# Digital and Predictive Quality Assurance of Ready-Mix Concrete in Large-Scale Construction Projects: Recent Advances and an Integrated Framework

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## Abstract

Ready-mix concrete (RMC) is a critical construction material for high-rise buildings, bridges, metro systems, airports, industrial facilities and other large-scale projects. Although centralised production improves uniformity and productivity, the final quality of RMC is influenced by variations in constituent materials, aggregate moisture, batching accuracy, admixture dosage, transportation time, concrete temperature, workability loss, placement, compaction and curing. Conventional quality assurance and quality control (QA/QC), based mainly on periodic sampling and compressive-strength testing, remains essential but provides only discrete observations of a continuously varying production and construction process. Recent advances in automated batching, Internet of Things (IoT) sensing, computer vision, artificial intelligence (AI), machine learning (ML), concrete maturity monitoring, Building Information Modelling (BIM) and Digital Twins are creating opportunities to transform RMC quality management from reactive inspection to continuous and predictive assurance. This paper critically reviews these developments and proposes an Integrated Predictive Quality Assurance and Quality Control Framework (IPQCF) for large-scale construction projects. The framework combines material qualification, smart batching, digital batch traceability, transportation monitoring, site acceptance, sensor-assisted curing, statistical process control, predictive analytics and BIM/Digital Twin-based lifecycle documentation. Recent industrial research using 9,007 genuine RMC production records demonstrates the practical feasibility of early compressive-strength prediction, while plant-scale deep-learning studies show the potential of computer vision for continuous workability assessment. The proposed framework is intended to complement, rather than replace, code-prescribed acceptance testing. Integration of established testing procedures with digital monitoring and predictive analytics can improve traceability, identify quality deviations earlier, reduce rework and support more reliable and sustainable concrete construction.

**Keywords:** Ready-mix concrete; quality assurance; quality control; artificial intelligence; machine learning; Internet of Things; computer vision; digital twin; concrete maturity; construction quality.

## 1. Introduction

Ready-mix concrete has become indispensable to contemporary large-scale construction because it enables controlled production, high delivery rates, mechanised placement and improved consistency when compared with conventional site mixing. The quality of RMC directly influences structural safety, serviceability, durability, construction productivity and lifecycle cost.

In India, IS 4926 establishes requirements for the production and supply of ready-mixed concrete. Internationally, ASTM C94/C94M provides widely recognised requirements for ready-mixed concrete production and delivery. Nevertheless, compliance with an approved mix design and batching procedure does not by itself guarantee uniform in-situ performance.

Concrete quality may vary because of changes in cementitious materials, aggregate grading and moisture, batching tolerances, effective water content, admixture dosage, transportation time, ambient conditions, concrete temperature, mixer operation, workability loss, site water addition, pumping, placement, vibration and curing.

Conventional QA/QC systems address these risks through material approval, plant calibration, trial mixes, slump testing, temperature measurement, specimen preparation and compressive-strength testing. These procedures remain fundamental. However, two major limitations are increasingly evident in large projects.

First, quality control is largely **sample-based**. Only selected batches are directly tested even though major construction projects may receive hundreds of concrete deliveries within a short period.

Second, the principal hardened-concrete acceptance information is often available only after the concrete has already been placed and incorporated into the structure. If inadequate strength is identified after several days or weeks, subsequent construction may already have progressed, resulting in additional investigation, testing, delay, strengthening or replacement.

The emerging objective is therefore to move from a predominantly reactive sequence:

**Production → Sampling → Testing → Non-conformity → Investigation → Corrective Action**

toward a more proactive system:

**Production → Continuous Monitoring → Early Prediction → Warning → Preventive Action → Verification**

The main objective of this paper is to critically review recent technological developments that support this transition and to propose an integrated QA/QC framework suitable for large-scale RMC construction.

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## 2. Evolution of RMC Quality Management

Quality Assurance and Quality Control are closely related but perform different functions.

Quality Assurance establishes confidence that materials, equipment, production procedures and construction operations are capable of consistently meeting specified requirements. Quality Control verifies actual conformity through measurement, inspection and testing.

In conventional practice, QA/QC tends to be organised around separate activities such as plant inspection, delivery checks, fresh-concrete testing, cube or cylinder testing and site records. The emerging approach seeks to integrate these activities through digital information.

Table 1. Conventional and emerging RMC quality management

| Parameter | Conventional practice | Emerging practice |
|---|---|---|
| Material control | Periodic testing | Digital material records and trend analysis |
| Batching | Automated weighing | Continuous production monitoring |
| Aggregate moisture | Periodic determination | Continuous moisture sensing |
| Transportation | Delivery ticket | GPS, transit time and telemetry |

| Parameter | Conventional practice | Emerging practice |
|---|---|---|
| Workability | Manual slump test | Slump test supported by computer vision |
| Temperature | Spot measurement | Continuous digital monitoring |
| Strength | 7-day and 28-day testing | Physical testing plus early prediction |
| Curing | Manual supervision | Embedded sensors and maturity monitoring |
| Data analysis | Pass/fail assessment | Statistical trends and predictive analytics |
| Traceability | Batch or pour records | Batch-to-element digital traceability |
| Corrective action | Reactive | Preventive and predictive |
| Documentation | Paper/PDF records | BIM/cloud/Digital Twin |

The most important shift is therefore not the replacement of conventional testing, but the addition of continuous monitoring and predictive intelligence.

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## 3. Smart Batching and Production Control

Automated batching represents the foundation of modern RMC quality management. Contemporary batching plants can electronically record the quantities of cementitious materials, aggregates, water and admixtures for every batch.

A reliable digital production record should include:

- batch number;
- production date and time;
- approved mix-design identification;
- target and actual material quantities;
- aggregate moisture values;
- water corrections;
- admixture dosage;
- concrete temperature;
- truck identification;
- dispatch time; and
- delivery location.

Continuous review of these parameters can reveal production drift before non-conforming concrete is produced.

Aggregate moisture monitoring is especially important because incorrect moisture correction changes the actual water content of the concrete. This can influence workability, strength, shrinkage and durability.

The next development beyond automated batching is **closed-loop production control**, in which real-time measurements are used to adjust water or other production parameters within approved limits.

Such systems improve consistency and reduce dependence on manual adjustments.

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4. Digital Batch Identity and Traceability

Large projects require a reliable method for tracing concrete from production to its final location in the structure.

A unique digital identity should ideally connect each batch with:

- material source;
- mix design;
- batching plant;
- mixer truck;
- transportation history;
- site acceptance results;
- pour location;
- structural element;
- test specimen; and
- final strength result.

Fig. 1. Proposed batch-to-element traceability system

**Raw Material Lots**
↓
**Approved Mix Design**
↓
**Batch ID**
↓
**RMC Plant Record**
↓
**Mixer Truck ID**
↓
**GPS and Transit Record**
↓
**Site Acceptance**
↓
**Pour ID**
↓
**Structural Element**
↓
**Cube/Cylinder and Sensor ID**
↓
**Final Quality Record**

This creates a form of **concrete genealogy**.

If a low-strength result occurs, the affected batch and corresponding structural elements can be identified immediately. Similarly, if a problem is discovered with a particular raw-material lot, all related batches can be traced.

For mega-projects, this level of traceability can substantially improve investigation, auditability and accountability.

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5. IoT and Real-Time Monitoring

The Internet of Things enables connected sensors and equipment to generate continuous quality information.

Potential applications in RMC include monitoring:

- aggregate moisture;
- plant temperature;
- concrete temperature;
- delivery duration;
- truck location;
- mixer-drum operation;
- environmental conditions;
- curing temperature; and
- concrete maturity.

Table 2. Applications of digital sensing in RMC

| Construction stage | Parameter | Technology | Purpose |
|---|---|---|---|
| Materials | Aggregate moisture | Moisture sensor | Water adjustment |
| Production | Batch quantity | Load cells | Production verification |
| Transport | Location | GPS | Delivery tracking |
| Transport | Transit duration | Digital time record | Workability risk control |
| Transport | Drum operation | Telemetry | Mixing history |
| Fresh concrete | Temperature | Digital sensor | Thermal control |
| Fresh concrete | Workability | Vision/sensor system | Consistency assessment |
| Post-placement | Temperature | Embedded sensor | Curing verification |
| Post-placement | Maturity | Temperature-time monitoring | Early strength estimation |

The key advantage of digital sensing is that it produces **time-series information**, rather than a single isolated reading.

This is particularly useful for high-strength concrete, mass concrete, long transport distances and fast-track construction.

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## 6. Computer Vision for Fresh-Concrete Quality Control

Computer vision is one of the more innovative recent developments in concrete QA/QC.

Traditional slump testing remains widely used and technically reliable when performed correctly. However, it provides only occasional measurements.

Computer-vision systems can potentially observe concrete continuously during production or discharge.

A 2024 plant-scale study used video obtained from a camera installed above the discharge hopper of an operational batching plant. A deep-learning model based on transfer learning was used to classify concrete into four slump categories. The reported average precision was approximately 85%, with an average F1 score of approximately 87%.

These results indicate that image-based systems may provide a useful supplementary layer of quality monitoring.

Fig. 2. Computer-vision-based workability assessment

**Concrete Discharge**
↓
**Video Capture**
↓
**Frame Processing**
↓
**Deep-Learning Analysis**
↓
**Workability Classification**
↓
**Accept / Warning**
↓
**Digital Record**

The main advantages are:

- non-contact monitoring;
- potential observation of every batch;
- automatic documentation; and
- rapid identification of unusual concrete behaviour.

However, computer vision should currently be considered a supplementary technology. Standard acceptance tests should continue unless an alternative method has been formally validated and approved.

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## 7. Artificial Intelligence and Early Strength Prediction

The delayed availability of 28-day compressive-strength results is one of the strongest motivations for predictive concrete quality control.

Machine-learning models can analyse multiple production variables simultaneously, including:

- cementitious content;
- water content;
- supplementary cementitious materials;
- aggregates;
- admixtures;
- concrete temperature;
- slump;
- weather conditions;
- transportation time; and
- early-age strength.

Recent industrial research demonstrates that such models are moving beyond small laboratory datasets.

A 2026 study analysed **9,007 genuine RMC production records** collected from an operating plant between 2016 and 2024. Several machine-learning algorithms were compared using actual production and environmental data.

The study demonstrated that 28-day compressive strength could be estimated substantially earlier when plant data and early-age strength information were available.

The importance of this work lies in its industrial scale and real-world variability.

Fig. 3. Predictive quality-control process

**Batch Data + Material Data + Weather + Transit Information + Fresh-Concrete Tests + Early Strength**

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**Machine-Learning Model**

↓

**Predicted Later-Age Performance**

↓

**Low Risk** → Routine QA/QC

**Moderate Risk** → Increased Monitoring

**High Risk** → Additional Testing and Investigation

The most appropriate use of ML is therefore as an **early-warning tool**.

It should not be used to replace mandatory strength testing unless explicitly permitted by the governing standard and project specification.

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8. Explainable AI for Engineering Decisions

Prediction alone is insufficient for structural-quality management.

Engineers must understand why a system identifies a batch as high risk.

Explainable Artificial Intelligence can help identify the variables that most strongly influence a prediction.

For example, a dashboard could report:

**Predicted 28-day performance:** Below expected trend
**Quality risk:** High

**Principal contributing factors:**

- elevated water content;
- unusually long transportation time;
- higher concrete temperature;
- abnormal slump; and
- lower-than-expected early strength.

This makes the prediction more useful for root-cause analysis and corrective action.

Explainable AI is particularly important in construction because quality decisions involve contractual, technical and safety implications.

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9. Statistical Process Control

Artificial intelligence should not overshadow established statistical quality-control techniques.

Statistical Process Control remains highly effective for identifying:

- increasing variability;
- gradual strength reduction;
- changes in mean performance;
- abnormal slump trends;
- unusual batching behaviour; and
- recurring quality deviations.

Control charts and moving trend analysis can identify process deterioration even when individual results continue to satisfy minimum acceptance requirements.

This allows action to be taken before an actual failure occurs.

The emerging approach should therefore combine:

**Physical Testing + Statistical Process Control + Digital Sensors + Predictive Analytics**

rather than depend on any one technique.

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10. Smart Curing and Concrete Maturity

RMC quality control should continue after concrete placement.

Correctly produced concrete can still fail to achieve intended performance if curing is inadequate.

Embedded wireless sensors can monitor temperature during early-age hydration and support maturity-based evaluation.

Concrete maturity relates the temperature history of concrete to its strength development. When a valid strength–maturity relationship has been established for the specific concrete mixture, maturity monitoring can assist decisions concerning:

- formwork removal;
- post-tensioning;
- reshoring;
- construction loading;
- curing duration; and
- opening concrete elements to service.

This approach is particularly valuable in fast-track projects because site decisions are based on actual measured conditions rather than only assumed curing durations.

Nevertheless, maturity monitoring must be properly calibrated for the specific concrete mixture and used in accordance with applicable standards.

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## 11. BIM and Digital Twin-Based Quality Management

Building Information Modelling provides the opportunity to connect quality records with physical structural elements.

Instead of recording only:

**Cube No. 742 – 46.5 MPa**

a BIM-linked QA/QC system can store:

**Tower A → Level 12 → Column C17 → Pour P42 → Batch B742 → Cube 742 → 46.5 MPa**

This transforms laboratory information into a spatially meaningful quality record.

Digital Twin technology extends this concept further by connecting the virtual model with continuously updated information from the physical project.

Fig. 4. Digital Twin architecture for RMC quality management

**PHYSICAL SYSTEM**

Batching Plant → Mixer Truck → Construction Site → Concrete Element → Sensors

↕

**DIGITAL DATA EXCHANGE**

↕

**DIGITAL SYSTEM**

BIM Model → Quality Database → Statistical Analysis → AI/ML → Digital Twin

↓

**DECISION LAYER**

Dashboard → Engineer → Alert / NCR / CAPA

↓

**Feedback to Production**

For large projects, this architecture offers substantial advantages in auditability, investigation and long-term quality documentation.

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## 12. Proposed Integrated Predictive QA/QC Framework

Based on the reviewed developments, this study proposes an **Integrated Predictive Quality Assurance and Quality Control Framework (IPQCF)**.

Fig. 5. Integrated Predictive QA/QC Framework

**1. Material Qualification**
Cement + SCM + Aggregate + Water + Admixture

↓

**2. Mix Qualification**
Laboratory Trial → Plant Trial → Approved Mix

↓

**3. Smart Production**
Automated Batching + Moisture Correction + Batch ID

↓

**4. Digital Transportation**
Truck ID + GPS + Transit Time + Temperature

↓

**5. Site Acceptance**
Slump + Temperature + Sampling + Vision-Assisted Monitoring

↓

**6. Placement Traceability**
Pour ID + Structural Element + Placement Record

↓

**7. Smart Curing**
Temperature Sensors + Maturity Monitoring

↓

**8. Performance Verification**
Early Strength + 7-Day + 28-Day Strength + NDT where required

↓

**9. Quality Intelligence**
Statistical Process Control + AI/ML + Explainable AI

↓

**10. Quality Decision**
Accept / Warning / NCR / CAPA

↓

**11. Digital Twin Record**
Permanent Batch-to-Element Quality History

The proposed framework contains three complementary layers.

Table 3. Three-layer IPQCF structure

| Layer | Primary function | Principal tools |
|---|---|---|
| Verification | Confirm compliance | Standard tests and inspections |
| Monitoring | Detect process deviation | Sensors, GPS, telemetry, computer vision |
| Prediction | Identify emerging quality risk | SPC, AI/ML and Digital Twin analytics |

The verification layer provides contractual and regulatory evidence. The monitoring layer provides continuous process information. The predictive layer provides early warnings before major non-conformities develop.

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13. Corrective and Preventive Action

Traditional quality systems tend to respond after a non-conformity has already occurred.

Digital QA/QC allows the project team to introduce preventive action at an earlier stage.

Fig. 6. Data-driven CAPA workflow

**Quality Deviation or Predictive Warning**

↓

**Verify the Measurement**

↓

**Identify Affected Batch**

↓

**Locate Structural Element**

↓

**Root-Cause Analysis**

↓

**Material / Batching / Transport / Placement / Curing**

↓

**Risk Assessment**

↓

**Corrective Action + Preventive Action**

↓

**Effectiveness Verification**

↓

**Update QA Database**

The final feedback stage creates a learning quality system in which past deviations improve future monitoring and decision-making.

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14. Implementation Challenges

Despite the potential benefits, several technical and organisational challenges remain.

### 14.1 Data quality

AI and predictive systems are only as reliable as the data used to develop them. Missing records, incorrect test identification and poor sensor data can substantially reduce reliability.

### 14.2 Calibration and validation

Sensors, cameras and automated systems require documented calibration and periodic validation against recognised test procedures.

### 14.3 Model transferability

A predictive model developed using data from one RMC plant may not automatically perform accurately for another plant because of differences in materials, environmental conditions and production practices.

Local calibration is therefore essential.

### 14.4 Interoperability

Batching software, laboratory systems, BIM platforms, sensors and site-management tools often operate independently.

Effective digital QA/QC requires common data structures and reliable interfaces.

### 14.5 Regulatory and contractual acceptance

Digital technologies should support engineering judgment and code-based testing. Their use as substitutes for mandatory tests requires formal acceptance by the governing authority and project specification.

### 14.6 Cybersecurity and data ownership

Digitally connected quality systems require clear procedures for data ownership, modification rights, retention, access control and cybersecurity.

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## 15. Research Gaps and Future Directions

Several research areas require further development.

Table 4. Key research gaps

| Current limitation | Future research need |
|---|---|
| Small laboratory datasets | Large multi-plant industrial datasets |
| Black-box ML | Explainable AI |
| Isolated monitoring | Plant-to-element digital integration |
| Strength-focused models | Multi-performance prediction |
| Static BIM | Continuously updated Digital Twins |
| Generic ML models | Locally adaptive models |
| Reactive NCR systems | Predictive CAPA |
| Fragmented databases | Common digital quality environment |

Future work should also address durability prediction, uncertainty quantification, low-carbon concrete quality control and physics-informed machine learning.

The long-term objective should be a digital system capable of continuously learning from production, testing and in-service performance while maintaining alignment with established engineering principles.

## 16. Discussion

The main recent trend in RMC QA/QC is not the emergence of a single new technology. It is the **integration of multiple information sources into a unified quality-management system**.

Three major transformations can be identified.

First, QA/QC is moving from **sample-based assessment toward batch-level quality intelligence**. Automated batching records, sensors and computer vision can potentially generate information for every concrete batch.

Second, quality management is moving from **reactive detection toward predictive intervention**. Machine-learning studies using real industrial data demonstrate that potential performance problems can be identified earlier than conventional 28-day testing.

Third, project records are moving from **document-based traceability toward element-based traceability**. BIM and Digital Twins allow concrete production, transportation, placement and testing data to be linked directly to the structural element.

The most robust future QA/QC system will therefore combine conventional physical testing with statistical control, continuous sensing, predictive analytics and digital traceability.

This approach provides redundancy and improves engineering confidence.

## 17. Conclusions

This paper reviewed recent developments in QA/QC of ready-mix concrete and proposed an Integrated Predictive Quality Assurance and Quality Control Framework for large-scale construction projects.

The following conclusions are drawn:

1. Conventional RMC QA/QC remains essential but provides only discrete and partly retrospective information.
2. Automated batching and digital batch identification provide the foundation for modern quality traceability.
3. IoT-based sensing can extend quality monitoring across materials, batching, transportation, placement and curing.
4. Computer vision offers a promising supplementary tool for continuous workability assessment.
5. Recent plant-scale deep-learning research demonstrates that fresh-concrete workability classification can be automated with useful accuracy.
6. Machine learning has significant potential for early strength prediction. Industrial-scale research using 9,007 genuine RMC production records demonstrates that predictive models can be developed from real production data.
7. Explainable AI is important because engineering decisions require interpretable reasons for quality warnings.
8. Statistical Process Control remains essential and should operate alongside digital technologies.

9. Embedded temperature monitoring and maturity methods can improve curing control and early-age decision-making.

10. BIM and Digital Twins provide the potential for complete batch-to-element traceability.

11. The proposed IPQCF combines verification, continuous monitoring and predictive analysis within one structured quality-management framework.

12. Digital technologies should supplement, rather than replace, mandatory code-based acceptance procedures unless formally validated and approved.

13. The future direction of RMC QA/QC is a transition from **reactive quality control toward continuous, traceable and predictive quality assurance**.

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Highlights

- Reviews recent digital advances in QA/QC of ready-mix concrete.
- Integrates smart batching, IoT, computer vision, AI/ML, maturity monitoring and Digital Twins.
- Proposes an Integrated Predictive QA/QC Framework for large-scale concrete projects.
- Positions predictive analytics as a supplement to conventional acceptance testing.
- Emphasises batch-to-element traceability and preventive quality management.
- Provides a practical pathway from reactive inspection to predictive quality assurance.

Graphical Abstract

**CONVENTIONAL QA/QC**

Materials → Batching → Slump → Sampling → 7/28-Day Strength

↓

**DIGITAL QUALITY LAYER**

Smart Batching + IoT + GPS + Computer Vision + Maturity + Statistical Analysis + AI/ML

↓

**PREDICTIVE QUALITY ASSURANCE**

Continuous Monitoring → Early Warning → Investigation → CAPA

↓

**DIGITAL TWIN**

Batch → Truck → Pour → Structural Element → Permanent Quality Record

**Outcome:** Improved Traceability • Earlier Detection • Reduced Rework • Better Reliability • Sustainable Construction