Probabilistic Assessment of Coarse Aggregate Reliability for Infrastructure in Northeast India using Bayesian Networks and Variable Elimination Method

Al-Rashid Mohammed Harun[1*] and Hazarika Palash Jyoti[2]
1. Department of Civil Engineering, Gauhati University, Guwahati, Assam, 781014, INDIA
2. Civil Engineering Department, Assam Engineering College, Assam, 781013, INDIA
*harunalrashid1@gmail.com; mohammedharunalrashid607@gmail.com

Abstract
Coarse materials are critical in construction, playing a pivotal role in the durability and structural integrity of concrete and other infrastructure components, particularly in disaster-prone regions. This research investigates the resilience and reliability of coarse materials sourced from various quarries in Assam, Northeast India, which is essential for disaster prevention and infrastructure resilience. By employing Bayesian Networks and the Variable Elimination technique, a comprehensive probabilistic framework was developed based on nine essential laboratory tests including water absorption capacity, specific density, flatness index, elongation index, stability, material crushing strength, material impact strength, alkali-silica reaction and Los Angeles abrasion strength. Specimens were collected from 18 sites and the assessment results were analyzed to determine the probabilistic conditions of each node in the Bayesian network.

The findings revealed significant variations in material quality across different locations, with some areas exhibiting reduced reliability and increased vulnerability to structural failures. These insights are crucial for implementing targeted interventions such as enhancing quality control, sourcing higher-grade materials and optimizing construction techniques to improve disaster resilience. Additionally, regular monitoring and maintenance can mitigate potential infrastructure failures, thereby strengthening disaster preparedness. This study provides valuable insights to support the Assam Road Research and Training Institute (ARRTI) and similar organizations in improving construction practices and ensuring the long-term resilience of infrastructure projects in the region.

Keywords: Coarse Aggregates, Reliability Assessment, Bayesian Networks, Variable Elimination Method and Infrastructure.

Introduction

In the construction sector, coarse aggregates are essential because they are used to make concrete, road bases and other building materials. These aggregates are obtained from natural deposits such as riverbeds or, more frequently, from quarries where rocks are collected, crushed and graded to the necessary specifications. Granular materials with particle sizes larger than 4.75 mm are typically defined as these aggregates[12]. The quality and features of coarse aggregates greatly impact the longevity and structural integrity of the built environment. Since geological formations determine the physical and chemical qualities of aggregate material, extracting coarse aggregates from quarries requires a thorough understanding of these formations.

According to Xu et al[22], quarries are frequently found in areas with a variety of acceptable and plentiful rock types, including sedimentary, metamorphic and igneous rocks. Due to natural processes including weathering, erosion and sedimentation, these geological formations include a range of rock types and characteristics[2]. For example, igneous rocks with great durability and hardness, like granite and basalt, are widely sought after for building applications. Despite being widely utilized, sedimentary rocks like sandstone and limestone must be carefully inspected because of their varied strengths and porosities. Because of their increased strength and resistance to weathering, metamorphic rocks like schist and quartzite are also used in building[14].

Coarse aggregates are essential in the building industry environment. They make up the majority of the material, giving it compressive strength and minimizing cement-related shrinkage and cracking[17]. The size, shape, texture and grading of these aggregates have an impact on the mechanical and workability characteristics of concrete. Comparably, aggregate composition influences concrete's durability, especially concerning its capacity to withstand chemical assaults from sulfates and chlorides[12]. Understanding these properties is crucial for ensuring that the aggregates used in construction meet the required standards and performance criteria. The mineral makeup of the source rocks largely dictates the chemical characteristics of coarse aggregates[18]. For example, aggregates made from siliceous rocks such as quartzite have exceptional durability and are very resistant to chemical weathering.

On the other hand, calcareous aggregates like those made of limestone, might be more prone to chemical interactions with acidic materials. The appropriateness of aggregates for different building applications is also influenced by physical characteristics such as density, porosity and absorption[20].

https://doi.org/10.25303/184da019029

For heavy-duty projects like foundations and load-bearing buildings, for instance, aggregates with high density and low porosity are recommended. More porous aggregates could be appropriate for applications needing improved drainage. Rapid urbanization and infrastructural development in Northeast India, particularly in Assam, underscore the importance of assessing the geotechnical properties of coarse aggregates[16].

Assam, often referred to as the gateway to Northeast India, is experiencing significant growth in urban and rural infrastructure[19]. The region’s unique geographical setting, coupled with its rich geological diversity, presents both opportunities and challenges in sourcing high-quality aggregates. The demand for durable and sustainable construction materials is escalating as the State invests in roads, bridges, residential complexes and commercial buildings to cater to its growing population and economic activities.

A variety of rock types, from older Precambrian rocks to more recent sedimentary deposits, make up the geological formations of Assam and the larger Northeast area[5]. Because of the variability of the geology, it is important to carefully evaluate the aggregates that are accessible to make sure they are suitable for building. The region's tropical climate, which is characterized by high humidity and a lot of rain, further complicates the process of choosing aggregates resistant to these kinds of circumstances. Evaluating the geotechnical characteristics of coarse aggregates extracted from quarries is essential in guaranteeing the dependability and durability of building projects. Understanding the qualities of locally derived aggregates will greatly aid in the sustainable development of the region, especially considering Assam's fast urbanization and its importance as a connecting factor to other northeastern states[6].

The objective of this study is to thoroughly examine these facets, offering an all-encompassing evaluation of the geotechnical characteristics of coarse aggregates sourced from specific quarries. The focus will be on their appropriateness for diverse construction uses within the distinct Northeast Indian setting as shown in figure 1.

Additionally, our research can offer significant assistance to the Aggregate Section of the Assam Road Research and Training Institute (ARRTI), a critical ARRTI section that is essential to the State of Assam's construction sector. Ensuring the longevity and safety of building materials is largely made possible by the laboratory quality control tests carried out in this department. Furthermore, by helping to promote more widespread changes in industry norms and processes, our results may be extremely beneficial to other comparable agencies and organizations engaged in building and materials testing. Enhancing the calibre and durability of building projects while optimizing resource use and reducing costs is the goal of this focused strategy, which will also propel improvements in the building industry in the area.

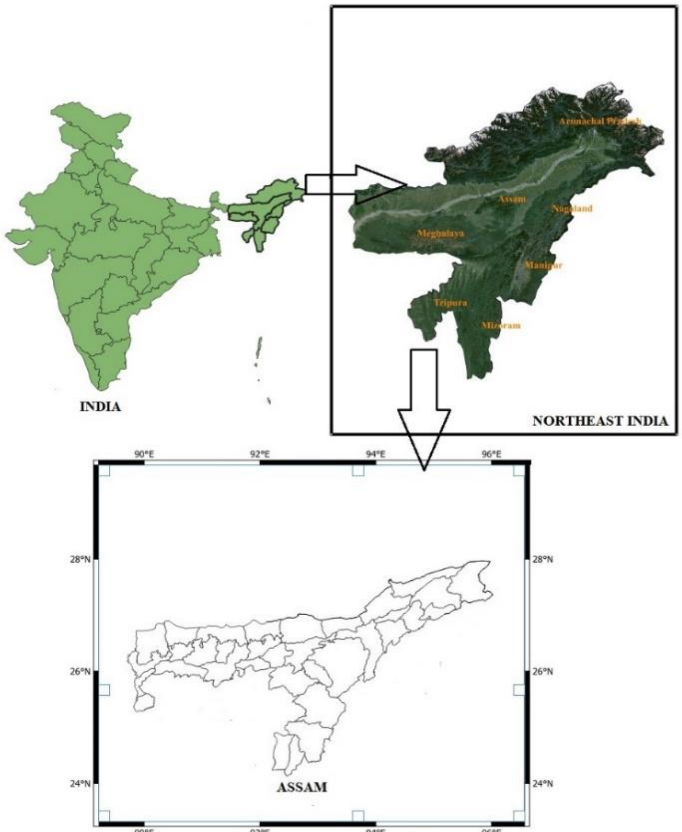

Fig. 1: Shapefile of Assam, Northeast, India.

Material and Methods

The framework of the work is shown in figure 2. Initially, this work involves reviewing literature related to laboratory tests of coarse aggregate. Subsequently, several tests for coarse aggregate were identified and a hierarchical Bayesian network of several coarse aggregate tests reliability was developed where the parent node is considered as reliable. The lower and upper limits for each test are then documented. Based on these limits, the probability state values for each node in the developed network are determined. Samples of coarse aggregates are collected from various locations and the identified tests are performed on each sample, with the results evaluated accordingly. Based on these results, probability values are assigned to each node. Finally, the probability of infrastructure reliability for various locations is calculated using the variable elimination method and some recommendations are provided based on the evaluated values.

Bayesian Network: A Bayesian network (BN) is a graphical model that represents the probabilistic dependencies between a set of various random variables[13]. This model can characterize uncertainty associated with the variables of a model[1]. In recent years, various researchers have used extensively BN modeling for hazard vulnerability assessment[21]. In addition, BN frameworks are utilized for the assessment of susceptibility and hazard in infrastructure systems[15]. Probabilistic modeling outcomes can thus be deduced from the posterior distribution of variables given the available information. BNs consist of various nodes like parent, child and intermediary nodes. Intermediary and child nodes contain Conditional Probability Tables (CPTs), while parent nodes contain prior probabilities.

Figure 3 shows a BN with two nodes, node C and node D, representing a parent and a child respectively. The nodes have two probability states: 'Yes-Y' and 'No-N'. Now, as node C is the parent node, it will have prior probabilities as, P(C-Y) which means the probability of C in the Y state and P(C-N) which means the probability of C in the N state. But as node D is the child node, it will have a CPT with probabilities P(D-Y|C-Y) (Probability of D being in state Y given C is in state Y), P(D-N|C-Y) (Probability of D being in state N given C is in state Y), P(D-Y|C-N) (Probability of D being in state Y given C is in state N) and P(D-N|C-N) (Probability of D being in state N given C is in state N).

Variable Elimination Method: The variable elimination (VE) technique is a generic precise inference approach in probabilistic graphical models like Bayesian networks and Markov random fields[24]. VE is a well-known technique in BN for probabilistic[23]. In general, this technique works with the network's time and space exponentials. This approach has the virtue of being both generic and simple. Given certain data, the VE algorithm calculates the posterior probability of an event after the prior probability and conditional probability associated with the dependent nodes. This approach removes the parent node before calculating the posterior probability of child node[4]. Considering figure 1, the prior probability of node A is shown in equation (i).

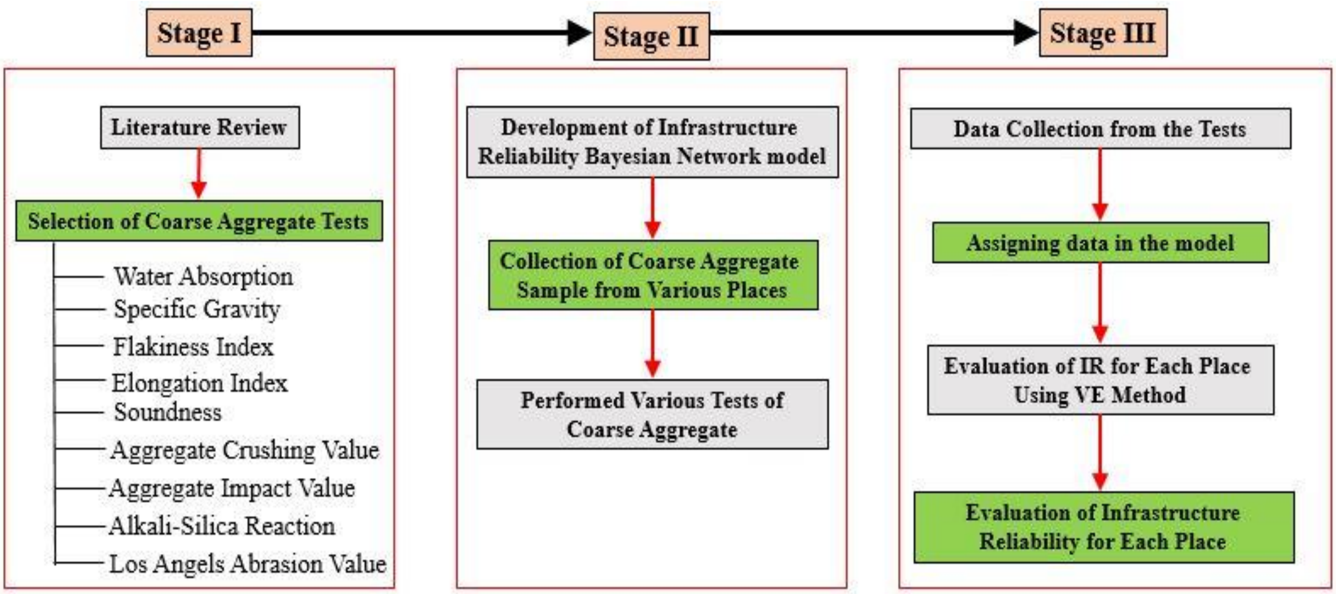

Fig. 2: Framework of work

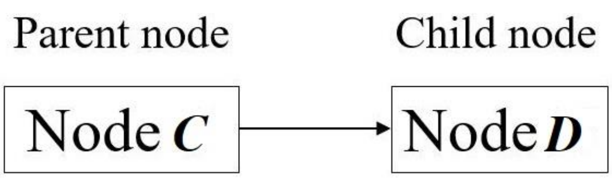

Fig. 3: Bayesian Network with 2 nodes.

$$P(C-Y)=a$$
$$P(C-N)=1-a \quad \text{(i)}$$

and the CPT for Node *B* is shown in equation (ii):

$$P(D-Y\,|\,C-Y)=c$$
$$P(D-N\,|\,C-Y)=1-c$$
$$P(D-Y\,|\,C-N)=d \quad \text{(ii)}$$
$$P(D-N\,|\,C-Y)=1-d$$

Then multiply {*P*(*A*)} with {*P*(*B*|*A*)} considering the same states of variables *A*, as shown in equations (iii):

$$P(D-Y\,|\,C-Y)=a\times c$$
$$P(D-N\,|\,C-Y)=a\times(1-c)$$
$$P(D-Y\,|\,C-N)=d\times(1-a) \quad \text{(iii)}$$
$$P(D-N\,|\,C-N)=(1-d)\times(1-a)$$

The posterior probability of B may then be calculated by adding the probability of assuming the same state of factors, as indicated in formulas (iv):

$$P(D-Y)=(a\times c)+(d\times(1-a))$$
$$P(D-N)=(a\times(1-c))+((1-d)\times(1-a)) \quad \text{(iv)}$$

Results and Discussion

Development of Bayesian Network for Infrastructure Reliability: In this study, an initial review of literature was conducted, identifying nine experiments for coarse aggregate. The lower and upper limits for all these experiments were documented and are listed in table 1. Experiment 1 (E1) is a water absorption test, it measures moisture absorption. A high E1 value means high porosity which decreases durability and increases vulnerability to freeze-thaw cycles. Low E1 value increased durability and quality. Experiment 2 (E2) is the specific gravity of coarse aggregate, it indicates the density and strength of the aggregate. Low specific gravity can imply weak, porous aggregates that reduce the strength and durability of concrete. High specific gravity generally means denser, stronger aggregates.

Experiment 3 (E3) is the Flakiness Index (FI) and experiment 4 (E4) is the Elongation Index (EI), both indicate the workability and strength of aggregates by their shape and texture. More E3 and E4 values mean irregular or elongated particles in the concrete, which can affect the workability and bond strength, resulting in structural deficiencies. Experiment (E5) is a soundness test, it evaluates the durability of aggregates under various weathering conditions. A low E5 value means there will be a strength degradation of aggregate during freeze-thaw or wetting-drying cycles, reducing the structural lifespan and integrity. Experiment 6 (E6) is the aggregate crushing value test, it measures the crushing resistance under gradual compressive load. High E6 values mean weak aggregates which may reduce the concrete load-bearing capacity and low E6 values mean very strong and durable aggregates.

Experiment (E7) is the aggregate impact value (AIV) test, it is the same as E6 but the only difference is that in this case load is applied suddenly. High values mean the aggregate may get fractured under impact and may compromise the structural integrity. Low values indicate tough and resilient aggregates. Experiment (E8) is an alkali-silica reaction (ASR) test, it is used for the potential of deleterious reactions between aggregate silica and alkalis in cement. High ASR potential can lead to expansive reactions causing cracking and structural failure. Aggregates with low ASR potential are preferred to avoid these issues. E9: Los Angeles abrasion value test measures the resistance to wear and abrasion. High abrasion values indicate aggregates that will wear down quickly under traffic or environmental conditions, potentially leading to surface degradation and reduced lifespan. Low values suggest durable aggregates.

It is noted that except for nodes or tests E1 and E2 (which are also performed for structural buildings), all other nodes are conducted for pavements. Therefore, it can be concluded that the selected nodes are relevant to both housing and transportation infrastructure. Given the importance of these tests for the mentioned infrastructures, it can be inferred that they significantly impact infrastructure reliability. Consequently, a Bayesian network was developed, as shown in figure 4. In this network, infrastructure reliability is the parent node, indicating that it depends on the outcomes of the considered tests, which serve as child nodes. Each child node has a prior probability, while the infrastructure reliability node has a conditional probability. For each node, three probability states: low (L), medium (M) and high (H) are assigned.

The probability state for each child node is determined based on the lower and upper limits of the tests. Details of the probability states for each node are provided in table 2. For each child node, there are a total of nine Conditional Probability Tables (CPTs) for the Infrastructure reliability (IR) node. For instance, consider that IR is dependent on E1 and both nodes have three probability states: low (L), medium (M) and high (H). E1 will have three prior probabilities: P(E1-L) for the probability of E1 being low, P(E1-M) for the probability of E1 being medium and P(E1-H) for the probability of E1 being high.

Consequently, IR will have nine CPTs, P(IR-L|E1-L): Probability of IR being low given E1 is low, P(IR-L|E1-M): Probability of IR being low given E1 is medium, P(IR-L|E1-H): Probability of IR being low given E1 is high, P(IR-M|E1-L): Probability of IR being medium given E1 is low, P(IR-M|E1-M): Probability of IR being medium given E1 is medium, P(IR-M|E1-H): Probability of IR being medium given E1 is high, P(IR-H|E1-L): Probability of IR being high given E1 is low, P(IR-H|E1-M): Probability of IR being high given E1 is medium, and, P(IR-H|E1-H): Probability of IR being high given E1 is high. Therefore, for nine child nodes, a total of 81 CPTs are developed for IR. It is important to note that the probability states for the child nodes can have different implications for IR.

In some cases, a low probability state for a child node indicates low IR probability while in other cases, it may indicate high IR probability. For example, a low value of E1 represents a high probability of IR whereas a low value of E2 represents a low probability of IR. The CPTs are developed accordingly to reflect these relationships.

Infrastructure Reliability: After finalizing the network, a total of 18 places are selected for the collection of coarse aggregate samples, as shown in figure 5. The locations are chosen from quarry areas, meaning they are near water bodies where aggregates can be obtained. These locations are divided into two parts: some areas are near the Brahmaputra River regions, while others are near the Barak River regions. From each place, total of 20 samples of coarse aggregate are collected. This means a total of 360 (=18x20) samples are collected in this study. Some of the pictures of the collected samples are given in figure 6. Here, the size of collected coarse aggregate samples is between 10mm to 40mm.

For each sample, nine experiments were performed, so a total of 3240 (= 360 x 9) tests were performed. The prior probabilities of the child node are assigned based on the 20 samples. For example, say for E1, out of 20 samples, 12 have low values, 5 have medium values and 3 have high values. Then the P(E1-L) will be 0.6 (12/20), P(E1-M) will be 0.25 (5/20) and P(E1-H) will be 0.15 (3/20). After assigning the prior probability of each child node from the experiment values and the CPTs between child and parent nodes, the infrastructure reliability (IR) is evaluated using the variable elimination method. The evaluated values for each place are shown in figure 7.

The figure presents the probability of infrastructure reliability (IR) across 16 different places, categorized into three states: low, medium and high. From the figure, it can be seen that P1, P2, P3, P4, P5, P7, P8, P10 and P16 have more probability values for high state. P6, P9, P13, P14, P15, P17 and P18 have more probability values for low state and P11 and P12 have more probability values for medium state. For instance, place P1 has a 0.394 probability of low reliability, 0.285 probability of medium reliability and 0.439 probability of high reliability. In contrast, place P17 exhibits the highest probability for low reliability at 0.695 and the lowest probability for high reliability at 0.354.

Interestingly, some places like P16 and P18 show a relatively balanced distribution but still favor either low or high reliability significantly. P16, for example, has a notable high-reliability probability of 0.555. Places P7 and P8 stand out with higher probabilities for high reliability at 0.543 and 0.537 respectively. But places such as P6, P9 and P13 have higher probabilities in low-reliability states indicating potential issues.

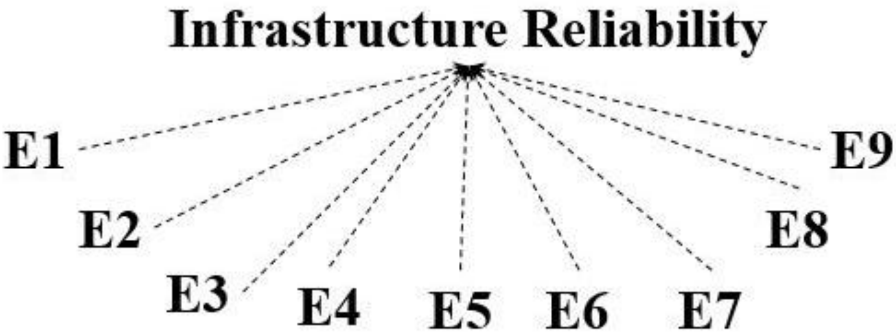

Fig. 4: A Bayesian Network of Infrastructure Reliability

Table 1
Laboratory Test of Coarse aggregate with lower and upper limits.

Node	Laboratory Test	Low	High
E1	Water Absorption[8]	0.5%	1%
E2	Specific Gravity[8]	2.5	3.0
E3	Flakiness Index (FI)[7]	0	30%
E4	Elongation Index (EI)[7]	0	30%
E5	Soundness[10]	0	• 12% with Sodium Sulphate • 18% with Magnesium sulphate
E6	Aggregate Crushing Value[9]	0	30%
E7	Aggregate Impact Value[9]	0	30%
E8	Alkali-Silica Reaction (ASR)[11]	0.04%	0.1%
E9	Los Angels Abrasion Value[9]	0	40%

https://doi.org/10.25303/184da019029

Table 2
Details of probability state for each child node (Laboratory Test of Coarse aggregate).

Node	State	Ranges	Remarks
E1	L	0.5 to 0.67%	Suggests better quality and durability
	M	0.67 to 0.84%	Suggests moderate quality and durability
	H	0.84 to 1%	Suggests low quality and durability
E2	L	2.5 to 2.67	Low specific gravity can imply weak, porous aggregates that reduce the strength and durability of concrete.
	M	2.68 to 2.84	Medium specific gravity generally moderate dense and strong aggregates
	H	2.85 to 3.0	High specific gravity generally means denser, stronger aggregates
E3	L	0 to 10%	Low FI values indicate non-flaky aggregates, which can enhance workability and bond strength in concrete, leading to potential structural strength.
	M	11 to 20%	Medium FI values indicate semi-flaky aggregates with moderate workability, bond strength and structural strength.
	H	21 to 30%	High FI values indicate flaky aggregates, which can reduce workability and bond strength in concrete, leading to potential structural weaknesses
E4	L	0 to 10%	Low EI values indicate non-elongated aggregates, which can enhance workability and bond strength in concrete, leading to potential structural strength.
	M	11 to 20%	Medium FI values indicate semi-elongated aggregates with moderate workability, bond strength and structural strength.
	H	21 to 30%	High FI values indicate elongated aggregates, which can reduce workability and bond strength in concrete, leading to potential structural weaknesses.
E5	L	0 to 3%	Severe reduction in the lifespan and integrity of the structure
	M	4 to 7%	Moderate reduction in the lifespan and integrity of the structure
	H	8 to 12%	No reduction in the lifespan and integrity of the structure
E6	L	0 to 10%	Low values suggest strong, durable aggregates
	M	11 to 20%	Medium crushing values indicate moderate aggregates
	H	21 to 30%	High crushing values indicate weak aggregates that could reduce the load-bearing capacity of concrete.
E7	L	0 to 10%	Low AIV indicates very tough, resilient aggregates
	M	11 to 20%	Medium AIV indicates moderate tough, resilient aggregates
	H	21 to 30%	High AIV means the aggregate is more likely to fracture under impact, compromising the structural integrity.
E8	L	0.04 to 0.059%	Low ASR potential does not lead to expansive reactions causing cracking and structural failure.
	M	0.06 to 0.079%	Moderate ASR potential can lead to expansive reactions causing cracking and structural failure
	H	0.08 to 0.1%	High ASR potential leads to expansive reactions causing cracking and structural failure.
E9	L	0 to 13.3%	Low values suggest durable aggregates
	M	13.4 to 26.7%	Medium abrasion values indicate aggregates that will take time to wear down under traffic or environmental conditions, potentially leading to surface degradation and reduced lifespan.
	H	26.8 to 40%	High abrasion values indicate aggregates that will wear down quickly under traffic or environmental conditions, potentially leading to surface degradation and reduced lifespan.
Infrastructure Reliability (IR)	L	0 to 33%	Samples are not preferred for infrastructure construction.
	M	34 to 66%	Samples can be used to construct small or low-cost infrastructure.
	H	67 to 100%	Samples are good for infrastructure construction.

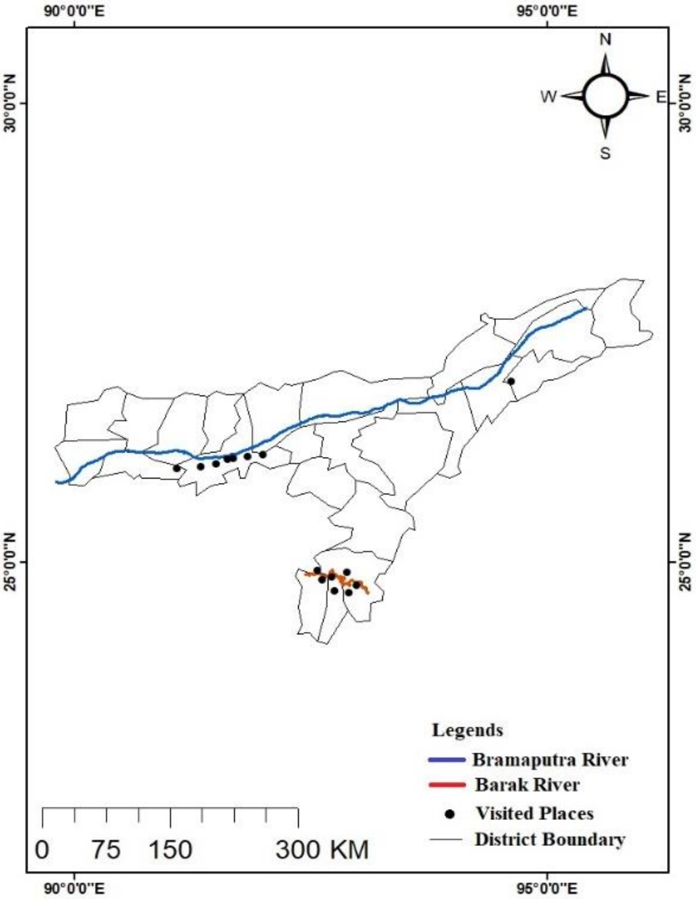

Fig. 5: Sample collection locations

(a) Amingaon sample

(b) Amsing sample

(c) Azara sample

(d) Badarpur sample

(e) Katakhal sample

(f) Kumbirgram sample

(g) Mayang sample

(h) Palashbari sample

(i) Panikhati sample

(j) Rongpur sample

(k) Silcoori Grant sample

(l) Sonarbarighat sample

https://doi.org/10.25303/184da019029

(m) Srikona sample

(n) Sualkuchi sample

Fig. 6: Collected Samples from various places

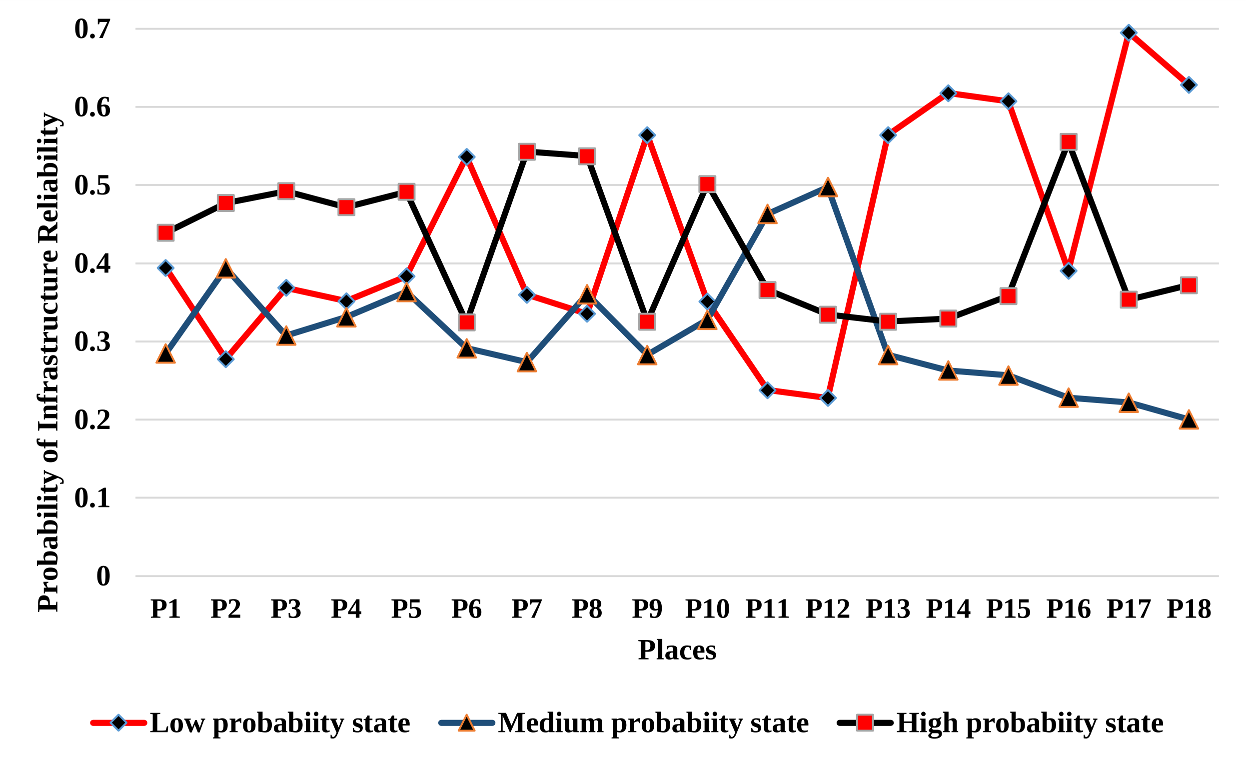

Fig. 7: Probability values for each place

The result highlights that there is a large variation in infrastructure reliability among various locations, some places have a high probability of low reliability. For example, places such as P6, P9, P13, P14, P15, P17 and P18 have higher probabilities of reliability in low state, which indicates that potential concerns need to be addressed to improve the infrastructure robustness. By conducting a thorough investigation of the particular elements that mainly cause the low reliability in these locations, these places can be made more reliable. This can be achieved by analyzing the outcomes of the many tests carried out on coarse aggregates of that location. After finding all the issues, a focused intervention should be executed, otherwise economy of that location will go down.

For example, someone who wants to construct an infrastructure and an aggregate of that location, continuously falls short of the necessary requirements. In that case, the owner may be interested in obtaining aggregate from other locations. Schedule routine maintenance and monitoring to take care of any new problems as soon as they arise. Regular monitoring will help in the detection of infrastructure degradation at an early age, which also helps in timely repairs.

The data makes it possible to focus on the exact level of infrastructure reliability at the moment which facilitates resource allocation and well-informed decision-making. By identifying regions with low reliability before large failures occur, preventive actions can be put into place, lowering the likelihood of catastrophic infrastructure breakdowns. The greatest impact on total infrastructure reliability is ensured by allocating resources efficiently to the most crucial locations. The developed framework can be applied in other infrastructures to calculate reliability. So, this will help in the case of upcoming infrastructure development projects. The evaluated values offer a thorough picture of infrastructure reliability at various places which will definitely help the stakeholders of the concerned places for the improvement of infrastructure quality and longevity.

Conclusion

Initially, various experiments of coarse aggregate were selected with the help of existing literature. Then BN model for infrastructure reliability is developed after identifying various key laboratory tests. Then various experiments were performed to evaluate the quality and reliability of coarse aggregates used in infrastructure. In this study, the samples are collected from 18 places, from each place 20 samples are collected and for each sample, 9 experiments are performed including a water absorption test, specific gravity test, flakiness index, elongation index, soundness test etc. Finally, infrastructure reliability of coarse aggregate is calculated using BN and variable elimination method. The overall reliability of infrastructure in different locations is evaluated by assigning probability state values to each node of the developed BN.

This work benefits disaster mitigation as infrastructure reliability is essential in reducing the effects of natural disasters. The durability of structures against various natural disasters increases when high-quality coarse aggregates are used. By taking a proactive stance, the risk of catastrophic errors is decreased, saving lives and lowering financial damages. Moreover, this methodology's data-driven decision-making process guarantees the effective distribution of resources to the most susceptible locations, boosting overall readiness for disasters.

Acknowledgment

Both the author acknowledges the support extended by the District Disaster Management Authority (DDMA), Assam Don Bosco University, Assam Down Town University and Assam Engineering College, for providing the various samples and laboratory information of course aggregates in Northeast India.

References

1. Aghababaei M. and Mahsuli M., Component damage models for detailed seismic risk analysis using structural reliability methods, *Structural Safety*, **76**, 108-122 **(2019)**

2. Aladejare A.E., Ozoji T., Lawal A.I. and Zhang Z., Soft computing-based models for predicting the characteristic impedance of igneous rock from their physico-mechanical properties, *Rock Mechanics and Rock Engineering*, **55(7)**, 4291-4304 **(2022)**

3. Carrasco S., Cantor D., Ovalle C. and Quiroz-Rojo P., Shear strength of angular granular materials with size and shape polydispersity, *Open Geomechanics*, **4**, 1-14 **(2023)**

4. Chavira M. and Darwiche A., Compiling Bayesian Networks Using Variable Elimination, *IJCAI*, **7**, 2443-2449 **(2007)**

5. Deb P., Debnath B., Hasan M., Alqarni A.S., Alaskar A., Alsabhan A.H. and Hashim K.S., Development of eco-friendly concrete mix using recycled aggregates: Structural performance and pore feature study using image analysis, *Materials*, **15(8)**, 2953 **(2022)**

6. Gupta M.D., Growth trend and potential of horticulture in Northeast India, *Journal of Horticultural Sciences*, **17(2)**, 530-542 **(2022)**

7. IS 2386 (Part 1): 1963, Methods of Test for Aggregates for Concrete - Part 1: Particle Size and Shape, Bureau of Indian Standards, New Delhi, India **(1963)**

8. IS 2386 (Part 3): 1963, Methods of Test for Aggregates for Concrete - Part 3: Specific Gravity, Density, Voids, Absorption and Bulking, Bureau of Indian Standards, New Delhi, India **(1963)**

9. IS 2386 (Part 4): 1963, Methods of Test for Aggregates for Concrete - Part 4: Mechanical Properties, Bureau of Indian Standards, New Delhi, India **(1963)**

10. IS 2386 (Part 5): 1963, Methods of Test for Aggregates for Concrete - Part 5: Soundness, Bureau of Indian Standards, New Delhi, India **(1963)**

11. IS 2386 (Part 7): 1963, Methods of Test for Aggregates for Concrete - Part 7: Alkali Aggregate Reactivity, Bureau of Indian Standards, New Delhi, India **(1963)**

12. Kazemi F., Asgarkhani N. and Jankowski R., Machine learning-based seismic response and performance assessment of reinforced concrete buildings, *Archives of Civil and Mechanical Engineering*, **23(2)**, 94 **(2023)**

13. Koller D. and Friedman N., Probabilistic graphical models: principles and techniques, MIT Press **(2009)**

14. Malik F.N., Ricles J., Yari M. and Nissar M.A., Physics Informed Recurrent Neural Networks for Seismic Response Evaluation of Nonlinear Systems, *arXiv*, preprint, arXiv:2308.08655 **(2023)**

15. Marrone S., Nardone R., Tedesco A., D'Amore P., Vittorini V., Setola R., De Cillis F. and Mazzocca N., Vulnerability modeling and analysis for critical infrastructure protection applications, *International Journal of Critical Infrastructure Protection*, **6(3-4)**, 217-227 **(2013)**

16. Mishra S. and Mistry R., Reviewing some properties of ultra-high performance concrete, *International Journal Engineering Research Technology*, **6**, 108-121 **(2020)**

17. Ngo T.Q.L., Wang Y.R. and Chiang D.L., Applying artificial intelligence to improve on-site non-destructive concrete compressive strength tests, *Crystals*, **11(10)**, 1157 **(2021)**

18. Pötzl C., Siegesmund S., López-Doncel R. and Dohrmann R., Key parameters of volcanic tuffs used as building stone: a statistical approach, *Environmental Earth Sciences*, **81**, 1-29 **(2022)**

19. Sen M.K., Dutta S. and Kabir G., Modelling and quantification of time-varying flood resilience for housing infrastructure using

dynamic Bayesian Network, *Journal of Cleaner Production*, **361**, 132266 **(2022)**

20. Strack C.M., Barnes E., Ramsey M.A., Williams R.K., Klaus K.L. and Moser R.D., Impact of aggregate mineralogy and exposure solution on alkali-silica reaction product composition and structure within accelerated test conditions, *Construction and Building Materials*, **240**, 117929 **(2020)**

21. Wang S., Hong L. and Chen X., Vulnerability analysis of interdependent infrastructure systems: A methodological framework, *Physica A: Statistical Mechanics and its Applications*, **391(11)**, 3323-3335 **(2012)**

22. Xu J., Gui H., Chen J., Li C., Li Y., Zhao C. and Guo Y., Hydro geochemical Process and Quality Assessment of Surface Water Around Fuli Abandoned Quarries Area, Northern Anhui Province, China, *Polish Journal of Environmental Studies*, **31(2)**, 1857-1868 **(2022)**

23. Zhang N.L. and Poole D., A Simple Approach to Bayesian Network Computations, In 7th Canadian Conference on Artificial Intelligence, Springer, New York, 171-178 **(1994)**

24. Zhang N. L. and Poole D., Exploiting causal independence in Bayesian network inference, *Journal of Artificial Intelligence Research*, **5,** 301–328 **(1996)**.

(Received 25th August 2024, accepted 26th October 2024)