5 shows scatter plots of the mean square error. In all figures, three significant models of data emerged; The mean square error was very tiny and near to zero, there is no particular tendency for the distribution pattern and the error intensity distribution for all data is uniform.

Both graphs shown in Figure 6 show the best fit between the actual and expected road conditions, which indicates the ability of this model to accurately simulate time series. Therefore, this proposed model is considered effective by being able to accurately calculate the degradation model of roads in Iraq. Where the outputs represent the results obtained using the hybrid technology, while the goal represents the observed results in the way under study. Figure 5 indicates that the results converged very closely during the training or final production phases.

The impetus for this study was to develop a new methodology to predict the deterioration of roads in Iraq. This methodology consists of two parts: (1) examine the ability of MA-ANN to elicit consistent components and non-consistent components, in addition to the filtering process for different time series from noise, and, (2) verify the reliability of the (hybrid MA-ANN) model to predict the time-series deterioration of roads in Iraq.

TABLE 3. performance evaluation and validation

Model	Data Stage	RMSE	MAE	MARE	CE
	Training	0.092	0.0081	0.0058	0.981
MA-ANN	Testing	0.091	0.0079	0.0056	0.987
	Validation	0.094	0.0077	0.0049	0.977

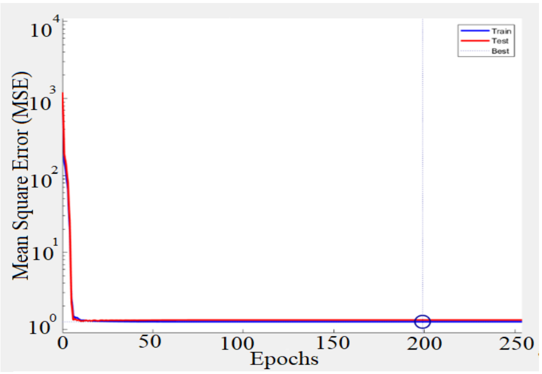

Figure 5. Mean square error

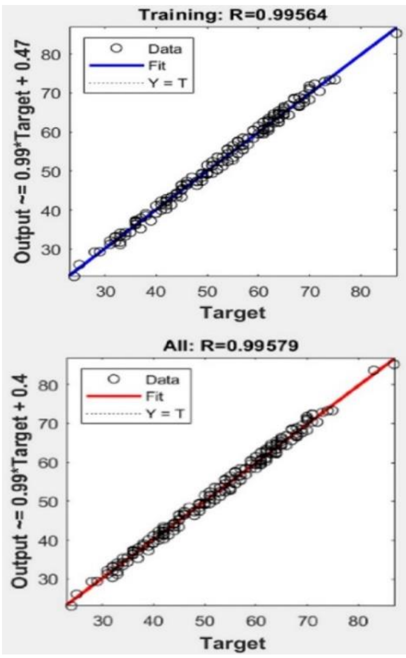

Figure 6. Ma-ANN algorithm performance for the validation data

The technique of combining Markov chains and ANN was reliable and effective when simulating the road degradation model in Iraq. This paired technique has validation-stage correlation coefficients R = 0.981 for the collected data. This study can be considered as proof in order to encourage road maintenance planning departments to adopt the integrated technology, to accurately predict the degradation model of roads in Iraq.

8. CONCLUSION

The road management need for planning was the ideal justification for doing this study by finding hybrid techniques that provide accurate forecasting of the road's status during different phases of time, leading to optimal planning for a comprehensive and effective maintenance approach. This study came to meet the requirements of southern Baghdad road to maintenance in order to develop an innovative methodology to predict the road state according to studying various factors.

The output of the (MC-ANN) was highly accurate and yielded an RMSE of 0.02109 and 0.006758 for the data collected for the selected route. Which had more accurate results and better performance than the (ANN) algorithm, which resulted in RMSE of 0.02342 and 0.007657 for the same data, respectively. The technique of combining (ANN) and the Markov chain was reliable and effective when predicting the state of the southern Baghdad road. The developed model (MC-ANN) can be considered a very powerful and flexible tool for highway engineers to be effectively used in planning and budget estimation activities. The developed prioritization model was built based on the current circumstances of Iraq. So, the factors entered into the (MC-ANN) can be changed with regard to the changes in future circumstances.

The study reached that the prediction results of the hybrid approach were compared with the data collected for the chosen road and it was found very close with a slight mean square error of 0.0195, and a correlation coefficient of 0.94 between inspected and predicted road conditions when using a valid collected dataset. That means the reliability of the technique used to give prediction results is very close to reality.

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Persian Abstract

چکیده

پیش‌بینی دقیق وضعیت جاده‌ها برای خدمات زیرساختی چالش برانگیز است، به‌ویژه زمانی که افزایش حجم ترافیک در نظر گرفته شود. به این ترتیب، این اولین مطالعه انجام شده در عراق است که بر پیش‌بینی وخامت وضعیت جاده‌ها و ارتباط آن با حجم ترافیک سالانه، با استفاده از داده‌های پیمایشی جمع‌آوری‌شده طی دوره بین سال‌های ۲۰۱۹ تا ۲۰۲۱ تمرکز دارد. هدف اصلی مطالعه انجام‌شده، بازرسی دقت بود. قابلیت اطمینان و توانایی ترکیبی از تکنیک‌های پیش‌بینی، این ترکیب شامل زنجیره‌های مارکوین (MCs) و شبکه‌های عصبی مصنوعی (ANN) با نام (MC-ANN) برای پیش‌بینی دقیق وضعیت راه‌ها میان‌مدت تا بلندمدت (سالانه). یافته های اصلی این تحقیق مجدد به شرح زیر است: الف) MCs یک روش قدرتمند است که برای پیش بینی شرایط آینده بسته به شرایط قبلی استفاده می شود. ب) مدل‌سازی شبکه‌های عصبی مصنوعی که قادر به تولید مدل قابل‌اعتمادتری از وضعیت جاده بر اساس تغییر حجم ترافیک جاده‌ای انتخابی، شرایط آب و هوایی و سن جاده هستند، انجام شد. این مطالعه به ضریب همبستگی ۰.۹۴ بین وضعیت جاده بازرسی شده و پیش‌بینی‌شده هنگام استفاده از مجموعه داده‌های جمع‌آوری‌شده معتبر، و میانگین مجذور خطای جزئی ۰.۰۱۹۵ رسید.