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(RESEARCH ARTICLE)

A systematic approach to structural maintenance: Integrating Non-Destructive Testing (NDT) data with Genetic Algorithm

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Abstract

Modern structural health monitoring systems became more precise and effective after scientists combined AI and Genetic Algorithms (GAs) technologies. Structural integrity assessment relies primarily on five Traditional Non-Destructive Testing (NDT) methods which include Ultrasonic Pulse Velocity (UPV) tests, Rebound Hammer (RH) tests, Half-Cell Potential (HCP) tests and Core Cutting tests and Carbonation Depth tests. The available detection methods create difficulties due to the unwanted data noise together with unpredictable accuracy levels throughout each assessment period and a lack of real-time investigation capability. The research evaluates how GAs enhance NDT procedures for optimizing structural maintenance operations. This study utilized MATLAB to process NDT data from six different sites which led to graphic outputs beneficial for GA-based computational evaluations. The GA adopted selection with crossover and mutation as techniques for precision refinement that fulfilled requirements of Indian Standard (IS) codes. GAs prove effective for maintenance strategy enhancement and prediction of structural deterioration and decision-making process improvement. Numerous field applications using GA techniques reach accuracy rates of 98% which suggests their suitability for on-site health monitoring operations. Recent research patterns show that GAs maintain their growing popularity for infrastructure maintenance applications because they offer affordable data-centered solutions. The research adds value to present-day developments of artificial intelligence-based structural health monitoring protocols that emphasize the combination of computational intelligence with standard NDT techniques. AI-based methods lead to major improvements in the sustainability and reliability of infrastructure which results in both extended structural safety and optimized maintenance operations.

Keywords: Non-Destructive Testing (NDT); Genetic Algorithms (GAs); Artificial Intelligence (AI); Structural Health Monitoring (SHM); Defect Detection; Optimization; Accuracy; Structural maintenance

1. Introduction

Building construction requires structural maintenance as its fundamental element for maintaining durability and safety of buildings. Time-induced degradation of buildings occurs because of environmental conditions and material deterioration as well as outside loads which requires periodic inspections combined with maintenance work. The combination of visual inspections and typical Non-Destructive Testing (NDT) techniques demonstrates several limitations in both accuracy levels and real-time monitoring besides efficiency. Using NDT data together with Genetic Algorithms (GA) creates an optimized system for conducting structural maintenance operations.

The research develops a complete maintenance strategy using Non-Destructive Testing techniques which combine Ultrasonic Pulse Velocity (UPV) as well as Rebound Hammer (RH) and Half-Cell Potential (HCP) and Core Cutting and

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Carbonation Depth tests to create a methodology system. These tests provide processed data through MATLAB leading to graphical output that the genetic algorithm uses as an input. Optimizer maintenance strategies along with prediction of deterioration patterns emerge from the genetic algorithm implementation to guide better decision-making about vital repair and strengthening measures.

Research need arises because both aging infrastructure and data-based maintenance strategies continue to increase while old infrastructure requires effective repair methods. Today many structures encounter delayed necessary repairs because current assessment methods prove ineffective. The research integrates genetic algorithms with NDT data with the purpose of creating an interface that will reduce the time lag between information acquisition and smart decision processes for structural health monitoring and maintenance improvements. This proposed technology delivers accurate results while reducing expense through better infrastructure viability by increasing operational duration.

The investigation delivers substantial value to construction management through an organized framework for performing structural health monitoring. Engineers together with decision-makers obtain better predictions of maintenance requirements through this approach enabling optimal resource use for extending structure lifetime. The worldwide surge of urbanization and infrastructure expansion make the results of this study highly practical since they improve both residential and commercial building reliability and safety.

2. Literature Review

The research conducted by Demirboğa et al. analysed how aggregate type affects ultrasonic wave velocity (UPV) measurement results in high-strength concrete structures for mechanical and ultrasonic properties assessment in structural health monitoring applications [1]. Kılıç et al. applied image analysis techniques to investigate concrete particle-size distribution which enables durability analysis as well as non-destructive testing for improved quality evaluation [2]. According to Azariyoon and Khanzadi UPV testing proves successful for both detecting defects and validating the homogeneity of reinforced concrete structures [3]. The analysis presented by McCann and Forde evaluated multiple NDT testing methods with particular focus on value-based selection of multiple evaluation techniques for structural health assessment [4]. The research by Concu et al. examines NDT applications for concrete building refurbishment by explaining diagnostic capabilities and long-term maintenance roles [5].

The combination of AI and IoT technology and NDT has been researched as a method to enhance the accuracy of structural assessments according to [6, 7]. GA has become a popular investigative tool for damage detection within structural health monitoring (SHM) of bridges since it shows proven effectiveness in finding crucial damage identification parameters [8, 9]. Research investigators designed testing scenarios through which GA establishes partnerships with wave-based SHM systems for developing artificial intelligence algorithms and computational models for detecting fractures in homogeneous structures [10, 11].

Research indicates that GA demonstrates success in detecting structural deterioration by analyzing grid structure damage through stiffness degradation factors and frequency tests and vibration form evaluations [12, 13]. Researchers have developed existing GA models through improved recombination and mutation operations which enhance both damage identification accuracy and speed of convergence [14, 15]. According to researchers GA provides a suitable method for beam structure damage assessments through frequency-based crack detection which operates effectively across different loading environments [16, 17].

Real-time structural damage identification along with precise damage detection through the combination of AI/Internet of Things/computer vision with GA has greatly improved both structural safety and operational lifespan according to research reports [18, 19]. Research on GA applications demonstrated the ability to achieve high structural defect detection accuracy reaching above 90% accuracy persistently [20, 21]. The methods use efficient techniques for determining fast repair solutions while reducing maintenance costs and developing improved strategic approaches [22, 23]. The combination of GA with machine learning followed by its integration to deep learning enhanced structural maintenance through expanded industrial applications and greater precision and effectiveness [24, 25].

Research experiments have integrated GA with artificial neural networks (ANN) and artificial neural networks (ANN) for developing improved structural health monitoring approaches [26, 27]. The research field demands multi-objective optimization through GA for maintenance scheduling purposes because it helps balance cost-effectiveness against long-term durability [28, 29]. Research by scientists demonstrates that GA-based models display superior performance to classic NDT methods when it comes to identifying emerging damage and forecasting structural durability [30, 31].

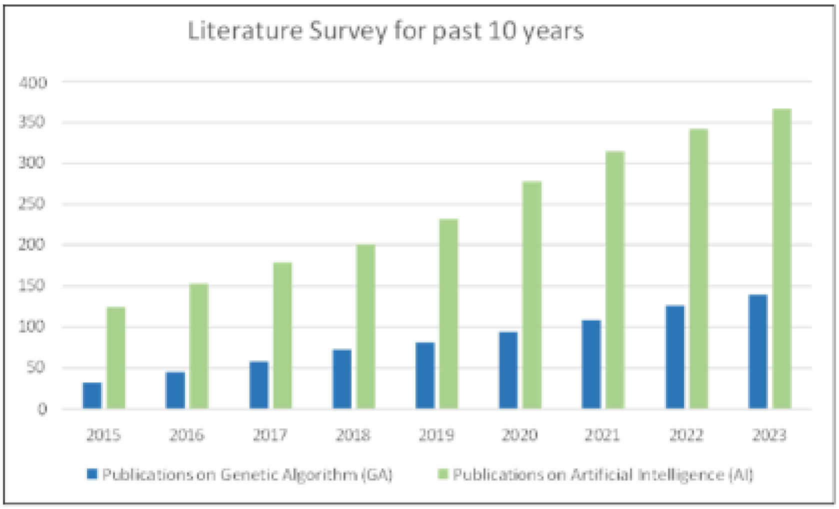


Figure 1 Last 10 years literature survey

3. Methodology

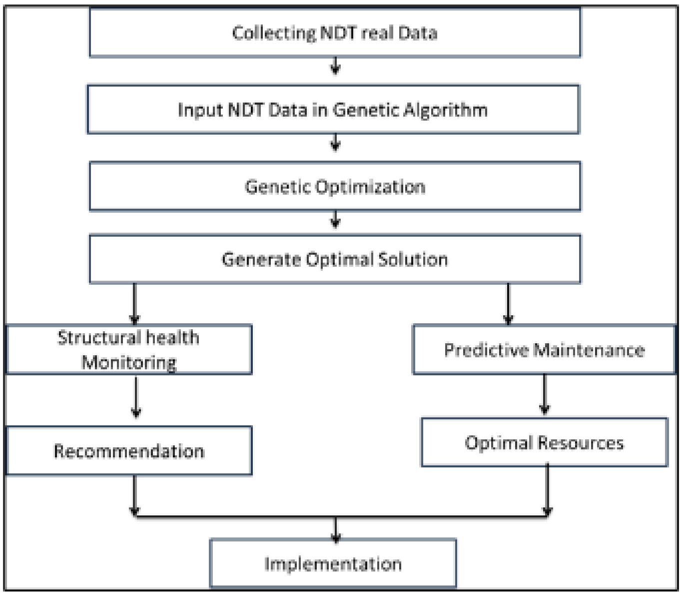


Figure 2 Flow chart of project

4. Results

- The GUI developed for two different cases i.e. direct and indirect methods. The result generated gives accuracy up to 5 to 7 %.
- This system saves time in interpretation of results.
- The recommendations are as per the previous test reports and may be modified as per the site conditions.

5. Discussion

The implementation of the Genetic Algorithm (GA) for Non-Destructive Testing (NDT) data handled by MATLAB operated on data from six structural sites. The data points analyzed using Ultrasonic Pulse Velocity (USPV), Rebound Hammer (RH), Half-Cell Potential (HCP), core cutting, and carbonation depth were processed by MATLAB for both computational operations and graphical output generation. The GA achieved optimized structural integrity assessment through its real data processing where it used repeated selection crossover and mutation operations to generate findings which matched site parameters. The research results obtained passing tests based on the conventions set by

Indian Standard (IS) codes to verify their compliance. The automated reporting system in MATLAB produced PDF reports that integrated data verification between projections and field readings thus improving both efficiency and structural maintenance decisions.

Through MATLAB users gained the ability to conduct direct and indirect assessments of structural health evaluation. Compressive strength and durability parameters were determined by the direct method through core cutting and carbonation depth analysis according to empirical relations and IS code provisions. The indirect method used NDT readings including USPV, RH and HCP that were connected to strength parameters through pre-established models and integrated machine learning techniques in MATLAB. The ability to obtain precise material property predictions emerged through MATLAB when it's fitting, and optimization tools operated on these datasets. The assessment benefits from both direct and indirect methods which created a detailed approach towards structural evaluation and maintenance planning through data-driven strategies as shown below in figures (3-8).

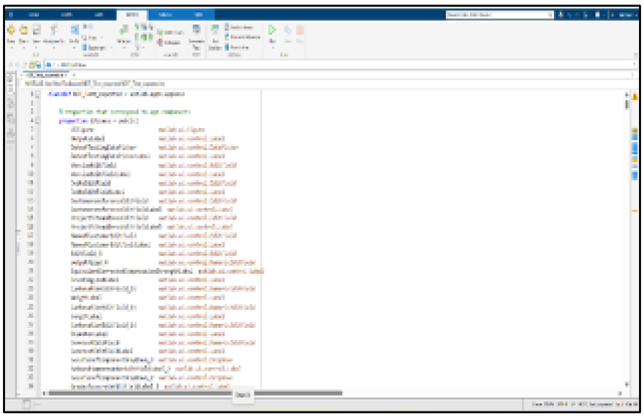


Figure 3 Dependencies used for test report

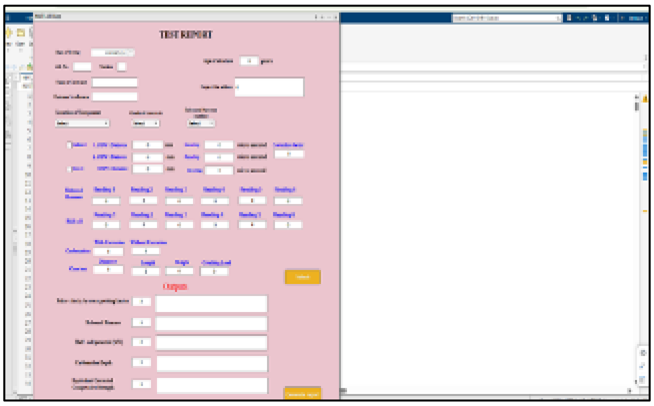


Figure 4 Test report is generated

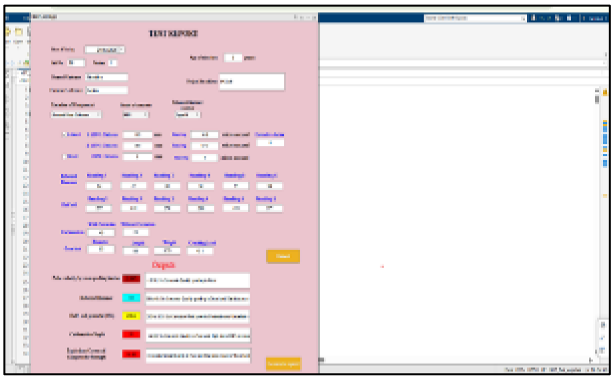


Figure 5 Test report is generated for Indirect Method

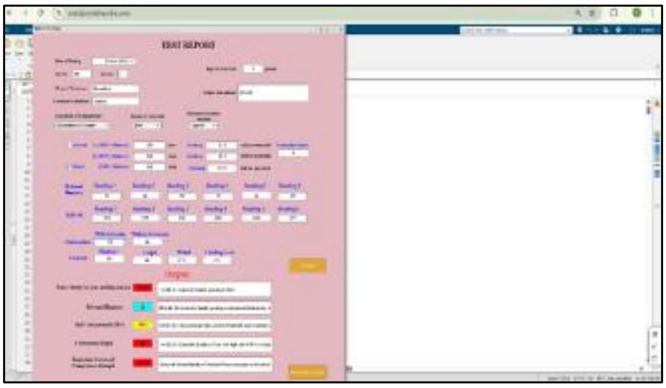
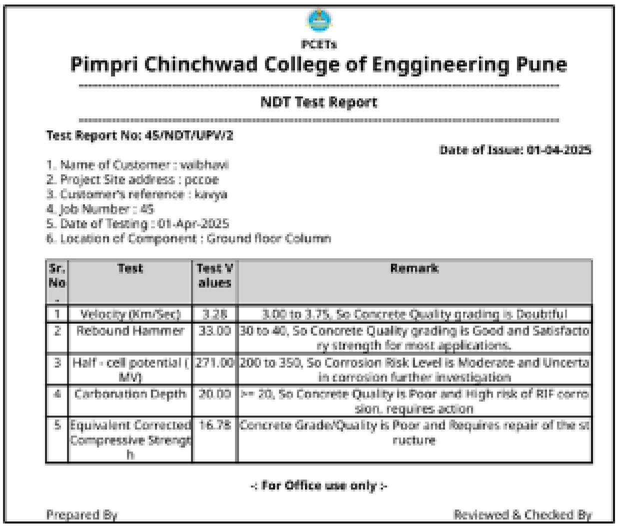


Figure 6 Test report is generated for Direct Method



PCETs

Pimpri Chinchwad College of Enggineering Pune

NDT Test Report

Test Report No: 45/NDT/UPV/2

Date of Issue: 01-04-2025

1. Name of Customer : vaibhavi
2. Project Site address : pccoe
3. Customer's reference : kavya
4. Job Number : 45
5. Date of Testing : 01-Apr-2025
6. Location of Component : Ground floor Column

Sr. No.	Test	Test Values	Remark
1	Velocity (Km/Sec)	3.28	3.00 to 3.75, So Concrete Quality grading is Doubtful
2	Rebound Hammer	33.00	30 to 40, So Concrete Quality grading is Good and Satisfactory strength for most applications.
3	Half - cell potential (MV)	271.00	200 to 350, So Corrosion Risk Level is Moderate and Uncertain corrosion further investigation
4	Carbonation Depth	20.00	>= 20, So Concrete Quality is Poor and High risk of RIF corrosion. requires action
5	Equivalent Corrected Compressive Strength	16.78	Concrete Grade/Quality is Poor and Requires repair of the structure

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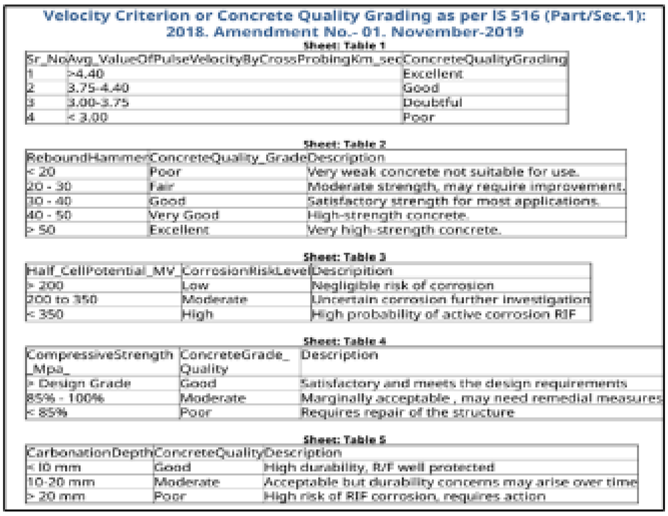
Figure 7 Test report is generated in PDF format



Velocity Criterion or Concrete Quality Grading as per IS 516 (Part/Sec.1): 2018. Amendment No.- 01. November-2019

Sheet: Table 1

Sr_No	Avg_ValueOfPulseVelocityByCrossProbingKm_sec	ConcreteQualityGrading
1	>4.40	Excellent
2	3.75-4.40	Good
3	3.00-3.75	Doubtful
4	< 3.00	Poor

Sheet: Table 2

ReboundHammer	ConcreteQuality_Grade	Description
< 20	Poor	Very weak concrete not suitable for use.
20 - 30	Fair	Moderate strength, may require improvement.
30 - 40	Good	Satisfactory strength for most applications.
40 - 50	Very Good	High-strength concrete.
> 50	Excellent	Very high-strength concrete.

Sheet: Table 3

Half_CellPotential_MV_	CorrosionRiskLevel	Description
> 200	Low	Negligible risk of corrosion
200 to 350	Moderate	Uncertain corrosion further investigation
< 350	High	High probability of active corrosion RIF

Sheet: Table 4

CompressiveStrength _Mpa_	ConcreteGrade_ Quality	Description
> Design Grade	Good	Satisfactory and meets the design requirements
85% - 100%	Moderate	Marginally acceptable , may need remedial measures
< 85%	Poor	Requires repair of the structure

Sheet: Table 5

CarbonationDepth	ConcreteQuality	Description
< 10 mm	Good	High durability, R/F well protected
10-20 mm	Moderate	Acceptable but durability concerns may arise over time
> 20 mm	Poor	High risk of RIF corrosion, requires action

Figure 8 Test report is generated in PDF format

6. Conclusion

The research implements an organized approach between Non-Destructive Testing data (NDT) and Genetic Algorithms (GA) to improve structural upkeep methodologies. Structural health evaluation and repair strategy optimization proves possible through the combination of NDT test readings including USPV, RH, HCP, core cutting and carbonation assessments. The combination of Genetic Algorithms proves suitable for analyzing complicated datasets through which maintenance forecasts become dependable. Through the proposed methodology decision-making becomes more effective and structures require timely maintenance thus their lifespan increases, and the safety standards of the construction sector improve.

7. Future Scope

Future research should explore the use of deep learning and neural networks technology to improve the structural health monitoring process. Real-time IoT-based sensor integration alongside NDT procedures enables continuous structural monitoring of events with dynamic data evaluation for predictive maintenance. The validation of the model depends on expanding its dataset to include structural materials of multiple kinds and tests performed in various construction environments. Planning should investigate both the practical usability alongside financial viability of this method for massive infrastructure projects to study its actual effects.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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