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Synergizing GIS and genetic algorithms to enhance road management and fund allocation with a comprehensive case study approach

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This study identifies a critical knowledge gap, revealing how the deterioration of roads, compounded by extensive usage and additional factors, poses significant risks to the road networks' functionality. Without a robust fund allocation and prioritization strategy, the extent of this risk may be overlooked, adversely affecting the performance of essential infrastructure elements. Our research introduces an integrated decision-making model for existing road infrastructures to address this gap. This innovative approach combines a Geographic Information System (GIS)-based road management model with a fund allocation prioritization strategy, enhanced by an optimization engine via a genetic algorithm. The primary aim is to precisely determine Maintenance and Repair (M&R) interventions tailored to the condition states, thereby improving the Pavement Condition Index (PCI) of the road segments. The research is structured around three key objectives: (1) develop a detailed GIS-based road management database incorporating inspection data and attributes of road infrastructure for proactive M&R decision-making; (2) efficiently allocate funds to maintain service delivery on deteriorated roads; and (3) pinpoint the optimal type and timing of M&R interventions to boost the condition and performance of the road segments. Anticipated results will provide asset managers with a comprehensive decision support system for executing effective M&R practices.

Keywords Asset management, Geographic information system, Fund allocation, Maintenance and repair, Pavement condition index

Public infrastructure assets are the crucial aspects that exhibit economic and social countries' development and blossoming and bestow communities the tools to thrive and prosper, such as clean water, shelter, energy, mobility, and communication services^{1,2}. The pivotal issue here is how to appropriately appraise these assets physically, which is crucial to ensuring the utmost merit of public services and the perpetual prosperity of the communities^{3–6}. Meanwhile, enhancing the road infrastructure conditions in Egypt has engrossed all considerations to amplify and meet the international road infrastructure quality and standards. However, despite all the substantial progress consummated since 2010, some major road infrastructure drawbacks still require scrutiny and a broad spectrum of enhancements^{7,8}.

Despite the COVID-19 pandemic challenges that overwhelmingly praised the continued progress in entire countries worldwide, Egypt is still ponderously fixating on infrastructure road rehabilitation and enlargement, remarkably, road networks. In this regard, 7000 Km of Pavement is being constructed⁹. A total of 23,500 km will be expanded to approximately 30,500 km, and it will be prone to routine and periodic maintenance, which is requisite to evade further degradation by the end of 2022, with an approximated backlog expense of 9.8 billion US

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dollars. The significant need to expand and maintain existing projects resulted in a continued burden on Egypt's public finances⁹. Since 2011, Egypt's population has increased by nearly 20 million, and the number of vehicles on the road has almost doubled. Since 2014, the Egyptian government has been focused on expanding the country's road network, and Egypt's Vision 2030 marks the country's road network expansion and maintenance as a top priority. Maintaining the country's road network yields economic benefits as the government markets it¹⁰.

The research identifies a critical issue: as roads age and suffer from misuse, their deterioration significantly increases the risk to their operational functionality. Effective funding allocation and prioritization strategies can mitigate these risks, enhancing overall road performance^{11–13}. Current models for funding allocation in road infrastructure are inadequate for making informed prioritization decisions. Over time, significant progress has been made toward efficiently distributing limited Maintenance and Repair (M&R) funds across multiple assets. Nevertheless, developing an integrated approach for managing existing road infrastructures—combining a GIS-based management model with a prioritization model that utilizes an optimization scheme powered by a genetic algorithm—remains a substantial challenge in asset management. This study addresses this gap by proposing a structured and methodological approach to GIS-based funding allocation and prioritization.

This paper aims to expand on previous research by addressing the identified knowledge gap by developing an integrated decision-making model for existing road infrastructures. This model combines a GIS-based road management system with a fund allocation and prioritization strategy incorporating a genetic algorithm optimization scheme. The objective is to accurately identify and assign the most appropriate Maintenance and Repair (M&R) interventions based on the condition state to improve road segments' overall Pavement Condition Index (PCI), using a case study from Egypt. Specifically, the goals of this study are to: (1) create a GIS-based management database that integrates existing data and insights gained from inspections and attributes of road segments to facilitate proactive M&R decisions; (2) efficiently allocate available funds for the maintenance and repair of deteriorated roads to continue their service delivery; and (3) accurately determine the optimal type and timing of M&R interventions to enhance the condition and performance of road segments. The expected outcomes of this research will provide asset managers with a robust decision support system that enables effective M&R funding allocation and prioritization for road infrastructure segments to meet their projected service levels.

The paper is organized as follows: Section "Literature review" uncovers previous studies' endeavors to thoroughly discern the symbolic importance of the proposed methodology and the gaps in knowledge that the research seeks to address. Section "Research Methodology" unearths the integrated decision-making approach for existing infrastructure roads and explains how to depict the suggested research aims. Section 4 affirms and corroborates the proposed scheme by integrating it with an actual implementation to investigate the research initiatives exhibited in this study. Ultimately, Sect. 5 sums up the paper's observations and suggestions for future approaches.

Literature review

The management of road assets represents a critical and complex challenge within the immense field of infrastructural management. Recent research initiatives have introduced various methods that promise more consistent and optimized management techniques to address the growing challenges associated with aging road networks. These are all holistic methods that will involve using a systematic process and technique to enhance the management of road networks throughout the continuum of their lifecycle. Accordingly, this section will describe the different models and methodologies developed to forecast, mitigate infrastructure deterioration, optimize maintenance interventions, and refine economic evaluations. The section broadly describes the present state of road asset management.

Strategies and innovations in road asset management

To adequately meet public expectations, infrastructure assets, particularly roads, are costly to constitute and further during the maintenance phase^{14,15}. The underpinning aspect of asset management is optimization; however, existing techniques for optimization are still in the infancy stages of single infrastructure management, which severely restricts the advancement and adoption of asset management strategies¹⁶. Meanwhile, a heap of approaches that enable a more consistent and optimized management technique has been developed to tackle the escalation in aging road networks. An organization's methodical actions and procedures to manage its road networks, maximizing performance, risk, and expenditures throughout its entire lifecycle, are called asset management. These techniques and methods are essential for lessening expenditures while the asset is progressively working, prolonging its useful life, and lowering decommissioning and replacement costs^{17,18}.

In this context, a deterioration forecast is a practical approach in the management cycle of infrastructure roads, aiming at predicting the road's deterioration behavior to engender an anticipated deterioration paradigm as time passes¹⁹. Numerous models have been constructed to forecast infrastructure asset degradation. Zhang and Damnjanović²⁰ used reliability functions to indicate the likelihood of pavement failure. They claimed that the probability of altering the infrastructure status from one state to another is considered stochastic due to several non-observed factors that affect the existence of statistical errors or accidental errors in the information. Therefore, Zhang and Damnjanović²⁰ implemented a method that varies with time and involves probability. This method explicitly calculates the average degradation rate at different times, considering that this rate can change unpredictably. Nevertheless, the deterioration of infrastructure assets is thoroughly affected by utilization, age, road material, and construction process, as this information is variable and depends on its nature. Among these influencing factors, age is the most widely employed factor in condition inspection operations for modeling the infrastructure assets' deterioration²¹.

In a study by Esmaeili and colleagues²², an Artificial Neural Network (ANN) and regression methods were employed to develop a model predicting the deterioration of pavement conditions in Alberta's highway network. This model utilized multi-year pavement condition data from Alberta, focusing on indicators like the International Roughness Index and rutting to enhance maintenance planning. Santos et al.²³ optimized the inspection intervals of highway bridges using Markov and neural network-based predictive deterioration models. These models, leveraging extensive databases, offer more accurate deterioration forecasts, enhancing bridge safety and serviceability. Nevertheless, Bianchi and Hebdon²⁴ introduced an innovative inverse-GAN approach using deep learning to create and modify structural bridge images. This method, trained on data from bridge inspection reports, predicts infrastructure deterioration, aiding in maintenance decision-making.

Besides, Moscoso et al.²⁵ developed a 'two-step cluster analysis' deterioration model for bridges, considering factors like geometry and traffic volume. The model suggests that delayed maintenance sharply accelerates bridge deterioration, impacting lifespan. Lastly, Angelo and team²⁶ proposed a strategic pavement management system in Addis Ababa, Ethiopia, focusing on safety and pavement performance. This system incorporates deterioration models and lifecycle cost-risk analyses, significantly reducing fatal injuries and aiding in informed decision-making.

Abundant research has been directed to broaden the implementation of asset management systems for infrastructure roads; for instance, Jamshid¹⁴ examined the road asset management system from the perspectives of four key elements: goals, budget, assets, and performances. There are several issues at the policy level of analysis, including the establishment of long-term goals, the expansion of the road network, traffic safety action plans, environmental impact analysis, economic development, and others; at the budget level for planning year and multi-year financing plans, budget breakdown, and cost estimation; at the data management level for gathering inventory and condition data, database management, traffic data, and other information; and at the performance modeling level for predicting future condition, among others. The approach to network-level analysis simplified road network evaluation and used the analytic hierarchy process to rank asset, cost, and traffic regions. Furthermore, Dina et al. (2016) developed a thorough multi-infrastructure optimization model for roads and bridges to attain the objectives of comfort, integrity, and security for infrastructure assets. This model applies integer programming optimization techniques while taking budget funds as constraint conditions.

Speaking of Genetic Algorithms (GAs), Goforth et al.²⁷ depicted Asset Management (AM) systems as intricate networks comprising nodes and links that portray the essential elements for operation within an organization, encompassing the flow of information between these components. ISO 55,001, a global standard, sets forth the prerequisites for a successful AM system, reflecting the criticality of various system components via the weighting of network links. Key challenges in AM systems include information asymmetry, where decision-making is hindered by inconsistent information, and information overload, where excessive data impairs decision-making. These problems depict systemic risks due to the interdependency within the AM system. Goforth et al.²⁷ proposed strategies to mitigate these systemic risks, informed by various metrics and stakeholder feedback.

For this problem, Panagiotis et al.²⁸ developed a multi-objective dynamic optimization model that considers the costs of building and moving facilities, the transportation costs of resources between facilities or workplaces, as well as safety and environmental concerns brought on by the use of and connections between facilities. The latter factors are considered as preferences or limitations for how close or far away certain facilities are from other facilities or work locations. By including desirable preferences or restrictions in the decision-making process, the model allowed site managers to explore alternate situations and fine-tune ideal solutions based on their experience.

According to Milat²⁹, the customized evolutionary algorithm should be used to create resilient baseline schedules with enough time floats to mitigate the effects of unpredictability. By balancing the project's time, final profit, and general baseline stability in this way, the baseline answer is found. The suggested algorithm analyzes data from actual building projects, and the analysis's findings point to increased strength for resilient baseline schedules. The current multi-objective problem can be solved using the genetic algorithm, which makes it possible to use new technologies and approaches in construction management.

Mikolaj et al.³⁰ presented a comprehensive asset management system to bridge the economic approach to asset management with the technical procedure for the life cycle of road infrastructure, specifically its resilience and performance. The methodologies for determining asset value being provided are based on socioeconomic perspectives on the advantages that an asset provides to the community and technical considerations of the technical condition and remaining useful life of road infrastructure. Nevertheless, the impact of road asset management (RAM) on the productivity of Kenyan road agencies was examined³¹. Stakeholder theory served as the study's leading guide. It proposed a conceptual framework in which road agency performance was the dependent variable and road assets management was the independent variable. A correlation survey methodology was used to determine the association between the study variables. The study found that RAM considerably improved the performance of road agencies and advised that RAM be included in road agencies' policies in Kenya to improve the long-term state of Kenya's roads.

Saad and Hegazy³² emphasized the imperative of a strategic approach to managing asset rehabilitation, aiming to optimize funding via enhanced benefit-cost analysis, akin to marginal utility, for co-located assets. Their goal was to attain balanced and optimal decision-making in fund allocation. Further, Saad and Hegazy³³ explored how behavioral economics, particularly loss aversion, can influence decision-making in infrastructure project rehabilitation. Mohamed et al.³⁴ presented a framework using as-is Bridge Information Modeling (BrIM) to enhance inspection and maintenance processes. The framework converts 2D drawings into 3D BrIM models, enabling accurate condition assessment. Real-time data collection and structural defect modeling improve diagnostics and intervention planning.

The advancement of GIS-Based Road Asset Management has seen significant contributions in recent years. In this context, Ali³⁵ focused on developing a GIS-based system specifically for motorways in Pakistan, targeting the decline of the National Highway network. This system, known as GIS-based Highway Asset Management System (GHAMS), integrated a digitized database with ArcGIS for generating thematic maps, graphs, and charts, aiding in efficient maintenance and rehabilitation of the National Motorways. Mazhindu and Madamombe³⁶ explored the creation of a web-GIS tool for managing road infrastructure in Zimbabwe. Their tool utilized open-source GIS tools to enable users to visualize and query road assets, offering a cost-effective and user-friendly option for road asset mapping, which aids in decision-making processes.

Similarly, Sreelekshmi and colleagues³⁷ developed an Asset Score using the Analytic Hierarchy Process (AHP) and GIS. This score helps prioritize maintenance on road networks based on various factors like pavement condition, traffic volume, and congestion. Natsui et al.³⁸ introduced a Geographical Information and Road Asset Management System (GIRAMS), a web-based system that enhances the efficiency of road funding agencies in managing road networks and related infrastructures. It includes subcomponents like Advanced Road Asset Management (ARAMS), which is compatible with various economic analysis interfaces and features analytical tools for asset valuation and predictive models for road deterioration. Saepudin et al.³⁹ also focused on implementing GIS for road maintenance management in Bandung District. The goal was to improve road performance and service quality, especially in strategic sectors.

Advancements in predictive modeling for infrastructure maintenance and assessment

Advances in predictive models have received the highest attention in recent studies of management infrastructure. The models would enhance the quality of predictions and the reliability of forecasts in maintenance and condition assessment in transport infrastructure. In this context, Lavrenz et al.⁴⁰ researched the dependency relations of bridge members, deck, superstructure, and substructure, all pointing out that these do not deteriorate independently. The study adopted a 3SLS model to quantify the interdependencies, thereby showing an improvement in the forecast accuracy over the traditional models that used ordinary least squares (OLS).

Building on this foundational research, Saeed et al.⁴¹ critically examined the serviceability of highway bridge superstructures concerning concrete. Generally, such research assessment has assisted highway agencies in preparing for maintenance and rehabilitation activities since various concrete superstructures, including cast-in-place and pre-stressed concrete, were considered. Advancing this approach, Saeed et al.⁴² proposed a novel framework of a probabilistic modeling methodology for a more reliable prediction of conditions for the bridge infrastructure. This model adopts the history of both maintenance and intervention of in-service bridge components. It also considers some newly introduced explanatory variables that reflect the impact of intervention types on the future deterioration of the component.

Parallel to these efforts, Bhargava et al.⁴³ developed a method using risk-based multinomial models with Monte Carlo simulation to forecast the cost escalation pathways and severity in infrastructure projects. This method will propose a new approach to financial risk appraisal in project management. Concurrently, Volovski et al.⁴⁴ enhanced the accuracy of forecasting expenditures on maintaining highway infrastructure. This paper justified using the random-effects panel data methodology exercise to consider significant spatial and temporal differences that are important for the model estimation to be accurate.

Transitioning from structural to pavement analyses, Ahmed et al.⁴⁵ tackled the marginal costs of pavement damage with continuous heterogeneity in individual segments. This study focuses on the issue of equity in uniform average user fees charged to all pavement systems and utilizes a random-parameters (RP) regression model. Qiao et al.⁴⁶ further explored this study's implications for policy, which proposed an infrastructure repair evaluation framework using discrete choice models. Specifically, the focus lay in decisions on the maintenance, rehabilitation, and reconstruction of in-service bridge decks in a highway agency in the Midwestern USA.

Echoing the importance of systematic predictions in this context, Ahmad et al.⁴⁷ established the prediction of rest periods for the newly rehabilitated pavement on highways as a critical input into maintenance planning and budgeting. The developed methodologies aim to predict the rest period in a systematic way to support life cycle costing and long-term planning. This predictive theme was expanded by Yamany et al.⁴⁸, who tested the degree to which it was equally viable in developing state-specific pavement performance models compared to generalized ones. The study compared three approaches of modeling: fixed-parameter regression, random-parameters regression, and artificial neural networks (ANNs), using condition data from Interstates. The flexible pavements are across eight Midwestern states. The study indicated that state-specific models developed with the help of ANN are one of the benefits of pavement management systems.

Further refining predictive accuracy, Saeed et al.⁴⁹ developed a robust methodology for quantifying the impact of standard maintenance treatments on the condition ratings of pavements and bridge decks within the state highway of the Indiana Department of Transportation (INDOT). This research incorporates generating reset values for asset management software to evaluate long-term effectiveness to increase the life span of treated assets or to determine cost-benefit analysis for optimizing resource allocation and maintenance planning. Synthesizing these advancements, Richmond et al.⁵⁰ developed a new method of deterioration curve construction applicable to the pavement and other infrastructure asset service life. The approach further develops the existing approach by basing the shape of the deterioration curves on empirical data without preselecting a specific functional form.

Recent advances in optimization and safety for infrastructure management

Effective infrastructure management is essential for enhancing construction efficiency, minimizing risks, and optimizing resource allocation. Recent advancements in multi-objective optimization models, machine learning algorithms, and predictive maintenance strategies have significantly improved decision-making processes in the construction and transportation sectors. Studies have introduced innovative approaches to tackle challenges related to equipment utilization, traffic safety, disaster prevention, and predictive maintenance—offering

practical solutions to improve performance, cost efficiency, and sustainability. In this context, Shehadeh et al.⁵¹ developed a multi-objective optimization (MOO) model using Improved Particle Swarm Optimization (IPSO) to optimize highway construction operations such as excavation, hauling, grading, and compaction. The model considers factors like equipment count, speed, and capacity to generate optimal solutions and visualize the Pareto frontier. Compared to Genetic Algorithms (GA) and GPAWOA, IPSO achieved up to 35.4% time savings and 39.1% cost reductions, demonstrating superior performance. A real-world case study validated its effectiveness in balancing cost and time trade-offs, supporting decision-making for resource allocation and equipment utilization in highway construction.

Moreover, Almadi et al.⁵² analyzed factors contributing to highway crashes on I-69 in Flint, Michigan, known for its high crash and fatality rates. Using a multi-user driving simulator and a multinomial logistic regression (MNL) model, the study examined speed limits' effects on crash likelihood during inclement weather. Findings revealed that speeding and speed limit changes in snowy and icy conditions were major contributors to crashes. The study proposed Crash Modification Factors (CMFs) to mitigate crashes and enhance traffic safety on Michigan highways. Shehadeh et al.⁵³ also introduced a Slope Displacement Inspection and Management Algorithm (SDIMA) that uses GNSS data to detect slope displacements for disaster prevention on construction sites. Using a robust mathematical model, the algorithm identifies displacements exceeding 25 mm and distinguishes actual changes from errors. SDIMA outperformed existing methods with a Mean Absolute Error (MAE) of 3.157 mm, Root Mean Square Error (RMSE) of 4.754 mm, and an average processing time of 0.578 min, offering a low-cost, automated real-time monitoring and construction safety management tool.

Further, Alshboul et al.⁵⁴ investigated Predictive Maintenance (PdM) in concrete manufacturing to enhance construction management by predicting machinery failures and minimizing downtime. Using machine learning (ML) algorithms, the study evaluated seven classifiers, including CatBoost, XGBoost, and Random Forest (RF), based on metrics like F1-score, accuracy, and Recall. CatBoost performed best, achieving an F1-score of 0.985 and an accuracy of 0.984. Key predictors, such as vibration, pressure, and voltage, were identified as critical failure indicators. The results emphasize the importance of ML integration in construction management to improve maintenance forecasting and equipment reliability.

The literature review section comprehensively explored extensive previous studies in asset management for existing infrastructure assets. It delved into the significant challenges faced by agencies tasked with making critical decisions about rehabilitating infrastructure roads. This review highlighted the considerable effects of road rehabilitation on the condition and serviceability of infrastructure and on achieving the desired service levels. However, it was noted that no prior research has successfully developed a comprehensive decision-making model for existing infrastructure roads that combines a GIS-based road management system with a fund allocation prioritization model through an optimization approach. This gap underscores the ongoing need for innovative solutions in this area. Such advancements are particularly crucial for achieving quick and reliable assessments in real-world scenarios, explicitly emphasizing the context of Egypt.

Research methodology

This research introduces a groundbreaking integrated decision-making model for managing existing road infrastructure. The model fuses a GIS-based road management system with a fund allocation prioritization framework powered by an optimization scheme that utilizes a genetic algorithm. This innovative approach focuses on selecting and applying the most effective Maintenance and Repair (M&R) interventions based on the condition state to improve road segments' overall Pavement Condition Index (PCI). PCI is a widely recognized metric used to evaluate pavements' structural and functional performance based on visual assessments of surface distress. It provides a quantitative score ranging from 0 to 100, where higher values represent better pavement conditions. Specifically, PCI values are categorized as Excellent (85–100), Good (75–84), Fair (55–74), Poor (40–54), and Failing (< 40). The PCI calculation incorporates various pavement properties, including cracking (longitudinal, transverse, and alligator), rutting (wheel path depressions), surface smoothness (ride quality), potholes, and skid resistance. This study adopted a five-scale PCI rating system aligned with the General Authority for Roads & Bridges and Land Transport (GARBLT).

The selection of PCI acts as the primary indicator based on its reliability as a standardized metric, ability to integrate multiple pavement properties into a single composite score, and compatibility with predictive models such as Markov Chains for deterioration analysis. Additionally, PCI data seamlessly integrates into optimization algorithms like the GA used in this study to prioritize fund allocation and maximize pavement performance within budget constraints. The availability of historical PCI data from GARBLT further reinforced its selection as a practical and data-driven approach to M&R planning.

The proposed GIS-based road management and optimization framework addresses critical limitations in existing infrastructure management approaches by integrating spatial data analysis, deterioration forecasting, and fund allocation optimization into a unified decision-support system. Its robustness is rooted in three key aspects: (1) Data Integration and Visualization: The use of GIS technology enables seamless data integration, providing visual mapping of road segments and facilitating real-time monitoring of pavement conditions and deterioration patterns; (2) Predictive Modeling with Markov Chains: The model employs a Markov Chain deterioration prediction module to assess future pavement conditions based on probabilistic transitions, ensuring reliable forecasts for long-term planning; and (3) Optimization via GA: The framework incorporates GA-based optimization techniques to prioritize M&R interventions while adhering to budget constraints. The GA dynamically evaluates possible solutions, selecting interventions that maximize PCI improvements and minimize costs, demonstrating computational efficiency and resilience to variations in network size and budgetary conditions, as rendered in Fig. 1.

The motivation for developing this approach stems from the identified gaps in current infrastructure management systems, which cannot often integrate GIS-based visualization tools with optimization frameworks.

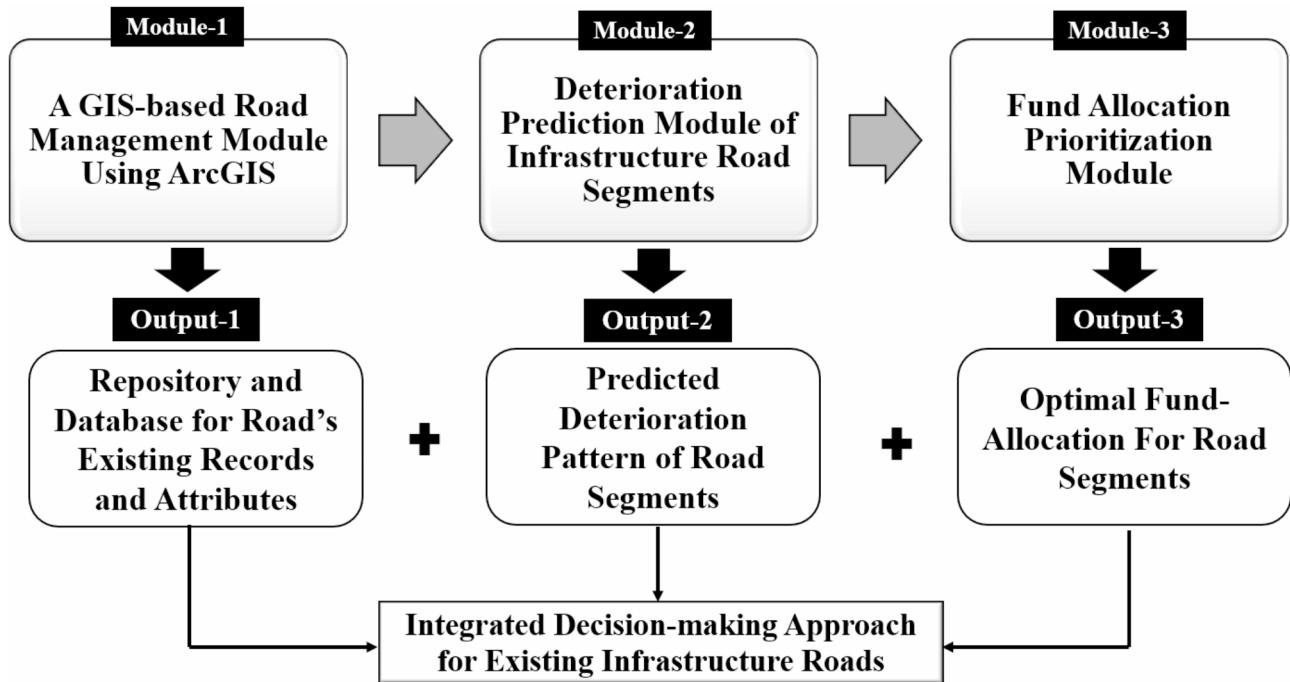


Fig. 1. Proposed research methodology.

Existing approaches focus on isolated aspects, such as deterioration modeling or cost estimation, without providing a holistic decision-making platform.

A GIS-based road management module using ArcGIS

A road management model based on GIS technology has been implemented, which constitutes a comprehensive database designed to merge detailed mapping and spatial analysis. It focuses on planning related to road infrastructure and includes various essential characteristics, namely: (1) Location Identity, (2) Physical Condition, (3) Traffic Characteristics, (4) Structural and Historical data, and (5) Maintenance and Repair (M&R) data. The GIS model captures the breadth and location of resources and assets, monitors their condition over time, and generates tabular and map-based graphical analyses that consolidate crucial data for managing informational, operational, and maintenance actions. A third-norm form binds the entire data amassed in the GIS-based model with one too many relationships to unveil patterns and correlations, which are arduous to attain without a spatial perspective.

The Physical Condition within the GIS-based road management module is designed as a multi-parameter evaluation system that integrates diverse pavement performance indicators to provide a holistic road infrastructure assessment. While the PCI serves as the core indicator, capturing visible surface distresses through a composite score, it is complemented by additional performance metrics that offer insights into structural and functional conditions. These include assessments of cracking types and severity, such as longitudinal, transverse, and alligator cracks, which highlight structural fatigue. These indicators collectively enable deterioration modeling, fund allocation prioritization, and M&R optimization using the GA-based framework described in this study. This comprehensive approach ensures that decisions are grounded in a multi-criteria evaluation that balances structural and functional performance considerations, enabling data-driven infrastructure management.

Deterioration prediction module of infrastructure road segments

Infrastructure roads frequently degrade toward the subsequent level or to a deficient condition as time passes. Within this context, Infrastructure road degradation is a stochastic process. Consequently, Markov Chain modeling is adopted to anticipate the future condition state from the current case employing a discrete Markov Chain time model.

Markov Chain imitates infrastructure road deterioration patterns by utilizing discrete variables via a series of steps at discrete points in time, as per defined probabilities. The initial step in the Markov Chain analysis involves using the current condition of road infrastructure segments to predict the different states of deterioration that road segments might undergo following the principles of the Markov Chain method. This deterioration sign assists in forecasting the road segments' efficiency throughout a time interval. The condition rating state adopted in this study comprises a 5-scale condition rating system, where 1 is an exemplary quality, and 5 depicts a fully deteriorated road segment. As a result, the transition matrix for anticipating the degradation process is a five-by-five matrix. Transition probabilities (P_{ij}) should fulfill two criteria⁵⁵.

$$P_{ij} \geq 0 \text{ for } i, j = 1, 2, \dots, k$$

$$\text{the } \sum_{j=i}^k P_{ij} \leq 1$$

The Markovian conditional probability matrix for a one-phase transition probability P_{ij} from state i to state j is identified as follows (Eq. 1):

$$\Pr \{X_{t+1} = j | X_0 = k_0, X_1 = k_1, \dots, X_t = k_i\} = \Pr \{X_{t+1} = j | X_t = i\} \quad (1)$$

In Eq. 1, $X_t = i$ states that the present state at time t is i , and $t+1$ is j ; $X_{t+1} = j$ depicts the next state at a time. Moreover, the deduction of the n -step transition matrix is portrayed in Eq. 2. In Eq. 2, $P[X(tn)]$ depicts the state probability matrix at time tn ; $P[X(0)]$ depicts the initial state probability matrix, and P depicts the transition probability matrix.

$$P[X(tn)] = P[X(0)] P^n \quad (2)$$

The study adopted the transition matrices Sati et al.⁵⁷ developed to anticipate the pattern of road segment deterioration. These transition matrices relied on the percentage prediction approach with a minimum one-year time span.

Fund allocation prioritization module

The prioritization and optimization process aims to rank the road segments for M&R interventions by maximizing the utilization of available funds to meet an expected service level. This process relies upon their Pavement Condition Index (PCI), retrieved from the General Authority for Roads & Bridges and Land Transport (GARBLT). During this stage, an optimization model employing a Genetic Algorithm (GA) functions as a probing algorithm (see Fig. 2). Using the GA method, every feasible solution is regarded as an independent “organism” that can yield other organisms with common attributes. Consequently, the primary motive for adopting the GA engine is that the optimization problem, presented hereby, is considered an exponentially and computationally complex formulation that encompasses a broad spectrum of decision variables.

Genetic algorithms work by managing a group of potential solutions, which are coded as chromosomes or strings. This group undergoes various genetic manipulations, including selection, crossover, and mutation, to create a new group with potentially improved solutions. In the selection phase, the most suitable individuals are elected from the existing group based on their ability to solve the problem, as indicated by their fitness values. These chosen individuals are then used in the crossover process, which combines elements from two or more parent solutions to form new offspring. Additionally, the mutation process introduces random changes to these new solutions, encouraging the exploration of uncharted areas in the solution space. This method allows for a more thorough examination of the solution space and helps prevent the algorithm from getting trapped in local optima. The newly formed group of solutions is evaluated for effectiveness, and this cycle continues until a specific endpoint is reached, like a maximum number of generations or a desired fitness level. The best-performing solution at the end of the genetic algorithm process is considered the optimal solution for the problem⁵⁸.

Encoding the chromosome

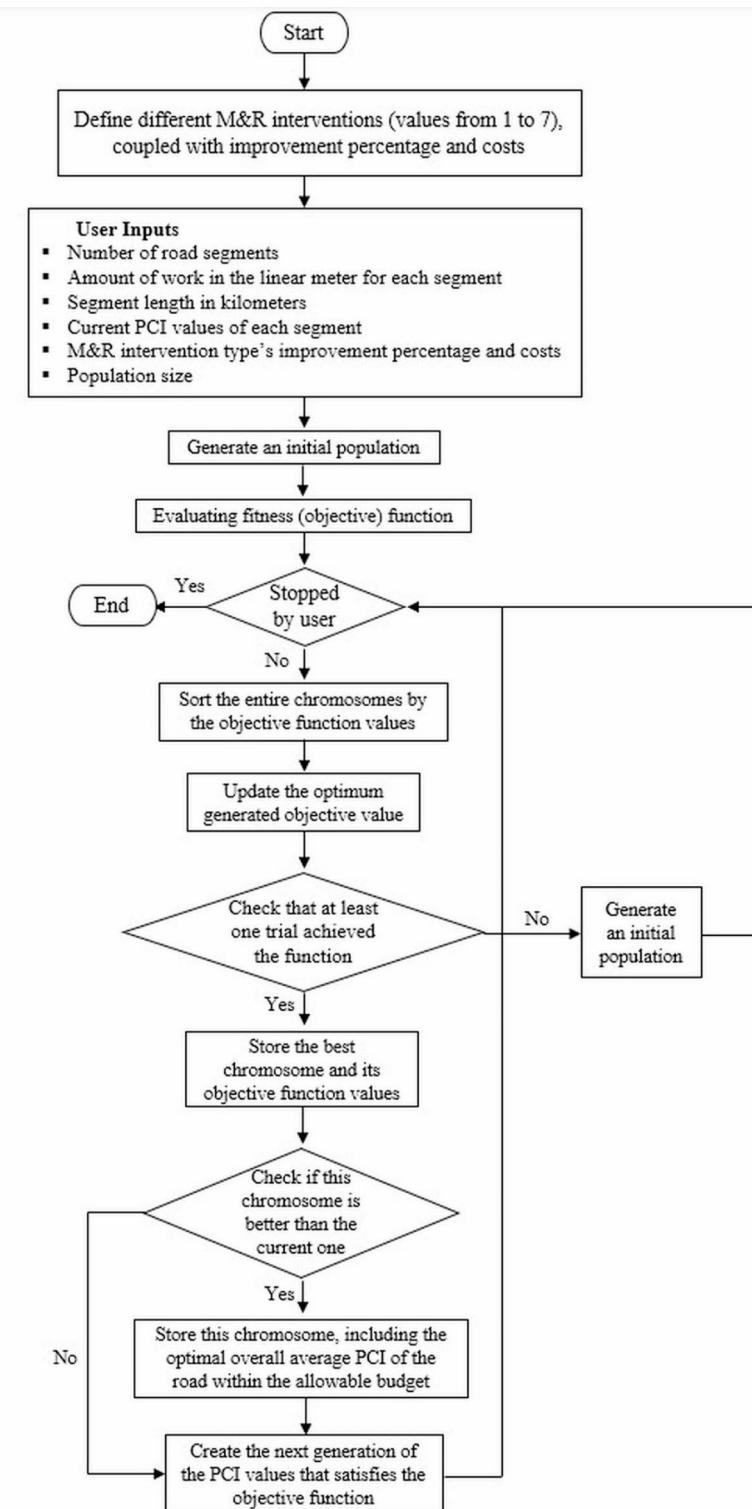
In GA, a solution to an optimization problem is embodied as a “chromosome,” a data structure that encodes a batch of parameters denoting the solution. In the context of this research, a chromosome structure was encoded using different configurations of defined different M&R interventions (values from 1 to 7) coupled with correlative M&R intervention improvement percentage and M&R intervention cost. A sequencing chain of elements encoded a chromosome structure, each portraying a road segment and including an index indicating its defined M&R intervention type.

Each road segment’s PCI value is combined with the projected M&R costs per year to evaluate each chromosome’s solution. These values are estimated based on relevant indicators present within the chromosome. The chromosome represents the cumulative PCI of the entire road, encompassing all segments. Each gene within the chromosome corresponds to the PCI value, associated M&R costs for a specific road segment, and the necessary M&R intervention. The chromosome comprises strings, the length of which indicates the number of road segments. The goal of the optimization algorithm is to find the chromosome that optimally enhances the overall PCI of the road within the given budget. This process involves evaluating the fitness of each chromosome in the group and employing selection, mutation, and crossover processes to progressively evolve the group towards the best solution over several generations. Figure 2 displays the complete structure of the proposed genetic algorithm approach.

Objective function

The central goal of the GA model is to optimize the average PCI of the entire road, staying within the specified budget and using pre-established M&R intervention types over the 5-year planning horizon (t). This goal is evaluated based on the collective chromosomes in each generation. The chromosomes are then ranked according to their effectiveness in achieving the best outcome for the goal. The function is formulated and operated by varying the variable from 1 to 7, representing the different M&R types assigned to each road segment. Table 1 outlines the decision variables, associated M&R interventions used during optimization, the cost of each M&R intervention per unit, the unit of measurement, and the corresponding percentage improvement in PCI.

Additionally, the optimization model adheres to the constraints listed in Table 2. In this context, the objective function can be expressed as stated in Eq. 3, in which PCI_{it} represents the condition state of each segment (i)

**Fig. 2.** The Proposed GA workflow.

at year (t), calculated based on the initial condition and the expected improvement from the selected M&R interventions. By summing the PCI values over the planning period and all segments, the objective function ensures that the optimization model maximizes pavement performance while adhering to budget constraints. This time-dependent optimization approach enables dynamic decision-making, allowing for the evaluation of yearly interventions to maintain or improve road conditions, extend service life, and optimize fund utilization effectively.

X _{ij}	Decision Variable Number	Maintenance and Repair Interventions	Cost (EGP)/Unit	Unit	PCI Improvement %
X ₀	Value "0"	Do-Nothing	-	-	-
X ₁	Value "1"	Prevention Maintenance	30	Meter Linear	25%
X ₂	Value "2"	Very Slight Serviceability	47	Meter Linear	30%
X ₃	Value "3"	Condition Based Maintenance	76	M ²	40%
X ₄	Value "4"	Partial Repairing	94	M ²	50%
X ₅	Value "5"	Major Repairing	110	M ²	55%
X ₆	Value "6"	Renovation and Rehabilitation	116	M ²	70%
X ₇	Value "7"	Entire Replacement	210	M ²	90%

Table 1. Maintenance and repair intervention types.

Attribute	Description
Objective Function	Maximize the road's overall pavement condition index (PCI) within the allowable budget.
Variables	<ul style="list-style-type: none"> Different M&R interventions (values from 1 to 7). M&R decision per each year (binary values)
Constraints	<ul style="list-style-type: none"> Decision variable (M&R different strategies) ≥ 0 Decision variable (M&R different strategies) ≤ 7 Decision variable (M&R different strategies) is an integer value. M&R decision per segment per each year is a binary value Total allowable budget for M&R action plan (per 5 years). PCI per segment per each year ≤ 100 Overall PCI (objective function) ≤ 100

Table 2. Optimization model attributes.

$$\max \sum_{t=1}^5 \sum_{i=1}^n \text{PCI}_{it} \quad (3)$$

Initial population engendering susceptible to the objective functions

GA begins its evolutionary optimization process by constructing an initial population of parent chromosomes, typically a set number (N) of viable chromosomes. These chromosomes are then assessed and ranked based on predefined evaluation criteria. A crucial aspect of this process is the population size, which significantly influences both the computational time required and the potential for finding an optimal solution. As the population size increases, the likelihood of reaching a global optimum also rises, but at the cost of increased processing time. In this specific application, users have the flexibility to determine the population size based on their preferences. Each chromosome within the population is evaluated for its fitness, and its relative importance is calculated by dividing its fitness by the total fitness of all chromosomes. The fittest chromosomes are then selected to be preserved and passed on to the next generation. These selected chromosomes remain eligible for breeding while generating the remaining parents for the subsequent generation.

During each iteration of the GA, the crossover and mutation processes are applied to the parent chromosomes. These processes ensure that while the essential characteristics of the chromosomes are maintained, there is a variation in the order of M&R intervention types assigned to each road segment. This variation leads to the creation of new chromosomes. The GA is designed to prioritize the fitter chromosomes for further evolution and effectively analyze the PCI values and associated M&R costs. This dynamic approach facilitates a more efficient exploration of potential solutions, enhancing the algorithm's ability to find an optimal solution within the constraints of time and computational resources. In this regard, the initial population of chromosomes (potential solutions) was engendered mainly via a random initialization method, widely adopted in GA implementations attributable to its simplicity and efficacy in fulfilling a broad spectrum of search space. Randomly engendering the initial population permits the algorithm to discover a broad spectrum of solutions at the early stages, hindering the GA from converging prematurely on local optima. Additionally, various and randomly engendered initial populations promote a robust foundation for following genetic operations such as crossover and mutation, directing the solutions toward optimality^{27–29,34,59}.

Genetic operators

In the genetic algorithm process, the reproduction of the population occurs through two primary mechanisms: crossover and mutation, both serving as genetic operators akin to natural evolutionary processes. Crossover, the more commonly used method, involves selecting two parent chromosomes randomly, though their fitness levels influence the selection to favor superior chromosomes. This process includes exchanging genetic information between these parent chromosomes to produce offspring, with the exchange being random. In contrast to crossover, mutation represents a less frequent but impactful process. It entails randomly choosing a chromosome and making arbitrary changes to its genetic information. This mutation can introduce new characteristics to the population, helping to overcome stagnation in the evolutionary process and avoiding getting trapped in local minimums.

When two parents are selected to produce two offspring, the crossover operator divides the parents' genetic material into groups based on the M&R (Maintenance and Repair) intervention type. This division and subsequent gene swapping result in offspring inheriting M&R types from both parents. These offspring are converted into feasible PCI (Pavement Condition Index) values within the allocated budget. Once offspring are generated, they undergo a fitness evaluation. They are retained in the population only if their fitness surpasses other members. This cycle continues over several generations until an optimal solution is found. The user controls the number of generations, which acts as a stopping criterion for the process.

Additionally, the algorithm can be halted when a satisfactory solution meeting the overall PCI criteria is found. In such cases, the output will include the PCI for each road segment per year and the corresponding M&R type. If the desired solution is not reached, the algorithm continues to search for a better solution.

The optimization model is formulated using an optimization engine platform named Evolver TM Version 7.6, encompassing three primary features: objective function, decision variables, and constraints, as exhibited in Table 2. As displayed in Fig. 3, the primary input values and parameters of the optimization model are (1) the number of road segments, (2) the amount of work in square meters in each segment, (3) the PCI of each road segment, (4) the decision variables representing the M&R interventions (ranging from value 1 to value 7), as depicted in Table 1, within the planned time horizon, and (5) the optimization model objective function within planned time horizon, presenting the PCI of each road segment per year and M&R interventions associated cost demanded, if any, relying on developed optimization model variables and constraints. It is worth noting that the data collection on M&R intervention costs for each road segment is a variable parameter, relying upon the timing of cost acquisition, which will influence the quality of the generated optimization model outputs and impact the allocation of the available funding.

Decision variables and constraints formulation

Integer programming constructs the decision variables, in which the spectrum of decision variables is identified by the M&R operations number demanded in the model. The more extensive the decision variables, the optimization issue becomes significantly complicated by the computational formula. These decision variables are subjected to the constraints mentioned above, portrayed in Table 2. Once the objective function, variables, and constraints are defined, optimization is carried out, which induces a set of test solutions (M&R decisions for each year) and applies a genetic algorithm to maintain each test's outcomes constantly. For the decision variable, assume x_{ijt} as a binary decision variable, where i is the road segment, and j spans from 0 to 7, depicting the M&R intervention type deployed.

A series of constraints govern the mathematical formulation of the proposed optimization model to ensure feasible and effective decision-making for M&R interventions over a 5-year planning horizon. Equation (4) introduces a binary decision variable (x_{ijt}) that assigns one specific M&R action (j) to each road segment (i) annually, where $x_{ijt}=1$ indicates that action j is applied in year t , and $x_{ijt}=0$ means no action or an alternative

Segments #	Amount of work in Square Meter	Amount of work in Linear Meter	PCI	Road Length in Linear Kilometer
Segment #1	13500	1125	75	4500
Segment #2	10800	900	80	4500
Segment #3	10800	900	80	4500
Segment #4	5400	450	90	4500
Segment #5	5400	450	90	4500

Decision Variables						Sum
Repair Type	Y.1	Y.2	Y.3	Y.4	Y.5	
5	0	0	0	1	0	1
2	0	1	0	0	0	1
2	0	1	0	0	0	1
1	0	0	0	1	0	1
2	0	0	0	0	1	1

Year 2023		Year 2024		Year 2025		Year 2026		Year 2027	
PCI	Total Cost Per Year								
71.3	0.00	67.7	0.00	64.3	0.00	99.7	1,485,000.00	94.7	0.00
76.0	0.00	98.8	42,300.00	93.9	0.00	89.2	0.00	84.7	0.00
76.0	0.00	98.8	42,300.00	93.9	0.00	89.2	0.00	84.7	0.00

Each road's segment is maintained and repaired once a time among the planned time horizon

Fig. 3. Setting up and formulating the optimization model.

intervention is selected. Equation (5) restricts each segment to only one type of M&R action per year to enforce this exclusivity, preventing overlaps or conflicting repairs. The budget constraint in Eq. (6) ensures that the total cost of all selected interventions, calculated as the product of unit costs (cost_j) and segment areas (area_i), does not exceed the available budget, thereby optimizing fund allocation within the yearly financial limitations. Equation (7) calculates the updated PCI for each segment annually by adding the expected improvement (improvement_j) from the chosen M&R action to the initial PCI ($\text{basePCI}_{i(t-1)}$), reflecting the yearly impact of interventions on pavement performance. Lastly, Eq. (8) imposes a PCI threshold to ensure that the updated PCI_{it} does not exceed the maximum allowable value of 100, maintaining logical consistency with standard pavement rating systems. These constraints collectively establish a structured optimization framework that integrates budgetary limits, performance improvements, and decision exclusivity, enabling a systematic and data-driven approach for prioritizing M&R actions.

$$x_{ijt} \in \{0, 1\}, \text{ for all } i \text{ and } j = 0, 1, 2, \dots, 7 \text{ and } t = 1, 2, \dots, 5 \quad (4)$$

$$\sum_{j=0}^7 x_{ijt} = 1, \text{ for all } i \text{ and } t \quad (5)$$

$$\sum_{i=1}^n \sum_{j=1}^7 \cos t_j \cdot \text{area}_i \cdot x_{ijt} \leq \text{budget for all } t \quad (6)$$

$$\text{PCI}_{it} = \text{basePCI}_{i(t-1)} + \sum_{j=1}^7 \text{improvement}_j \cdot x_{ijt}, \text{ for all } i \text{ and } t \quad (7)$$

$$\text{PCI}_{it} \leq 100, \text{ for all } i \text{ and } t \quad (8)$$

Based on the objective function, many challenges can be addressed by the developed prioritization and optimization model: the required funds and their efficient distribution. The available budget computation is commonly linked to ascertaining the financing needed to preserve the PCI of road segments at a coveted standard. The prioritization and optimization model is advantageous and valuable for decision-makers with different target priorities. These priorities could distinguish decision-making entities or authorities, like asset executives, asset managers, and maintenance and repair agencies. Consequently, all policy-maker considerations are encompassed by prioritization and optimization by creating significant weights for each reference.

The PCI improvement values in Table 1 are derived from empirical studies, industry standards, and historical performance data from GARBLT. These values represent the expected percentage improvement in PCI after implementing specific M&R interventions. For example, prevention maintenance is estimated to improve PCI by 25% based on observed reductions in surface distress and deterioration rates following preventive treatments, such as sealing cracks and surface coatings. Accordingly in the decision-making model, these values are integrated into the GA optimization framework to prioritize and schedule M&R activities. The process involves updating each segment's PCI annually based on Markov Chain deterioration predictions. When an intervention is applied, the PCI improvement percentage is added to the segment's current PCI, ensuring that the projected condition after treatment is reflected in subsequent optimization cycles. The model evaluates trade-offs between improvement gains and costs, enabling fund allocation decisions that maximize overall pavement performance while adhering to budget constraints. This approach ensures a data-driven, cost-effective strategy for managing pavement conditions over time.

The cost values portrayed in Table 1 depict average unit costs, presented in Egyptian Pound (EGP), (per square meter or linear meter) for various M&R interventions based on historical data obtained from the GARBLT in Egypt. These values account for material, labor, equipment, mobilization, and traffic management expenses observed in recent road maintenance projects. The cost estimates cover a range of interventions, including preventive maintenance, which focuses on minor treatments such as crack sealing and fog sealing to slow deterioration and preserve pavement quality; condition-based maintenance, which targets localized repairs to address moderate distresses through patching and surface treatments; major repairs and rehabilitation, which involve structural interventions like overlaying or milling to restore pavement integrity; and complete replacement, which represents the most intensive intervention, involving complete reconstruction to restore serviceability. These cost inputs are integrated into the GA-based optimization model, enabling the simulation of budget constraints and prioritization of interventions that yield the highest improvement in PCI. The model effectively evaluates trade-offs between cost and improvement gains, enabling fund allocation decisions that maximize overall pavement performance while adhering to budget constraints.

Framework implementation

A 126-kilometer Cairo-Suez road in the northeast is enacted as an actual application to appraise the proposed research endeavor presented in this paper to validate and verify the developed approach. The road is divided into 28 segments, each with a pertinent unique ID number, as depicted in Figs. 4 and 5. The segments are uniformly divided, each spanning approximately 4.5 km. Initially, the GIS-based road management model was developed to integrate potent mapping and spatial examination with a thorough approach for contriving pertained to Cairo-Suez road segments, incorporating multiple and essential attributes, namely: (1) Location Identity, (2) Physical Condition, (3) Traffic Characteristics, (4) Structural and Historical data, and (5) Maintenance and Repair (M&R) data (see Fig. 4). The GIS model portrays a database to capture the breadth and location of resources and assets,

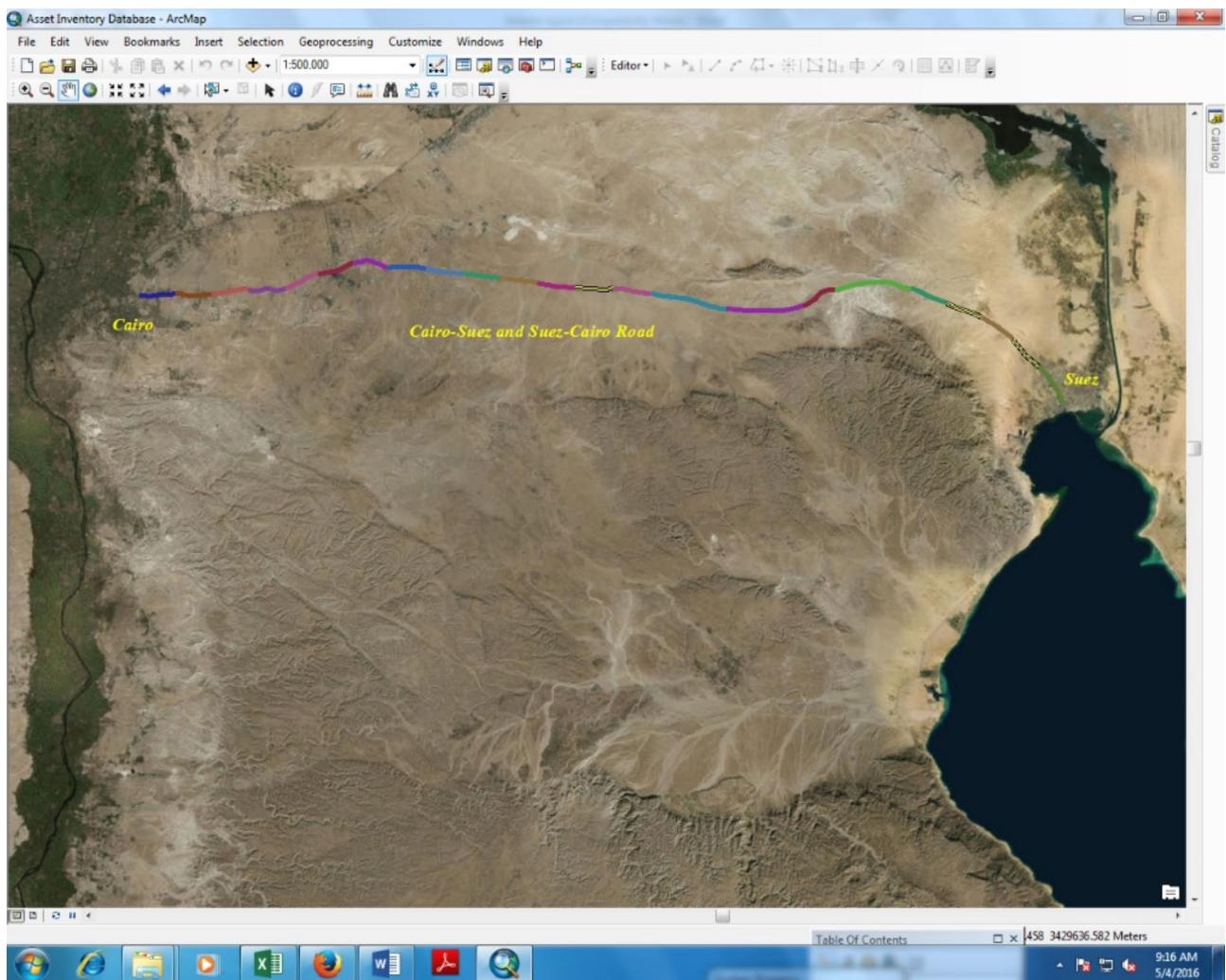


Fig. 4. Cairo-Suez road in ArcGIS.

monitors their condition over time, and generates tabular and map-based graphical analyses that consolidate crucial data for managing informational, operational, and maintenance actions, as depicted in Figs. 5 and 6. Figures 4 and 5, and 6 were created by the authors using ArcGIS 10.8.1, a leading geographic information system (GIS) software for spatial data visualization and analysis. The satellite imagery displayed in these figures was processed and integrated within ArcGIS to enhance spatial representation and provide a detailed geospatial context. The mapping process involved data integration, attribute analysis, and cartographic visualization to ensure an accurate representation of the Cairo-Suez road. ArcGIS allows for advanced geospatial analysis, enabling precise alignment of the road network data with satellite imagery⁵⁶.

Results and discussions of the deterioration prediction module

The PCI of each road segment, engender from GARBLT, is multiplied by the transition matrix developed by Sati et al.⁵⁷ (see Table 3). The transition matrix, adapted from Sati et al.⁵⁷, defines the probabilistic transitions between these condition states. Each entry (P_{ij}) in the 5×5 transition matrix represents the probability of transitioning from state i to state j within a year. The initial condition state of each road segment is represented as a 1×5 vector, which indicates the probability distribution of the segment across the five condition states. This vector is derived from the PCI values reported by GARBLT. The future condition state is calculated yearly by multiplying the 1×5 condition state vector by the 5×5 transition matrix. Thirty years (from 2022 to 2052) of predictions are rendered using the transition matrix Sati et al.⁵⁷ proposed to portray the deterioration pattern of the road using a discrete Markov Chain time model. The road current condition state (computed from the average value of each segment PCI) is multiplied by the transition matrix to compute the customized condition of the road. The condition scale adopted in this research ranges from 1 to 5, in which the corresponding condition rating of 1, 2, 3, 4, and 5 is 85 – 100%, 75 – 84%, 55 – 74%, 54% – 40%, and < 40%, respectively, as previously elaborated.

The future PCI is calculated by dividing the customized condition by 5, as displayed in Table 4. In Table 4, The Customized Condition (CC) is computed as a weighted average score representing a pavement segment's probabilistic condition state based on the Markov Chain deterioration model. In this model, pavement conditions

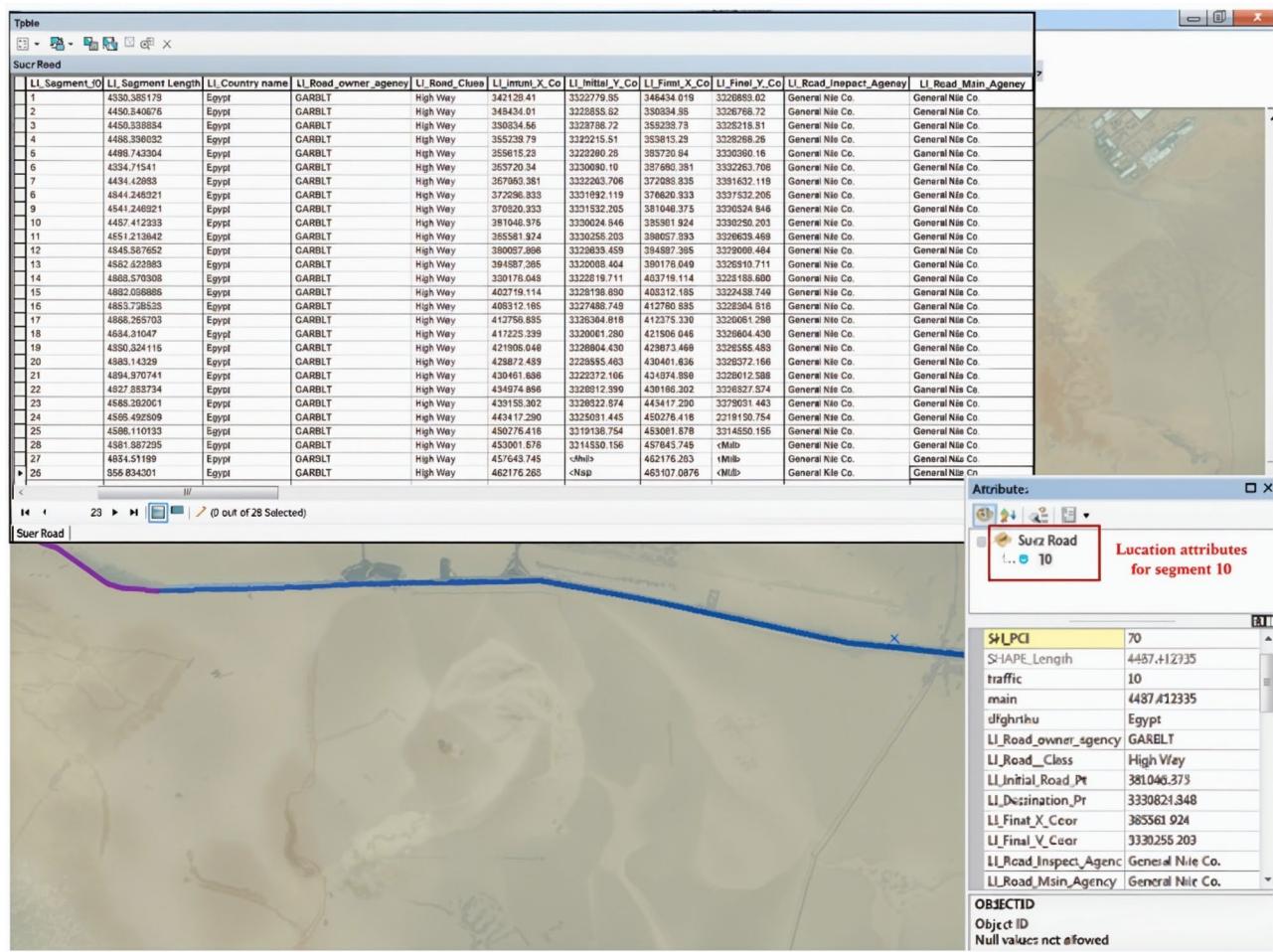


Fig. 5. Data for location identity attribute in ArcGIS.

are classified into five states—Excellent (5), Good (4), Fair (3), Poor (2), and Failing (1)—with higher scores representing better conditions. The CC value is calculated by multiplying the probability of the segment being in each state by its corresponding score and then summing these values. This process accounts for the likelihood of each condition state and provides a single value that reflects the average condition of the segment. For instance, in 2022, the condition probabilities for Segment #10 are 33% Excellent, 22% Good, 24% Fair, 10% Poor, and 11% Failing. The CC is computed as: $CC=(0.33 \times 5)+(0.22 \times 4)+(0.24 \times 3)+(0.10 \times 2)+(0.11 \times 1)=3.56$. The result (3.56) indicates that the segment's condition, on average, falls between Fair (3) and Poor (4), suggesting the need for maintenance intervention to prevent further deterioration. To support decision-making, the CC is converted into the Future PCI, which ranges from 0 to 100. This is achieved by dividing 3.56 by 5 and multiplying the result by 100, yielding a Future PCI of 71.20 for 2022.

Figure 7 portrays a sample of the anticipated likelihood of the road segments deteriorating pattern utilizing the discrete Markov Chain time model. For instance, concerning segment #6, after a 30-year time interval, the average entire PCI value of road segment #6 constituted 22.59 instead of 45 in 2022. Regarding segment #11, after a 30-year time interval, the average entire PCI value of road segment #11 constituted 28.55 instead of 85 in 2022. These results render the predicted significant degradation pattern of the road segments devoid of any maintenance intervention. Further, Fig. 7 indicates the shifting pattern in the PCI value, which often moves downward from higher to lower conditions until it almost reaches zero. Table 5 exhibits the PCI values in 2022 and 2052 and the percentage of deterioration rate apropos to each road's segment. Accordingly, segment #8 acquired a minimal deterioration rate of 43%; contrastingly, other segments revealed a rapid deterioration rate of 66%, as explicitly outlined in Table 5.

Results and discussions of fund allocation prioritization module

The planned time horizon for M&R interventions is five years, with an overall budget of 37 Million EGP throughout the entire five years. As previously described, the M&R intervention types are defined from 0 to 7, in which the PCI value of any succeeding year is calculated by multiplying the PCI value of the preceding year along with improvement percentages (shown in Table 1). Furthermore, the total cost entitled to M&R intervention apropos to the road segments is reckoned by accumulating the cost appointed and bargaining on

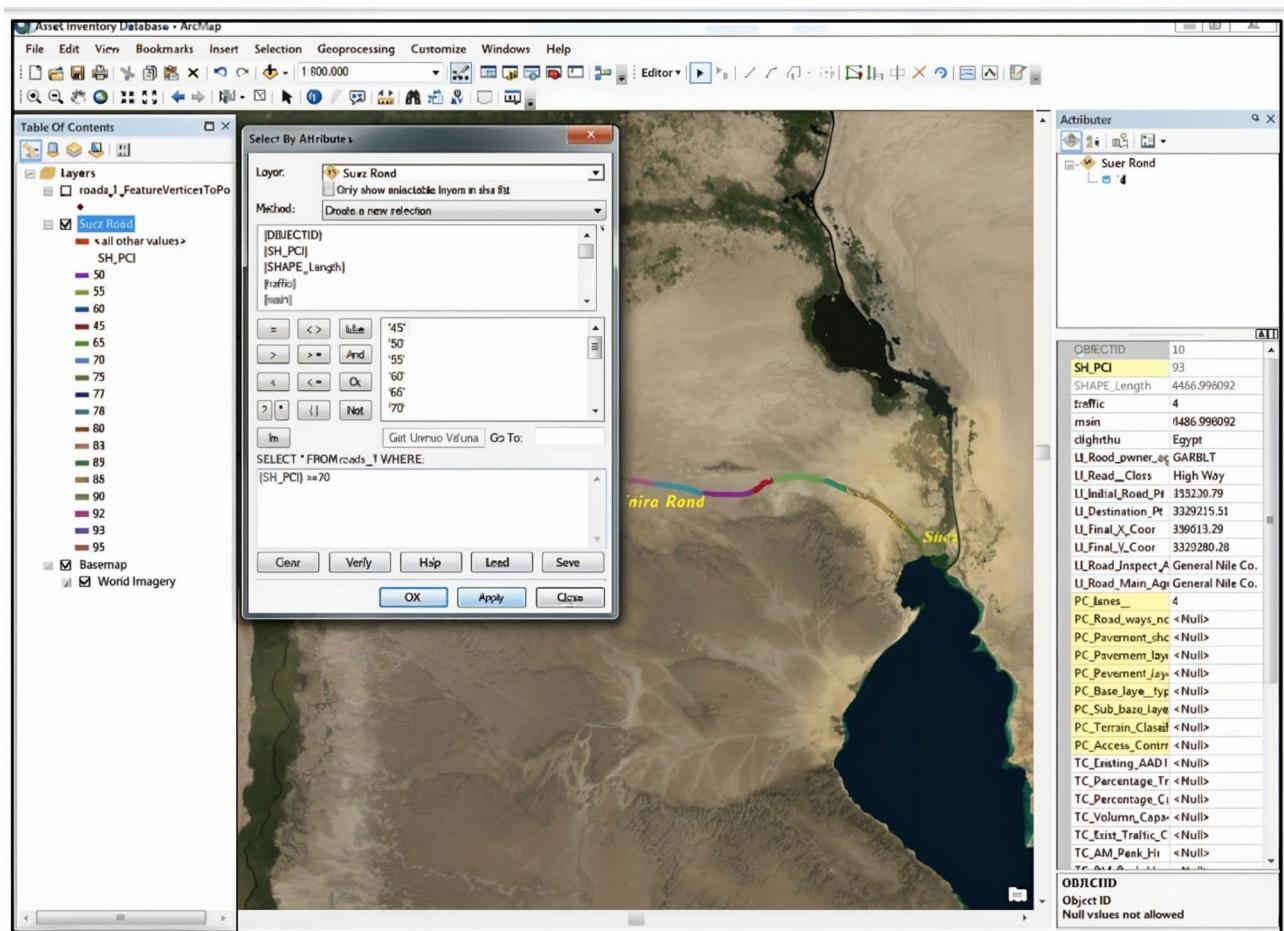


Fig. 6. Selecting a road segment by attribute.

the M&R intervention type designated due to optimization model outputs, as explicitly depicted in Table 1. After defining the objective function, decision variable, and constraints, as seen in Fig. 8, the optimization engine institutes running the model; it consumes a computation and running time of about 10 min using the Intel Core i7 computer. After running the optimization engine, the model unearthed a near-optimum M&R action plan that sighted all allocated constraints.

After running the optimization engine, the average PCI of the road segments has been enhanced from 71.8% (base case) to 80.11% after deploying the optimization model. Furthermore, the average PCI value of each road segment attested each year is explicitly rendered in Fig. 9. As determined by the optimization engine, the total cost of the M&R intervention action over the five years was 36,888,435 EGP (permitted, and the available budget is equivalent to 37 Million EGP).

Figure 10 depicts the annual cost allocation for M&R interventions graphically. These findings might also be clarified by the fact that the developed optimization model exerted an attempt to accomplish its objectives. By employing this examination, the model can document the proposed optimization model's adaptability and ability to yield the optimum budget allocation decisions for road segments, along with its customization to broader scenarios. Ultimately, Fig. 11 shows the final optimization model outcome, depicting the repair type adopted, year of employment, the PCI value of each road segment for each M&R planned year, commensurated expenditures, the average PCI of the entire road, and the total M&R expenditures throughout the 5 years.

Belatedly, a sensitivity analysis is carried out to appraise and quantify the economic implication of the total allowable budget per five-year maintenance plan on the PCI of the road segments, as displayed in Fig. 12. Figure 12 renders the base case PCI (generated from the optimization model) for the other six cases, ranging between -30% and 30% with a 10% increment. Findings unearthed that a 30% decline in the budgetary allotment will culminate in a PCI of 72.35%. Nevertheless, as demonstrated in Fig. 12, a 30% raise in the budgeted amount will culminate in a PCI boost to 84.86%.

Conclusion

This study's in-depth exploration of integrating Geographic Information Systems (GIS) and genetic algorithms for road management and fund allocation, focusing on Egypt's Cairo-Suez road, showcases a significant advancement in infrastructure management. The research highlights how this novel approach significantly enhances roads' Pavement Condition Index (PCI), leading to more efficient and effective maintenance strategies.

Segment No.	Current PCI Value	5	4	3	2	1
		Excellent	Good	Fair	Poor	Failing
Segment #1	75	0.43	0.22	0.19	0.05	0.11
Segment #2	80	0.48	0.24	0.17	0.00	0.11
Segment #3	80	0.48	0.24	0.17	0.00	0.11
Segment #4	90	0.58	0.42	0.00	0.00	0.00
Segment #5	90	0.58	0.42	0.00	0.00	0.00
Segment #6	45	0.01	0.27	0.13	0.14	0.45
Segment #7	46	0.01	0.29	0.14	0.14	0.42
Segment #8	40	0.00	0.22	0.11	0.12	0.54
Segment #9	60	0.13	0.36	0.18	0.15	0.19
Segment #10	70	0.33	0.22	0.24	0.10	0.11
Segment #11	85	0.58	0.14	0.16	0.10	0.02
Segment #12	86	0.58	0.21	0.08	0.13	0.00
Segment #13	88	0.52	0.37	0.05	0.06	0.00
Segment #14	88	0.52	0.37	0.05	0.06	0.00
Segment #15	90	0.58	0.42	0.00	0.00	0.00
Segment #16	75	0.43	0.22	0.19	0.05	0.11
Segment #17	78	0.43	0.27	0.19	0.00	0.11
Segment #18	50	0.02	0.32	0.15	0.15	0.36
Segment #19	42	0.00	0.23	0.12	0.13	0.51
Segment #20	40	0.00	0.22	0.11	0.12	0.54
Segment #21	58	0.07	0.36	0.16	0.15	0.26
Segment #22	60	0.13	0.36	0.18	0.15	0.19
Segment #23	85	0.58	0.14	0.16	0.10	0.02
Segment #24	86	0.58	0.21	0.08	0.13	0.00
Segment #25	88	0.52	0.37	0.05	0.06	0.00
Segment #26	86	0.58	0.21	0.08	0.13	0.00
Segment #27	75	0.43	0.22	0.19	0.05	0.11
Segment #28	75	0.43	0.22	0.19	0.05	0.11

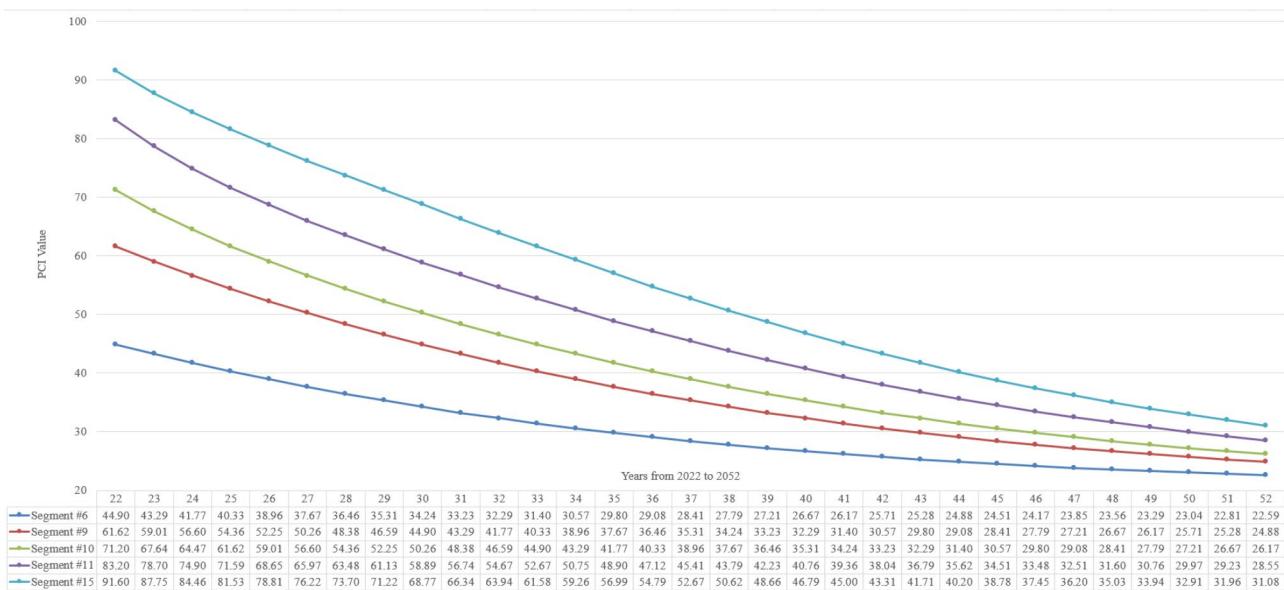
Table 3. The current condition state of each road segment.

Years	5	4	3	2	1	Customized Condition	Length of Pavements Deteriorated in Km	Future PCI
	Excellent	Good	Fair	Poor	Failing			
2022	0.330	0.220	0.240	0.100	0.110	3.56	1.30	71.20
2023	0.239	0.294	0.209	0.126	0.132	3.38	1.46	67.64
2024	0.173	0.337	0.190	0.140	0.160	3.22	1.60	64.47
2025	0.125	0.359	0.178	0.147	0.191	3.08	1.73	61.62
2026	0.091	0.366	0.170	0.150	0.224	2.95	1.84	59.01
2027	0.066	0.363	0.164	0.150	0.257	2.83	1.95	56.60
2028	0.048	0.353	0.159	0.150	0.290	2.72	2.05	54.36

Table 4. A sample of results triggered using a discrete Markov Chain time model for segment #10.

By meticulously analyzing the Cairo-Suez roadway, the study demonstrates the practical implications of this methodology in improving road conditions and optimizing budget allocation. The innovative combination of GIS and genetic algorithms presents a new frontier in infrastructure management, offering a model that can be adapted and applied to other regions and infrastructure challenges. This research's findings are pivotal for Egypt's road management strategies and set a precedent for global infrastructure maintenance practices. This study is a critical contribution to the ongoing discourse in infrastructure management and paves the way for future research in this area, offering insights and methodologies that could revolutionize how road maintenance and funding are approached worldwide.

The proposed approach represents a significant advancement over traditional methods by combining geospatial data management, condition monitoring, and predictive modeling within a unified framework. Unlike prior studies focusing on geographic analysis or mathematical optimization, this research bridges the gap by creating a decision-support system capable of simultaneously handling large-scale infrastructure data and budget constraints. Accordingly, key advantages of the proposed model include: (1) Integrated GIS and

**Fig. 7.** A sample of deterioration behavior using a Markov-based model.

Segment No.	PCI in the year 2022	PCI in the year 2052	Deterioration Rate (%)
1	75	27.41	63
2	80	28.21	65
3	80	28.21	65
4	90	31.08	65
5	90	31.08	65
6	45	22.59	50
7	46	22.59	51
8	40	22.81	43
9	60	24.88	59
10	70	26.17	63
11	85	28.55	66
12	86	29.17	66
13	88	29.88	66
14	88	29.88	66
15	90	31.08	65
16	75	27.41	63
17	78	27.87	64
18	50	23.29	53
19	42	22.21	47
20	40	22.04	45
21	58	24.17	58
22	60	24.88	59
23	85	29.17	66
24	86	29.17	66
25	88	29.88	66
26	86	29.17	66
27	75	27.41	63
28	75	27.41	63

Table 5. Degradation rate for each road segment.

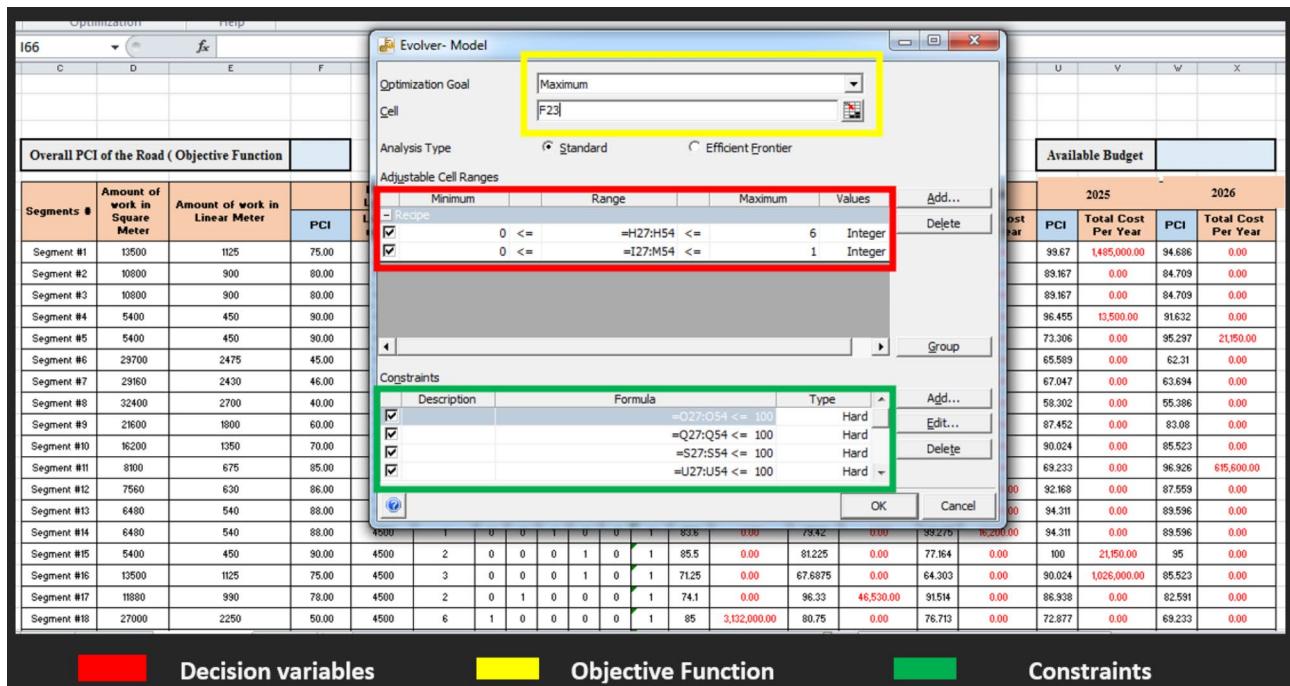


Fig. 8. Optimization model formulation.

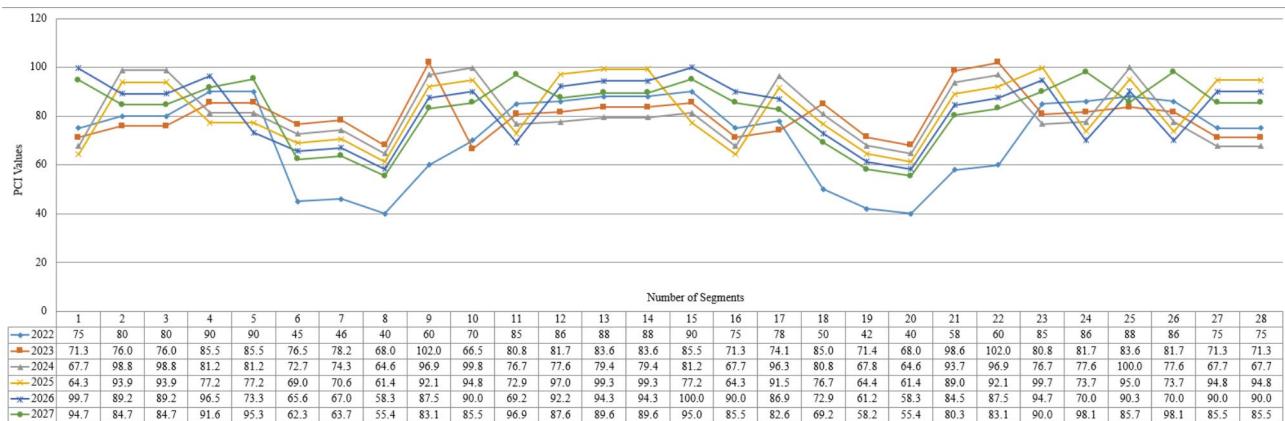
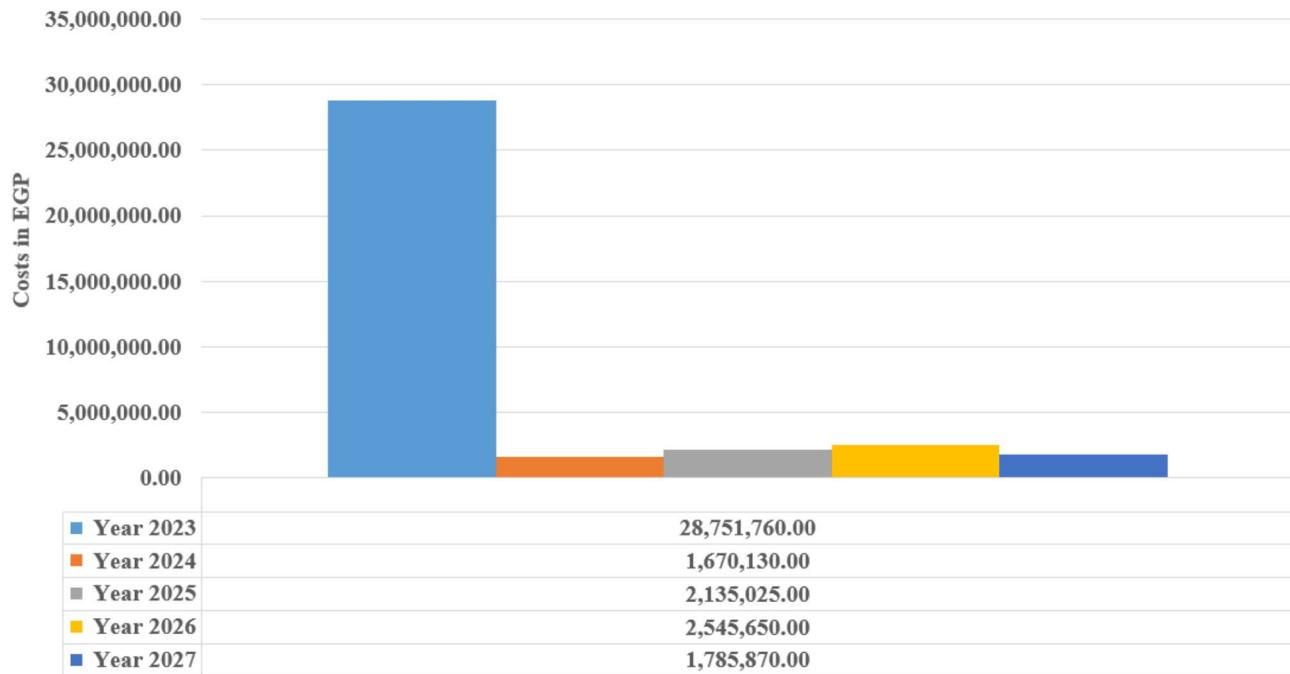


Fig. 9. PCI values from 2022 and 2027.

Optimization Framework: The approach leverages GIS technology for capturing, visualizing, and managing spatial and attribute data, enabling asset managers to make data-driven decisions efficiently; **(2) Markov Chain Deterioration Modeling:** Predicts pavement performance trends over time, allowing for proactive planning and minimizing unexpected failures; **(3) Genetic Algorithm Optimization:** Provides a robust prioritization strategy, enabling optimal allocation of limited funds while maximizing improvements in pavement conditions, as demonstrated in the case study; **(4) Scalability and Adaptability:** The framework can be easily adapted to various road networks and infrastructure systems, making it suitable for diverse geographic and economic contexts, and **(5) Improved Decision-Making:** By incorporating performance forecasts and budget constraints, the model ensures that M&R decisions are cost-effective and impact-driven, addressing both short-term and long-term infrastructure needs. The case study of the Cairo-Suez road demonstrates the practical application of this model, showcasing its ability to enhance PCI values and effectively prioritize M&R interventions. Results indicate a measurable improvement in road performance while adhering to budgetary limits, validating the efficiency and applicability of the proposed framework.

The research paper presents a novel approach for optimizing Egypt's road management and fund allocation using GIS and genetic algorithms. However, it has certain limitations and areas for future exploration: (1) The study is confined to the Cairo-Suez road, limiting its generalizability to other regions or road conditions; (2) The reliance on existing data sources may introduce biases or inaccuracies in the model's outputs, and (3) The genetic algorithm's computational intensity might limit its applicability in real-time or for more extensive road

**Fig. 10.** M&R expenditures from the year 2023 to 2027.

Overall PCI of the Road (Objective Function) 80.11			PCI at 2022 (Initial Condition) 71.82						M&R Cost (5 Years) 36,888,435				Available Budget 37,000,000							
Segments #	Amount of work in Square Meter	Amount of work in Linear Meter	Road Length		Decision Variables					Sum	Year 2023		Year 2024		Year 2025		Year 2026		Year 2027	
			PCI	Linear meter	Repair Type	Y.1	Y.2	Y.3	Y.4		PCI	Total Cost Per Year	PCI	Total Cost Per Year	PCI	Total Cost Per Year	PCI	Total Cost Per Year	PCI	Total Cost Per Year
Segment #1	13500	1125	75	4500	5	0	0	0	1	0	71.3	0.00	67.7	0.00	64.3	0.00	99.7	1,485,000.00	94.7	0.00
Segment #2	10800	900	80	4500	2	0	1	0	0	0	76.0	0.00	98.8	42,300.00	93.9	0.00	89.2	0.00	84.7	0.00
Segment #3	10800	900	80	4500	2	0	1	0	0	0	76.0	0.00	98.8	42,300.00	93.9	0.00	89.2	0.00	84.7	0.00
Segment #4	5400	450	90	4500	1	0	0	0	1	0	85.5	0.00	81.2	0.00	77.2	0.00	96.5	13,500.00	91.6	0.00
Segment #5	5400	450	90	4500	2	0	0	0	0	1	85.5	0.00	81.2	0.00	77.2	0.00	73.3	0.00	95.3	21,150.00
Segment #6	29700	2475	45	4500	6	1	0	0	0	0	76.5	3,445,200.00	72.7	0.00	69.0	0.00	65.6	0.00	62.3	0.00
Segment #7	29160	2430	46	4500	6	1	0	0	0	0	78.2	3,382,560.00	74.3	0.00	70.6	0.00	67.0	0.00	63.7	0.00
Segment #8	32400	2700	40	4500	6	1	0	0	0	0	68.0	3,758,400.00	64.6	0.00	61.4	0.00	58.3	0.00	55.4	0.00
Segment #9	21600	1800	60	4500	6	1	0	0	0	0	102.0	2,505,600.00	96.9	0.00	92.1	0.00	87.5	0.00	83.1	0.00
Segment #10	16200	1350	70	4500	4	0	1	0	0	0	66.5	0.00	99.8	1,522,800.00	94.8	0.00	90.0	0.00	85.5	0.00
Segment #11	8100	675	85	4500	3	0	0	0	0	1	80.8	0.00	76.7	0.00	72.9	0.00	69.2	0.00	96.9	615,600.00
Segment #12	7560	630	86	4500	1	0	0	1	0	0	81.7	0.00	77.6	0.00	97.0	18,900.00	92.2	0.00	87.6	0.00
Segment #13	6480	540	88	4500	1	0	0	1	0	0	83.6	0.00	79.4	0.00	99.3	16,200.00	94.3	0.00	89.6	0.00
Segment #14	6480	540	88	4500	1	0	0	1	0	0	83.6	0.00	79.4	0.00	99.3	16,200.00	94.3	0.00	89.6	0.00

Fig. 11. M&R expenditures from the year 2023 to 2027.

networks. While the proposed GIS-based optimization model effectively prioritizes M&R interventions and optimizes resource allocation, several areas offer opportunities for further research to enhance its capabilities. Future studies could focus on integrating real-time data through Internet of Things (IoT) sensors to enable dynamic updates and adaptive decision-making in response to sudden changes in pavement conditions. Incorporating machine learning algorithms may also improve deterioration predictions by capturing non-linear patterns, thereby enhancing model accuracy. Expanding the framework to include multi-objective optimization can further balance economic, environmental, and social factors, promoting sustainability-focused decisions. Testing the model's scalability and adaptability across diverse geographic and economic contexts will help validate its flexibility and generalizability.

Additionally, integrating Life-Cycle Cost Analysis (LCCA) can assess the long-term cost-effectiveness of M&R strategies, ensuring optimized performance throughout the infrastructure's lifecycle. Finally, developing interactive tools and Decision Support Systems (DSS) with visualization features can improve stakeholder accessibility and decision-making transparency. These directions aim to advance the model into a next-generation infrastructure management tool with real-time analytics, sustainability assessments, and user-friendly interfaces to address evolving infrastructure challenges.

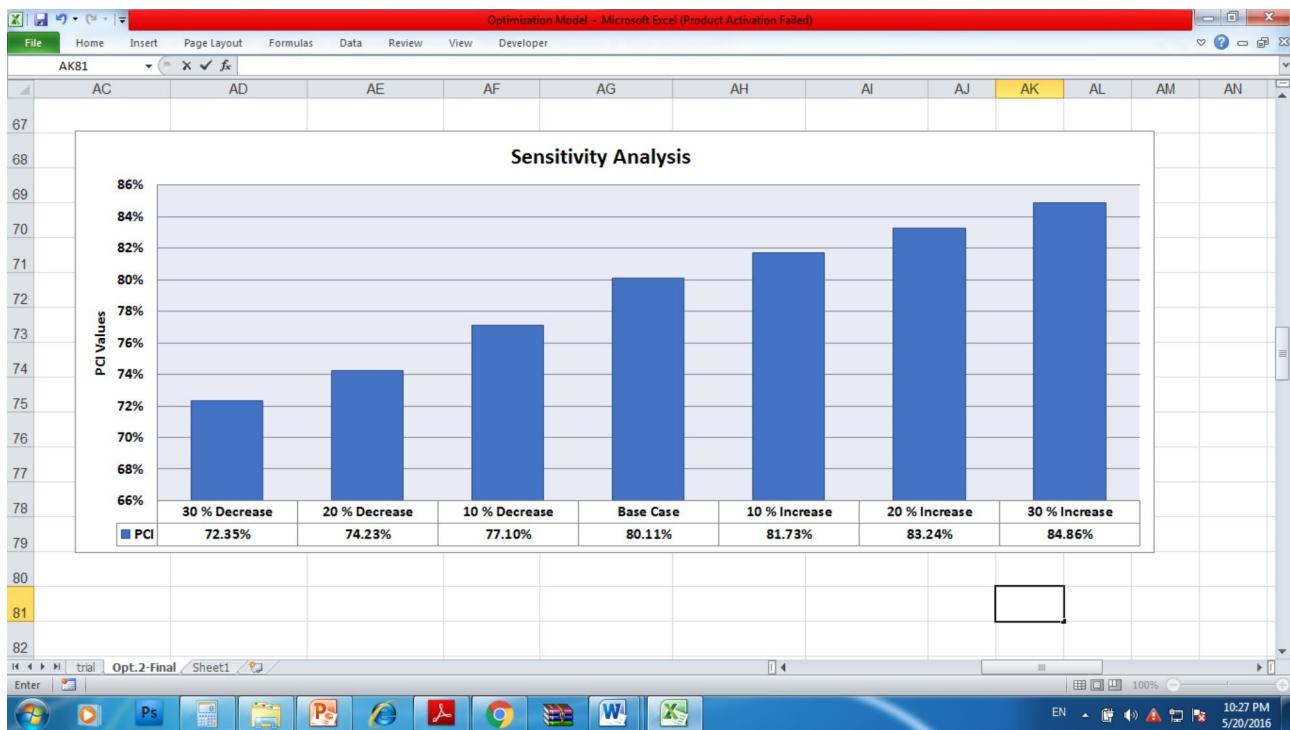


Fig. 12. Sensitivity analysis scenarios and results.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Author contributions

Ahmed Gouda Mohamed, Fahad K. Alqahtani, ElHassan Reda Ismail, and Mohamed Nabawy equally contributed to this research paper. Each author played an integral role in every aspect of the study. Ahmed Gouda Mohamed took the lead in conceptualizing the research theme and framework, contributing significantly to the development of the methodology. Fahad K. Alqahtani was instrumental in the data collection process and performed a critical analysis of the data. Mohamed Nabawy contributed extensively to the writing and preparation of the original draft, ensuring the manuscript's coherence and scientific accuracy. ElHassan Reda Ismail was pivotal in reviewing and editing the manuscript, providing essential insights and revisions to refine the final submission.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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