# Technologies that Support Pavement Management Decisions through the Use of Artificial Intelligence

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## ABSTRACT

*There has been a meteoric rise in the number of AI-based applications in road pavement engineering since the late 1980s. Key points in the decision-making process for pavement management include the use of such apps. They predict pavement degradation and do pavement diagnostics in the analysis phase. Contributing to the identification and selection of maintenance activities, they allow for the assessment of rehabilitation needs during the design phase. Lastly, they are utilized for rehabilitation and maintenance priority programming during the choice phase. They either stand in for new ways of doing things or work together to improve the system as a whole. This article aims to draw attention to the potential of artificial intelligence (AI) tools for pavement engineers by summarizing the results of recent research publications on the topic of AI in pavement management. Expert systems, hybrid systems, genetic algorithms, fuzzy logic, and artificial neural networks are all forms of artificial intelligence.*

**Keywords:** Pavement Management; Fuzzy Logic; Artificial Neural Network

## Introduction

Making a number of choices is a key part of pavement management's planning process. How can this be resolved? At what point? Just how? In what location? The act of deciding amongst potential actions with the aim of achieving an objective or set of objectives is known as decision making. Managers have long held the view that making decisions is an art form, something that requires practice and the ability to learn from mistakes. There are a number of reasons why decision-making is more challenging and complex now than it was in the past. Given the scale and complexity of operations, the prevalence of automation, and the domino effect that a single mistake can have across an organization, the number of viable options is bigger, and the penalty of making a mistake can be substantial as well. Decisions also need to be made swiftly, and the data needed for that may be hard to come by. As a result, managing pavements via trial and error is not an easy task. Managers now have a greater responsibility to master new methods and resources that will aid them in their most critical role: decision making.

Much of the decision-making in pavement engineering is dependent on the expertise and professional judgment of engineers and technicians. It is crucial to record as much of the existing knowledge and expertise as possible for the benefit of newcomers, contractors, road authorities, and consultants as a large number of experienced individuals are getting ready to retire [1–10].

Pavement management and maintenance can benefit from the ever-evolving new technology. Professionals in this sector must never stop researching potential uses for emerging technologies. The majority of technology that aims to replace human skill consists of expert systems. Their capacity to complement workforces in several specialized areas where human specialists are becoming more difficult to acquire and maintain, as well as their potential to increase productivity, make them of tremendous interest to enterprises. One such exciting new technology that has piqued the interest of many branches of engineering is artificial neural networks. The original motivation for this data processing system was to model its operation after the way the human brain handles data. Neural networks are able to learn from their mistakes, apply what they've learned to new situations, and derive important traits from data inputs. They have various benefits over more conventional approaches to model-when the process that has to be described is too complicated to be expressed explicitly in statistical or mathematical terms. On the other hand, several other AI technologies, such evolutionary algorithms and fuzzy logic, can be employed to bolster unique cases.

Aiming to assist academics in identifying situations where this new technology is applicable, this paper reviews and analyzes the possibility of applying artificial intelligence (AI) in pavement management and maintenance. To what extent have these issues been tackled? Which kind of artificial intelligence have been employed? We have accomplished everything we set out to do thus far. In your opinion, what are the roadblocks to going forward?

There are five main sections to this article. The first is Section 2, which provides an overview of the various decision assistance technologies. In Section 3, we take a quick look at a few AI technologies that can aid manufacturing decision makers. The decision-making process in pavement management is briefly explained in Section 4, which also sets the context of the data analysis element of a pavement management system. What follows is a survey of current and future uses of artificial intelligence (AI) tools for pavement management, including hybrid systems that include elements of expert systems, artificial neural networks, fuzzy logic, genetic algorithms, and so on. Section 6 comes to a close with the article's findings [11-33].

## Technology to Assist in Decisions

### Decision Support Systems as a Concept

Structured (or "programmed") and extremely unstructured (or "nonprogrammed") issues are both capable of yielding decisions. Algorithms can back up judgments in a structured problem 100%. It is common practice to rely on gut feelings when faced with an unstructured challenge. Semistructured issues are those that exhibit both structured and unstructured aspects. They require a mix of human judgment and established solution processes to solve. Since the 1960s, computers have been able to assist with organized and even some semistructured decision-making. A decision support system (DSS) with modeling skills can tackle less structured situations. A classic definition15 states that DSS is "a system that couples the intellectual resources of individuals with the capabilities of the computer to improve the quality of decisions." This means that DSS is a computer-based support system for management decision-makers dealing with semistructured problems, although there is no universally accepted definition of it. As a catch-all word, "DSS" can refer to any or each and every computer system that a company uses to aid in decision making.

### Main Tools for Assisting with Decisions

One or more decision-support technologies (tools) can offer decision-support. Turban45 says that the most important decision-making tools are

• Group decision support systems (GDSS) and other GSSs

Information systems for executives

• E-systems, or expert systems

"ANNs" stand for "artificial neural networks."

• HSSs, or hybrid support systems,

In order to help groups of decision-makers solve challenges with no clear framework, GDSSs use interactive computer-based systems. An EIS is a computerized system that provides critical performance indicators to assist executive work. You may find additional information about ANNs and ESs (now commonly referred to as knowledge-based systems) in Section 3. To get superior outcomes, many approaches in an HSS may cooperate or compete with one another. Analysis, design, and choosing are the three main steps in making a decision. Various stages of the decision-making process are associated with the decision technologies. The analysis step entails taking stock of the situation and figuring out what the decision-making difficulty is. At this stage, EISs and ANNs come in handy since they hunt for early signs of issues by constantly monitoring internal and external data. During the design process, we brainstorm, create, and evaluate potential solutions. First, we build, test, and validate a model of the problem. Then, we establish criteria to evaluate potential solutions. The results of utilizing different alternatives are anticipated. Either a human expert or an ES with the necessary competence might provide options for complicated situations. In the choosing step, you'll look for a solution, assess it, and then suggest it to the model. In this case, an ES can weigh the pros and cons of potential alternatives and provide a final recommendation. A GDSS can be useful for group decision-making during the choosing phase and for design-phase brainstorming exercises. It is ready to be implemented once the provided solution appears reasonable.

**Decision-Support Models**

DSSs are model dependent. The main concept is to conduct the analysis on a representation of reality instead of the actual world. Additionally, it is easier to conduct experiments by modifying the model than the actual system. Figure 1 shows the many categories into which Bemmel classifies 46 decision assistance models. Decision support models may be broadly classified into two types: quantitative and qualitative. The mathematical and quantitative subfields frequently employ training sets of data and are based on established statistical methods or artificial neural networks. The main strategies for selecting features involve analyzing their discriminating abilities and employing statistical methods. If you want to know how likely it is that something will happen, you may utilize statistical approaches. Typically, all characteristics (signs, symptoms, measurements, etc.) are utilized concurrently in decision making that relies on statistics or neural networks. It is important to remember that statistical approaches also rely on a qualitative model of characteristics and classifications. Using characteristics often suggested by expert systems, qualitative approaches may draw inspiration from or reflect human thinking. The purpose of an expert system is to mimic the thought process and understanding of a human problem solver in a certain area. They can be employed to resolve issues for which algorithmic solutions are unavailable. Boolean logic, also known as combinatorial logic or symbolic logic, is a good framework for understanding the symbolic reasoning procedures used by qualitative decision support systems, such as logical deduction.

**The Field of Artificial Intelligence and Decision Support Systems**

When making judgments, decision-makers mostly depend on their knowledge. Getting this information might take a long time. Having easy access to information is increasingly challenging as both the quantity and complexity of knowledge grow. The most prevalent technology used to replace human expertise is expert systems, which may improve decision makers' capabilities through the provision of knowledge and skill in data management and modeling. The goal is not to displace the experts but to increase access to their expertise. On the other hand, decision-situations can also benefit from a number of the other technologies discussed here. You might say that all of these things are AI applications. The word "artificial intelligence" can mean many different things. Artificial intelligence (AI) is a novel way of teaching computers to do tasks. It is widely acknowledged by specialists in the field that AI is involved with the study of human mental processes and the representation of those processes by computers, as will be explained in the parts that follow. Expert systems, genetic algorithms, fuzzy logic, artificial neural networks, and artificial neural networks are just a few examples of the applied AI tools that offer AI-based decision assistance, and AI itself offers the scientific basis for a number of rapidly expanding commercial technologies.

When it comes to addressing issues within a very specialized subject, expert systems (ESs) are computer algorithms that provide advice by simulating the way humans think and make decisions. Compared to other applied AI technologies that are still in the research phase, they are already in use and see higher usage.

A knowledge-based system, or ES, incorporates both a database of information and a method for drawing conclusions from that database. The knowledge base documents both static and dynamic data relevant to the situation at hand, as well as guidelines for drawing conclusions based on these facts and other forms of information often utilized by experts to arrive at a decision. The software that conducts the inference-making process and derives conclusions from the knowledge base is called the inference engine. It is also known as the rule interpreter or reasoning construction. A software interface is available on an ES, allowing users to input queries and other necessary data. In addition, the system may detail the steps taken to get a certain verdict.

**Neural Networks that Are Artificial**

Inspired by research into the neurological system and the brain, artificial neural networks (ANNs) are a form of AI-based modeling approach. In artificial neural networks (ANNs), a vast network of interconnected processing elements—the computational analogues of neurons—processes data. As a powerful tool for function approximation, ANNs are typically employed to approximate a complex input-output relation. Typically, they are given a mountain of data to help them estimate the true relationship. The output in reaction to an outside input signal is determined by the neuronal structure and connection weights. Many distinct kinds of ANNs exist. Multilayer perceptrons, which often use the backpropagation of error technique for training, are among the most well-known. Other prominent models include the Hopfield and Kohonen models, as well as the radial basis function.

When used to pattern matching, ANNs shine with a big database of previous samples. While digital computers may theoretically replicate neural networks, the very definition of a neural network suggests a non-digital computer. Some domains that need pattern recognition—like robotics, data analysis, diagnosis, forecasting, picture processing, pattern identification, and voice recognition—have found success with the ANN method [34–60].

**Neural Networks**

Fuzzy logic allows for partial (or even continuous) truths by expanding the concepts of logic beyond basic true and false values. When it comes to using common sense in decision-making contexts, imperfect information and reasoning are crucial components of competence. An essential idea in fuzzy logic is the fuzzy set, which allows for the continuous expression of membership degrees in fuzzy sets as probability values between zero and one. The degree to which an individual belongs to a collection may be expressed using fuzzy logic. A theoretical tree x in classical logic belongs to the set of tall trees, but in fuzzy logic it is partially in that set and might be said to be fairly tall. Among the many AI applications, fuzzy logic has shown to be the most helpful for ESs.

**Bioinformatics**

Heuristic search techniques that are intelligent are known as genetic algorithms (GAs). Key components of its design and execution in the computer are based on some of the known mechanisms of evolution. An example of a chromosomal representation of a problem's solution is a set of binary digits representing the possible outcomes of a decision-making vector. The objective value may be calculated for this set of data. Generic methods begin with a randomly generated population of solutions and then, with the occasional mutation, join sections of chromosomes to build new solutions. Natural selection allows the most optimal solutions from one generation to pass on their knowledge to the next by evaluating each new solution using a fitness function. Typically, the best answer is located close to an optimal solution to the decision-making issue after a number of iterations or combinations. A wide variety of large-scale combinatorial (hard) mathematical programming issues, such as large-scale scheduling difficulties, have found an application for GAs.

**Assisting with Pavement Management Decisions**

There are typically two tiers to the pavement management decision-making process: the network tier and the project tier. All pavements within an agency's purview must be evaluated as part of network-level management. Management at the network level primarily aims to create a priority program and work plan within total financial limitations. There is a program level and a level for selecting projects within this level. Prioritization is used to determine which projects should be executed each year of the program period at the project-selection level, which focuses on a specific area. Budgets are set and network-wide distributions are made at the program level. Next, at the designated points in the timeline, comes the project-level activity, which stands for the tangible execution of network choices.

Pavement management systems (PMS) were first used to define the whole spectrum of operations related to pavement provision in the late 1960s and early 1970s. The purpose of a pavement management system (PMS) is to help decision makers determine the best solutions for delivering and maintaining pavements in a usable state for a specific length of time, according to Haas (18). A PMS's purpose is to boost decision-making efficiency, inform users of the outcomes of their choices, help the agency work together, and guarantee that decisions taken at different levels of management are consistent with one another. What this means is that you have to weigh your options, make a decision, and then make sure it's executed economically and efficiently. Database (including condition and inventory data), data analysis, and system output are the three main parts of a PMS. The PMS's data analysis module is an essential component. Pavement performance modeling, rehabilitation requirements modeling, priority models, and models to evaluate rehabilitation and maintenance options are some of the analytical features offered by most pavement management software [61–72].

**Modeling the Performance of Pavements**

In order to determine the current condition levels or to anticipate the future condition, the majority of PMSs come with software. Examining the pavement's functional or structural behavior allows one to determine its performance, the most intriguing aspect of the pavement. Pavement management relies on performance modeling. Observed or measured structural or functional degeneration serves as the dependent variable in these models, which are associated with a collection of independent factors. Pavement ride quality data taken at regular intervals and compared with traffic statistics from the past can provide insight into the system's efficiency. Estimating the kind and timing of pavement rehabilitation and maintenance needs, as well as analyzing pavement life-cycle costs, are other applications of performance models. Based on a categorization proposed by Broten5, two main types of models may be thought of:

• Models that assume a constant value for the dependant variable (such the average number of years left to live) are known as deterministic models to a pavement's condition or durability). The majority of pavement management deterministic models rely on regression analysis. Since many ANNs may be seen as nonlinear regression models, they fall within this category.

• Models based on probability, which find a distribution of possible values for the dependent variable. In most cases,

Markovian theory is the foundation of the tic models employed in pavement management. The premise upon which this theory is based is that the present state is the only determinant of the chance that an object would move from one condition state to another. The percentage of pavement sections expected to either (1) remain in the current condition or (2) transition to a different condition state is estimated for each condition state depending on how they are constructed and if they incorporate mechanical factors like strain, stress, or deflection, performance models can be categorized as either mechanistic, empirical, or mechanistic-empirical. Experiments and real-world data provide the basis of empirical models. Both theoretical and practical aspects are taken into account by empirical-mechanistic models.

One of the biggest challenges in constructing performance models and trying to produce reasonable model mistakes is capturing the interactions between the many explanatory factors. Classical regression methods, often supported by field data, constitute the basis of the majority of deterministic performance models employed in pavement management up to now. However, the requirements of least-squares regression are rarely satisfied by these datasets. When creating regression models of pavement performance, it is important to keep in mind the limitations and complexity of stochastic and correlated errors in the measurements of the explanatory variables. These mistakes might provide misleading findings or underestimated errors during regression.

The engineer's a priori understanding of the equation is equally crucial to the success of regression analysis. In order to solve functional connections, which frequently exhibit nonlinearities and are thus poorly served by conventional regression algorithms, an adjustable strategy is required. To that end, artificial neural networks (ANNs), a nonlinear technology, provide an alternative.

**Modeling Rehabilitation Needs**

The pavement-management procedure uses analytical processes to determine the segment's repair needs. Roughness, condition index, structural adequacy, and surface friction are just a few examples of the condition metrics that may be used to configure these models to initiate rehabilitation. When determining if a section of pavement needs repair, a pavement maintenance system (PMS) may employ a combination of factors, such as roughness, condition index, and structural adequacy.

Limits can be put up to activate certain repairs when the triggering requirements have been selected. A road agency's established boundaries are based on a number of factors, including traffic volume, functional categorization, agency policy, and available resources. These limitations are often established using a decision tree or a matrix and subsequently implemented into the PMS [73-92].

**Approaches to Upkeep and Recovery**

In most cases, the procedure that an agency uses to choose between preventative and corrective maintenance and rehabilitation options is reflective of current practice. The organization has compiled a list of all the current maintenance and restoration options. In order to carry out a priority programming process, there is a method for ascertaining which ones are workable in certain cases. Design and investment decisions are based on the strategies developed by a small group of highly skilled engineers who apply their expertise, intuition, and experience. Formalizing this knowledge and making it accessible to more agencies is an urgent matter.

From a basic judgment to a decision stated in the pavement management software, there are a variety of realistic restoration methods to choose from. The PMS typically consults models to ascertain the most suitable solutions. Typically, these models are configured to identify and choose suitable repair options considering variables like pavement condition in the repair year, surface type, and traffic volume. Strategy matrices and decision trees are the go-to tools for making these kinds of choices. Both the kind of distress and the overall condition index can be used as drivers for selecting possible repair kinds in this case.

While some organizations may have a plethora of repair options at their fingertips, others may be limited to just a handful. The PMS program also makes use of models to choose the suggested repair option when many viable options have been discovered for a certain pavement segment. Essentially, these models are designed to follow the agency's previous practices by choosing the treatment option that has been employed most frequently. On the other hand, a more nuanced strategy would be to do a benefit-cost analysis to choose the winner.

### Rehabilitation and Maintenance Programming Priorities

Pavement management includes comparing investment options at the network and project levels under certain financial or budgetary limits. When there are not enough funds to cover all of the triggered projects, prioritization models are employed to decide which pavement segments will get financed first. Priority evaluation techniques could range from straightforward subjective rating to intricate optimization models. Determine which areas need rehabilitation or maintenance, how to do it, and when you want it done; then use that information to guide your priority programming. It is essential to consider every potential combination of these three questions in order to optimize the investment. Because of the complexity involved in developing a model to address all of these problems at once, the models used by the majority of agencies focus on only one or two of them. A pavement rehabilitation and maintenance priority program should be the end product of the comparison. For each part of a program's projects or maintenance, the best option in terms of cost is found. Durations of programs might vary from one year to another, or even span many years. A realistic strategy is to create a 5- or 10-year plan, but because we don't know what the future holds, we just lock in the first 2-3 years and then revise it once a year or twice a year. Nevertheless, decisions are not made by the priority programming. It only provides the developer with a helpful roadmap to follow.

### AI Use Cases in Pavement Maintenance

We have analyzed and provided 37 of the most current and significant works in the roadway pavement literature. The articles are categorized according to the artificial intelligence approaches used and the challenges they address. These techniques might include knowledge-based expert systems, artificial neural networks, fuzzy logic, genetic algorithms, and hybrid systems. As seen in Figure 2, the reviewed publications are organized in the same chronological sequence as the topics they cover in the pavement-management decision process. Due of their status as the pioneering AI approach in pavement management, the evaluation begins with applications including knowledge-based expert systems. Next, we will go over some examples of applications that have been built using fuzzy logic in conjunction with evolutionary algorithms and artificial neural networks. On the last page, the paper goes over some hybrid systems [93-108].

**Expert Systems Based on Knowledge**

One of the earliest uses of artificial intelligence in pavement management was knowledge-based expert systems. First, by determining the most important and practically viable repair option, expert systems may (1) represent the expertise, knowledge, and judgment of professional pavement engineers.

(2) to give the local engineer a way to analyze and plan pavement repair options in an interactive way.

23 The Catalog of Recommended Pavement Design Features compiles good-practice recommendations for design features of flexible and rigid pavements for highway engineers and pavement researchers. It forms the basis of DESIGNER, a knowledge-based expert system that assists highway engineers in selecting recommended features for highway pavements. C Language Integrated Production System (CLIPS) is the programming shell that powers the prototype's central component. After the designer inputs data about traffic loading, subgrade support, and climate, the system suggests features for the pavement, such as its cross section, structural design, and the materials needed to meet rigid and flexible pavement minimum performance requirements. There is a suite of tools for comparing various pavement design options in the system as well.

The main tasks addressed by OVERDRIVE include determining the effective thickness of the existing pavement structure, determining a new full-depth asphalt-concrete construction thickness, and assessing the consequent need for an overlay. OVERDRIVE is a rule-based expert system that helps local engineers design the structural thickness of flexi-ble pavement overlays. The foundational knowledge of OVERDRIVE was built through collaborative knowledge engineering with a pavement specialist and a synthesis of relevant reports, papers, and manuals pertaining to the Asphalt Institute's method for designing asphalt-concrete overlays on flexible pavements. It uses the EXSYS knowledge engineering shell to express over a hundred rules. The forward-chaining inference approach is used to fire the rules.

An integrated collection of interacting expert systems and algorithmic models called PARADIGM38 (Pavement Rehabilitation Analysis and Design Mentor) was developed via completed and ongoing research at the University of California at Irvine. The two primary systems that make up PARADIGM are SCEPTRE and OVERDRIVE. Assisting highway engineers in the design and development of cost-effective pavement restoration techniques, SCEPTRE (Surface Condition Expert for Pavement restoration) assesses pavement surface distress at the project level and other user inputs. According to Ritchie and colleagues (39), SCEPTRE 1.4 takes into account the procedures and circumstances prevalent in Washington State and is designed to handle state-maintained flexible pavements. This database is the brainchild of two pavement experts with decades of combined experience in pavement repair in the US states of Washington and Texas. About 140 production rules specified using the

EXSYS knowledge engineering shell are included in it. It employs the backward-chaining inference technique as its infer-ence mechanism. There are ten primary approaches to rehabilitation that are taken into account: doing nothing, filling cracks, fog sealing, friction courses, chip sealing, double chip sealing, thin, medium, and thick asphalt concrete overlays, milling, and replacement. A total of 24 rehabilitation techniques are possible by modifying them to add the recommendation to "prelevel" or "prelevel or mill" the pavement as an initial step in the process. Type, quantity, severity, current pavement performance, traffic volumes, and climate are the six fundamental parameters that determine the selection of feasible methods. Alligator cracking in wheel pathways, rutting, longitudinal cracking in wheel paths, and transverse cracking are the particular forms of surface distress that are taken into account. An external module is attached to SCEPTRE for the purpose of conducting cost-effectiveness analyses of potential rehabilitation procedures. A pavement-performance curve, which correlates pavement age with an aggregate assessment of pavement quality, is the basis of each strategy's study. This feature is essential for cost-effectiveness analysis [109–120] because it allows for the visual representation of predicted pavement degradation for all repair strategies.

An expert system is being built for the Huntington Town Highway Department in New York, according to Lee and colleagues 32. At the level of project selection, the system aids engineers in making decisions. When all other subjective considerations have been taken into account, the algorithm will recommend the best appropriate rehabilitation or maintenance method based on the current pavement conditions. The pavement database is searched through by the interface software to find the user-requested pavement segment, and the condition survey data is then returned to the knowledge base. Making use of distress data collected retrieving the necessary information from the database, the choice to reconstruct the section may be made. Judgmental elements, such as geometric design requirements, administrative information, pavement history, etc., that are not available from the database are the only ones that the user is asked for. The pavement database stores the final recommendation for future use by the PMS. The system can go a step further by outlining the specific steps to take in order to implement the suggested plan for pavement restoration and maintenance [121–124].

An expert system that was built to help local transportation authorities in developing nations manage pavement repair. The system's core is an expert system and an interactive algorithmic software. Using the pavement condition index (PCI) method, the algorithmic software generates a comprehensive diagnostic report on the pavement state, simulating the evaluation phase. Various maintenance options are determined and ranked by the rule-based expert system. Doing nothing, doing ten separate actions during maintenance intervals, performing periodic maintenance (thin or thick overlay), and strengthening (reconstruction) are the four basic M&R techniques that the system distinguishes. An further component of the system, a cost-estimating module, determines how much the allocated M&R alternative will cost in total. This part models an in-depth process for estimating manufacturing costs in order to calculate the overall budget and conduct an economic study of the M&R investments over the long run. The user enters distress data into a condition survey sheet, and the software calculates the PCI. This is how the complete system functions. Subsequently, the expert subsystem probes for details on the highway's performance (traveling speed, traffic volume, etc.) and past condition (PCI evaluation, maintenance rate, strengthening, and age since reconstruction or strengthening). Present distress types and severity, traffic volume, PCI of the section, rates of deterioration (both short- and long-term), level of prior maintenance, skid resistance, list of relevant M&R activities based on local circumstances, unit cost, and projected service life are all part of the report from this diagnostic phase. The relevant M&R operations are determined by the expert subsystem based on past knowledge.

The Indian government has just launched the Pavement Deterioration and Maintenance (PADMA29) initiative to test the viability of using ES for pavement management. Estimating the deterioration's causes and the best course of therapy are both handled by the rule-based approach. Taking into account the life-cycle costs of various overlays, it also gives information on the right material kind and thickness needed for rehabilitation measures. Bituminous surfacing problems can manifest in four main ways: surface defects, cracks, deformation, and crumbling in accordance with the method used to repair roads in India. Thirty pieces of information on the current state of the surface, material properties, and construction procedures must be entered by the user in order to pinpoint the source of a failure or distress. Expert knowledge or data from the PMS database is used to determine what caused the degradation. The program was built using DEKBASE, an expert system shell created at the Indian Institute of Technology in Madras, India, specifically for the Department of Civil Engineering. Field data collected from ten different pavement sections were used to calibrate the expert system model. The article's writers wrap up by discussing how well the system can determine the nature of the discomfort and the appropriate course of therapy.

**Conclusion and Summary**

Pavement management presents a number of choice challenges that are complicated in nature. Their data comes from a wide variety of complicated sources, and they are typically quite nonlinear. The purpose of using AI approaches into pavement management is to enhance decision support in many areas and push its bounds further. In this post, we have covered the basics of several AI approaches and found some uses for this cutting-edge innovation. Key steps in the decision-making process for pavement management include AI systems. They predict pavement degradation and do pavement diagnostics in the analysis phase. Contributing to the identification and selection of maintenance activities, they enable the assessment of rehabilitation needs during the design phase. Lastly, they are utilized for rehabilitation and maintenance priority programming during the choice phase. Some AI systems work in tandem to improve system efficiency, while others offer alternative, native ways to preexisting systems. The problem's characteristics and the decision support system's setup will dictate which of these key technologies to employ. Not using a particular tool or technique is important, but solving the choice issue successfully is. Artificial neural networks, being nonlinear regression models, excel in handling numerical data and extracting insights from numerical historical data. When tackling problems that need a high level of expert knowledge and human reasoning processes that cannot be adequately represented by a traditional algorithm, expert systems may be incredibly useful using a methodical approach to implementation. Combining expert systems with neural networks often produces very effective systems because to the significant differences between the two technologies. There are several documented uses for AI that demonstrate its superiority over more traditional approaches. Sadly, a great deal of these AI systems have relied on artificial data when they were formed. The true test will be in creating a program that, using field data, significantly outperforms the models typically employed by pavement engineers. In order to boost efficiency and improve the quality of decision-making, artificial intelligence (AI) based solutions are currently being integrated into pavement management. These systems are constantly changing. Pavement management engineers and administrators should not rely only on the system that emerges from incorporating AI approaches into these systems; rather, it should serve as a supplement to their expertise. Users and systems still need to work together for this to work. However, not every issue that pavement engineers face can be solved by this integration. It is important for pavement engineers to be aware of the models' limits in order to their scope of validity is where they put them to use.

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