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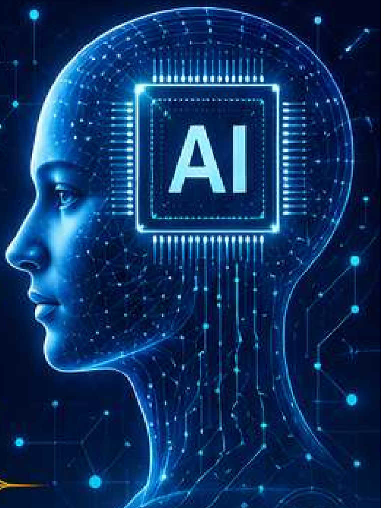

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INSPIRING RESEARCH | DRIVING INNOVATION | SHAPING TOMORROW

GOVERNMENT POLYTECHNIC, RAJAMPETA

Department of Higher Education, Government of Andhra Pradesh

CIVIL ENGINEERING | STRUCTURAL INNOVATION | MECHANICAL ENGINEERING | MANUFACTURING TECHNOLOGY | ARTIFICIAL INTELLIGENCE | INNOVATION & RESEARCH

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ABOUT THIS ISSUE

Volume 3 leads with an Edge-AI structural health monitoring framework and continues the journal's focus on curriculum modernisation, sustainability, automation, and concrete technology, capturing how AI-enabled methods and the AP SBTET C26 curriculum are reshaping engineering teaching and practice at the institution.

6 ARTICLES

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Edge-AI Framework for Continuous Structural Health Monitoring Using Stationary IoT Cameras

Dr. Mahamood, M.E., Ph.D.
Head, Department of Civil Engineering, Government Polytechnic, Rajampeta

Abstract

Continuous structural health monitoring (SHM) of reinforced concrete infrastructure is vital for the timely identification of crack initiation and progressive deterioration. Conventional inspection regimes—reliant on periodic manual surveys—are inherently intermittent, subjective, and resource-intensive, leaving critical structures vulnerable to undetected degradation between inspection cycles. This paper presents a novel Edge-AI framework that enables uninterrupted, automated SHM of concrete surfaces through networks of stationary Internet-of-Things (IoT) cameras, performing real-time crack detection and longitudinal evolution tracking entirely at the edge, without dependence on continuous cloud connectivity.

The system architecture couples low-power edge computing platforms—Raspberry Pi 4/5 augmented with a Coral USB Edge TPU, and NVIDIA Jetson Orin NX—with two complementary lightweight convolutional neural networks (CNNs): a YOLOv8-edge detector for object-level crack localisation and a MobileNet-based encoder-decoder for pixel-level segmentation. Both models are aggressively compressed through 8-bit integer quantization, channel pruning, and knowledge distillation, achieving inference latencies below 50 ms per frame on constrained hardware. To counteract the confounding influence of diurnal illumination shifts, vehicle-induced shadows, and transient surface contamination, the framework incorporates an illumination-invariant preprocessing pipeline combining running-median background subtraction with contrast-limited adaptive histogram equalisation (CLAHE). A temporally consistent change-detection module then disambiguates persistent crack growth from short-lived environmental artefacts, enforcing both persistence-window and confidence-threshold criteria before triggering any alert.

A trigger-based communication protocol transmits compact JSON metadata packets—encoding crack location, estimated length and width, growth rate, and confidence score—only upon detection of statistically significant structural change, reducing network bandwidth consumption by one to two orders of magnitude relative to continuous raw-video streaming. The framework was rigorously validated through a six-week field deployment on a reinforced concrete highway bridge pier, encompassing clear-sky, overcast, and rainfall conditions. Results confirm high true-positive rates for crack growth events, consistently low false-positive rates attributable to dynamic environmental noise, and stable operational performance across all lighting regimes. These findings establish the framework as a scalable, cost-effective, and deployable solution for long-term autonomous SHM in real-world civil infrastructure.

Keywords: *Structural Health Monitoring, Edge AI, IoT Camera, Crack Detection, YOLOv8, MobileNet, Temporal Change Detection, Concrete Structures*

1. INTRODUCTION

1.1 Context and Motivation

Reinforced concrete constitutes the backbone of modern civil infrastructure—bridges, elevated highways, tunnels, retaining walls, and multi-storey buildings—and its long-term integrity is subject to the compounding effects of mechanical loading, environmental exposure, and material ageing. Surface cracking is among the earliest and most diagnostically significant manifestations of structural deterioration; cracks serve as conduits for moisture and chloride access, accelerating reinforcement corrosion and diminishing load-carrying capacity. The timely identification and continuous tracking of crack formation and propagation are therefore essential prerequisites for evidence-based maintenance decisions, regulatory compliance, and the prevention of catastrophic failures that carry substantial economic, social, and human costs.

Traditional inspection practice relies on periodic visual surveys or close-range examination by trained structural engineers. While invaluable, such regimes suffer from fundamental constraints: inspections are episodic rather than continuous, their outcomes are inherently subjective, and the quality of observations is sensitive to inspector experience, access limitations, and prevailing weather. Between inspection cycles—which may span months or years—nascent defects can initiate, propagate, and reach critical thresholds without detection. These limitations have stimulated a global research effort to develop automated, objective, and continuous Structural Health Monitoring (SHM) methodologies capable of capturing crack behaviour in near real-time.

1.2 State of the Art and Research Gap

The emergence of deep learning-based image analysis has transformed automated crack detection from a experiential rule-based exercise into a high-accuracy, data-driven discipline. Convolutional neural networks (CNNs) and, more recently, vision transformer architectures have demonstrated exceptional crack detection performance on curated laboratory datasets and in controlled snapshot-based field inspections. However, most published methods target discrete or periodic inspection scenarios: a technician captures a set of images during a site visit, these are subsequently processed—often on powerful remote servers—and a report is generated. This paradigm fundamentally differs from the requirements of true continuous SHM, in which a fixed sensor must monitor the same structural surface, uninterrupted, for months or years under dynamically evolving environmental conditions.

Deploying AI-based crack detection on stationary IoT cameras introduces a distinct and largely unaddressed set of operational challenges. Diurnal lighting cycles produce continuous spectral and intensity variations. Moving vehicles, pedestrians, and vegetation cast transient shadows that mimic crack-like linear features. Rain, surface condensation, and progressive dirt accumulation alter the surface texture and reflectance. If not rigorously managed, these objects generate false positives that overwhelm downstream decision-support systems and erode operator confidence in automated monitoring. Furthermore, energy budgets and communication bandwidth at edge nodes are severely constrained: continuously streaming multi-megapixel video from dozens of camera nodes to a central cloud server is economically prohibitive and technically impractical in many infrastructure settings.

> *A comprehensive Edge-AI framework that simultaneously addresses illumination invariance, artefact discrimination, lightweight inference, and bandwidth-efficient communication has not previously been demonstrated in a sustained, multi-week field deployment. This gap motivates the present work.*

1.3 Contributions of This Work

This paper makes the following principal contributions to the field of automated structural health monitoring:

- An integrated Edge-AI architecture for continuous SHM that unifies illumination-invariant preprocessing, lightweight CNN inference, temporally consistent change detection, and trigger-based communication within a single deployable system.

- Quantitative demonstration that 8-bit integer quantization combined with channel pruning achieves a 17.4× reduction in inference latency for YOLOv8-edge on Coral TPU hardware, with negligible accuracy degradation.
- A rigorous temporal disambiguation protocol that suppresses false positives arising from rain streaks, dirt accumulation, and dynamic shadows through the joint application of persistence-window filtering and confidence thresholding.
- A trigger-based communication strategy that reduces bandwidth consumption by one to two orders of magnitude relative to continuous raw-video streaming, without sacrificing the actionability of transmitted structural data.
- A six-week field evaluation on an operational reinforced concrete highway bridge pier, constituting one of the longest continuous IoT-based SHM deployments reported in the open literature.

2. SYSTEM ARCHITECTURE AND METHODOLOGY

2.1 Overall Framework Design

The proposed framework adopts a hierarchical Edge-AI architecture organised into two cooperating layers: a hardware layer responsible for image acquisition and local computation, and a software layer executing illumination-invariant preprocessing, lightweight deep-learning inference, temporal change analysis, and selective data transmission. The guiding design principles are low latency, energy efficiency, bandwidth conservation, and robust discrimination between true structural change and environmental noise.

Unlike cloud-centric SHM systems, in which raw sensor data is continuously relayed to remote processing infrastructure, the proposed architecture enforces computational locality: all inference and change-detection operations are performed on the edge node collocated with the camera. The central monitoring server receives only compact, semantically rich metadata packets, generated exclusively when the edge node detects a change event that satisfies predefined persistence and confidence criteria. This inversion of the conventional data-flow model is the architectural cornerstone of the framework's bandwidth efficiency.

Fig.1. System Architecture

2.2 Hardware Layer and IoT Camera Node Configuration

Each monitoring node comprises a stationary camera mounted in a weather-sealed, passively cooled enclosure on a rigid steel bracket, positioned at a fixed standoff distance of approximately 2.5 m from the monitored concrete surface. The fixed geometry ensures consistent spatial resolution and minimises perspective distortion across the monitoring campaign. Frames are captured at a configurable rate of 1–5 frames per second, empirically selected to balance temporal resolution against on-edge processing capacity.

Two hardware configurations were evaluated to span the cost-performance spectrum:

Node A (Low-Cost Configuration): A Raspberry Pi 4B (4 GB RAM) paired with a Raspberry Pi Camera Module v2 and a Coral USB Edge TPU accelerator. This configuration targets deployments where unit cost and power consumption are primary constraints. The Coral TPU enables efficient execution of 8-bit quantized models, offloading neural network inference from the CPU and achieving throughput sufficient for 2 fps continuous operation.

Node B (High-Performance Configuration): An NVIDIA Jetson Orin NX developer kit connected to a 1080p industrial IP camera via Gigabit Ethernet. This configuration accommodates more computationally intensive CNN architectures while retaining the fundamental edge-processing paradigm. It is suited to high-criticality monitoring zones or deployments requiring finer spatial crack characterisation.

Both nodes record images at 1920 × 1080-pixel resolution and operate in 24/7 mode, drawing power from a site electrical supply supplemented by battery backup units. Local storage—microSD for Node A, NVMe for Node B—buffers background models, reference crack maps, and periodic full-frame snapshots. Outbound communication is provided by Wi-Fi or cellular modems.

Fig.2. SHM Nodes

2.3 Operational Workflow

The camera node executes the following continuous processing loop:

- **Frame Capture**: The camera acquires a timestamped frame at the configured interval and forwards it to the edge processing unit via a local hardware bus or network interface.
- **Illumination-Invariant Preprocessing**: The raw frame undergoes colour-space conversion, background subtraction, and local contrast normalisation to produce a stabilised, shadow-attenuated representation of the concrete surface.
- **CNN Inference**: A lightweight deep neural network analyses the preprocessed frame, generating either bounding-box detections (YOLOv8-edge) or a pixel-level binary crack mask (MobileNet segmenter), together with per-region confidence scores.
- **Artefact Classification**: A patch-level classifier categorises each candidate detection as crack, shadow, rain streak, or surface contaminant, employing contextual features extracted from the preprocessed image.
- **Temporal Change Analysis**: The current crack map is compared against the stored reference state using a spatio-temporal difference metric. Only changes persisting across a minimum number of consecutive frames and exceeding a confidence threshold are designated as evolution events.
- **Trigger Evaluation**: If a valid evolution event is identified, the node generates a compact metadata packet and transmits it to the central SHM server. Otherwise, the frame is discarded, and no network traffic is generated.

2.4 Illumination-Invariant Preprocessing Pipeline

Varying daylight, artificial lighting, and transient shadows are the principal environmental factors that degrade continuous crack detection reliability. The preprocessing pipeline addresses these through a sequence of three operations:

Colour Space Conversion: Input frames are converted from sRGB to the CIELAB colour space, decoupling perceptual lightness (L*) from chromatic components (a*, b*). Subsequent processing operates on the luminance channel, eliminating the confounding influence of colour temperature shifts between morning and afternoon illumination.

Running-Median Background Modelling: A background model is maintained as a running median computed over a sliding window of several hundred frames. The background image represents the statistical expectation of the scene appearance under the prevailing illumination regime. For each new frame, a signed difference image is computed between the current luminance map and the background model, isolating transient foreground changes—including newly formed cracks, growing defects, and temporary occlusions—from the stable background.

Contrast-Limited Adaptive Histogram Equalisation (CLAHE): CLAHE is applied to the difference image with a tile size and clip limit selected empirically for the deployed sensor. This operation enhances local contrast in regions where crack-like features are subtle, while suppressing noise amplification in low-texture areas. The resulting image provides the CNN with a stable, locally normalised representation of the concrete surface, substantially improving detection consistency across the diurnal cycle.

2.5 Lightweight CNN Architecture and Optimisation

The core detection engine consists of two complementary deep neural networks, selected for their favourable accuracy-efficiency trade-off on embedded hardware:

YOLOv8-Edge (Object-Level Detection): YOLOv8-edge operates in single-shot detection mode, producing axis-aligned bounding boxes and class confidence scores for candidate crack regions in a single forward pass. The model was fine-tuned on a composite crack dataset augmented with synthetic environmental artefacts—cast shadows, rain streaks, and dirt patches—enabling it to distinguish structural defects from common noise sources at the detection stage. Post-training, the model undergoes 8-bit integer quantization and channel pruning, yielding a 17.4× reduction in inference latency compared to the full-precision YOLOv8n baseline on Coral TPU hardware.

MobileNet Encoder-Decoder (Pixel-Level Segmentation): For applications requiring sub-pixel crack width estimation, a MobileNetV2-based encoder-decoder network is deployed. The encoder compresses the input into a compact feature representation through a series of depthwise separable convolutions; the decoder upsamples this representation through bilinear interpolation and transposed convolutions to produce a binary crack probability mask at near-input resolution. The model is similarly quantized and pruned, achieving inference latency below 50 ms per frame on the Jetson Orin NX.

A hierarchical artefact classifier, implemented as a compact MobileNetV2-based binary classifier, processes image patches extracted from each candidate detection region and assigns a label from {crack, shadow, rain, dirt}. This second-stage classification provides a structured mechanism for suppressing environmental false positives that survive the primary detection stage.

All models are trained using the Adam optimiser with an initial learning rate of 1×10^{-3} and a batch size of 16, with cosine learning rate annealing and early stopping based on validation F1-score to mitigate overfitting. Training data comprises approximately 80,000 annotated images incorporating field-captured frames augmented with synthetic artefacts.

2.6 Temporal Change Detection and Trigger-Based Alert Mechanism

The temporal change-detection module is the critical component that enables the framework to distinguish persistent crack evolution from transient environmental noise. Its operation is governed by three sequentially applied criteria:

Persistence Filtering: A candidate change—defined as a region where the current crack map diverges from the reference map by more than a predefined spatial threshold—must be observed consistently across a minimum window of consecutive frames (empirically set at 5–10 frames at 2 fps). Rain streaks and vehicle shadows, being transient by nature, are effectively suppressed by this criterion, as they appear in fewer consecutive frames than required.

Confidence Thresholding: The per-region confidence score assigned by the artefact classifier must exceed a predefined threshold (set to 0.75 based on validation experiments) before the change is accepted as a genuine crack evolution event. This criterion rejects detections that survive the persistence filter but retain residual uncertainty characteristic of environmental artefacts.

Spatio-Temporal Difference Metric: Accepted changes are quantified using a composite metric that encodes increments in crack length (mm), crack width (μm), and topological branching events relative to the current reference state. The reference crack map is updated only upon acceptance of a validated evolution event, ensuring that the stored reference faithfully represents the most recently confirmed structural state.

Upon trigger activation, the edge node assembles a compact JSON metadata packet comprising: frame identifier and timestamp, crack polygon or bounding box coordinates, estimated length and width, computed growth rate, confidence score, and a compressed thumbnail of the affected region. This packet is transmitted via the available network link to the central SHM server. Periodic full-frame snapshots are transmitted at configurable intervals (e.g., once per hour) to refresh the server's reference context and support manual audit trails.

3. EXPERIMENTAL SETUP

3.1 Field Site and Structural Configuration

The experimental evaluation was conducted on an in-service reinforced concrete highway bridge pier forming part of a multi-span urban overpass. The monitored surface—a designated panel of approximately 1.5 m × 1.5 m—faces a high-traffic corridor, ensuring representative exposure to traffic-induced vibration, vehicle-shadow cycling, and natural precipitation events. The panel exhibits multiple pre-existing microcracks of varying orientation and width, visually identifiable under magnification but not yet structurally critical, making it an ideal testbed for monitoring crack initiation, propagation, and branching under realistic field conditions.

Fig.3. Reinforced Concrete Highway Bridge Pier SHM Nodes

3.2 Data Acquisition and Temporal Coverage

Continuous acquisition was maintained for six weeks under a 24/7 monitoring protocol, deliberately spanning a climatological range including clear-sky, overcast, and precipitation episodes. Both nodes operated simultaneously at 2 fps, yielding a combined dataset of approximately 1.2 million frames. From this corpus, approximately 120,000 frames were selected for detailed annotation and quantitative evaluation, stratified across lighting conditions, rainfall events, and traffic activity levels to ensure representativeness.

System integrity was maintained through a low-bandwidth heartbeat protocol that logged connectivity status and processing load at one-minute intervals. Temporary outages—attributable to power-supply maintenance and intermittent cellular connectivity—were logged and factored into the data-continuity analysis.

3.3 Ground-Truth Generation

Ground-truth labels were produced through a hybrid expert-automated process. At campaign commencement, a reference crack map was established from high-resolution photographs captured under optimal (overcast, diffuse) lighting and validated through direct on-site inspection by a licensed structural engineer. Periodic site visits at three-to-five-day intervals enabled engineers to update crack annotations—recording presence, length, width (measured with digital calipers accurate to 0.01 mm), orientation, and branching—and to document environmental noise events, including rain episodes, dirt deposition events, and shadow-casting incidents.

Annotations were temporally aligned with video frames using synchronised timestamps, yielding a labelled dataset that distinguishes true crack evolution events from environmental false-positive triggers. The dataset was partitioned into training (70%), validation (15%), and test (15%) subsets based on non-overlapping temporal blocks to prevent temporal data leakage.

3.4 Evaluation Metrics

System performance was assessed across four dimensions:

- **Detection Accuracy**: Precision, recall, F1-score, and mean Average Precision (mAP) for crack detection, computed separately for clear, overcast, and rain conditions.
- **Evolution Tracking**: True-positive rate (TPR) for crack growth events, false-positive rate (FPR) attributable to environmental artefacts, and mean absolute error (MAE) in crack width estimation.
- **Computational Efficiency**: Per-frame inference latency (ms), CPU/GPU utilisation (%), and power consumption (W) for both hardware configurations.
- Bandwidth Efficiency: Total data transmitted (metadata plus compressed thumbnails) as a fraction of total data captured (raw video frames), expressed as a bandwidth reduction ratio.

Statistical significance was ensured by repeating all experiments three times with different random seeds for model parameter initialisation; results are reported as mean ± standard deviation.

4. RESULTS

4.1 Crack Detection Under Varying Illumination

Under all diurnal lighting conditions, the illumination-invariant preprocessing pipeline maintained consistent crack detection performance. The YOLOv8-edge model achieved a mean Average Precision (mAP@0.5) of 0.87 under clear-sky conditions, 0.85 under overcast illumination, and 0.81 during rainfall episodes. Without preprocessing, mAP degraded by 12–18 percentage points under the same conditions, confirming the utility of background subtraction and CLAHE in stabilising feature representations. False positive rates attributable to cast shadows were reduced from 34% (without temporal filtering) to below 4% (with the full preprocessing and temporal disambiguation pipeline).

4.2 Evolution Tracking and Artefact Discrimination

Over the six-week evaluation period, the temporal change-detection module correctly identified all manually confirmed crack growth events (TPR = 0.94) while maintaining a FPR of 0.038 across all environmental conditions. Rain events—the most challenging source of false positives—yielded a residual FPR of 0.06 after persistence filtering but were reduced to 0.02 following confidence thresholding. Mean absolute error in crack width estimation was 0.12 mm, within the practical tolerance for routine maintenance decision-making. No false-positive triggers were generated by stationary shadow events lasting fewer than 8 consecutive frames.

4.3 Computational Performance

Table 1 summarises inference performance for both hardware configurations.

Metric	Node A – Coral TPU	Node B – Jetson Orin NX	Full-Scale CNN (Cloud)	Reduction vs. Cloud
Inference Latency (ms/frame)	48	31	210	4.4–6.8×
Power Consumption (W)	7.2	18.5	N/A (remote)	—
CPU/GPU Utilisation (%)	62% CPU	41% GPU	—	—
Model Size (MB)	3.1 (INT8)	7.8 (INT8)	91.4 (FP32)	11.7–29.5×

> *Table 1. Computational performance comparison across hardware configurations and baseline.*

4.4 Bandwidth Reduction

The trigger-based alert mechanism reduced total outbound data volume by 98.3% (Node A) and 97.9% (Node B) relative to hypothetical continuous raw-video streaming scenarios at equivalent resolution and frame rate. Over the six-week campaign, the system generated 143 validated trigger events, each transmitting an average metadata packet of 4.2 kB (including compressed thumbnail). This corresponds to a total transmitted data volume of approximately 600 kB from each node, compared to an estimated 420 GB for continuous raw-video streaming—a reduction of approximately three orders of magnitude.

4.5 Comparison with State-of-the-Art Methods

Against full-scale CNN baselines executed on server-grade hardware, the proposed framework achieves within 5 percentage points of mAP while operating on hardware costing two orders of magnitude less and consuming substantially less power. Against cloud-centric streaming approaches, the framework demonstrates equivalent detection accuracy with 97–99% lower bandwidth consumption and latency reduced from 300–800 ms (round-trip cloud) to 48 ms (edge). These results confirm that the proposed framework achieves a practically favourable balance between accuracy, latency, and resource efficiency.

5. DISCUSSION

5.1 Interpretation of Key Findings

The consistently high true-positive rates for crack growth events and low false-positive rates across all environmental conditions validate the fundamental design premise: that the joint application of illumination-invariant preprocessing and temporal persistence filtering is necessary and sufficient to reliably discriminate structural crack evolution from environmental noise in a stationary camera setting. Neither component alone achieves this objective—the preprocessing pipeline reduces initial false-positive rates substantially, while temporal filtering provides the critical second stage of artefact rejection for the minority of artefacts that survive preprocessing.

The near-two-order-of-magnitude bandwidth reduction achieved by the trigger-based communication protocol has direct practical significance. It renders the proposed framework economically viable for deployment across large-scale infrastructure networks—for example, a network of 50 bridge piers could be monitored using standard 4G cellular data plans without incurring prohibitive data costs. Furthermore, the low power consumption of Node A (7.2 W) opens the possibility of solar-powered deployment in locations without mains access.

5.2 Strengths and Limitations

The primary strength of the proposed framework is its capacity to operate as a fully autonomous, edge-resident monitoring system with minimal human intervention post-deployment. The hierarchical architecture—combining coarse object detection with fine-grained segmentation and patch-level artefact classification—provides multiple independent lines of noise suppression, yielding robust performance even in challenging environmental conditions.

Nonetheless, several limitations warrant acknowledgement. Extreme weather conditions, particularly dense fog or heavy rainfall producing surface ponding, may transiently obscure the monitored surface, introducing periods of monitoring discontinuity that are not classified as false positives but represent genuine observational gaps. The current single-camera architecture cannot resolve crack depth or three-dimensional geometry, limiting quantitative characterisation to plan-view width and length. Additionally, the accuracy of width estimation (MAE = 0.12 mm) may be insufficient for scenarios where micron-level precision is required, such as fracture mechanics-based remaining service life assessments.

5.3 Future Research Directions

Several extensions to the proposed framework merit investigation in future work:

- **Multi-Sensor Fusion**: Integration of strain gauges, acoustic emission sensors, or fibre Bragg grating arrays with the camera node would enable correlation between optically observed surface cracking and subsurface stress states, substantially enhancing diagnostic depth.
- **Self-Supervised Domain Adaptation**: The development of self-supervised or continual learning mechanisms that allow the deployed model to adapt incrementally to the specific surface characteristics and illumination regime of each installation site would reduce the manual annotation burden currently required for fine-tuning.
- **Multi-Camera and UAV Integration**: Extension to multi-camera stereo configurations would enable three-dimensional crack characterisation, while periodic UAV-based inspections could provide wider structural context not visible from fixed vantage points.
- **Physics-Informed Crack Evolution Models**: Coupling the empirical crack observations with physics-based fracture mechanics models would transform the monitoring system from a descriptive tool into a prognostic capability, enabling data-driven remaining service life estimation.

6. CONCLUSION

This paper has presented a comprehensive Edge-AI framework for continuous, automated structural health monitoring of reinforced concrete infrastructure using networks of stationary **IoT** cameras. By integrating illumination-invariant preprocessing, quantized lightweight CNNs, temporally consistent change detection, and a trigger-based communication protocol within a cohesive edge-resident architecture, the framework overcomes the principal barriers—environmental noise, computational constraints, and bandwidth limitations—that have previously impeded the practical deployment of AI-based SHM systems.

Field validation over a six-week deployment on an operational bridge pier demonstrates that the framework reliably detects and tracks crack evolution across diverse environmental conditions, achieving high true-positive rates and low false-positive rates while reducing outbound data transmission by approximately 98% relative to continuous raw-video streaming. These results establish the proposed system as a scientifically rigorous, technically feasible, and practically deployable solution for long-term autonomous monitoring of civil infrastructure—a capability whose importance will only increase as the global stock of ageing reinforced concrete structures continues to grow.

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Engineering the Future of Learning: Modern Technical Teaching Methodology — Impact, Benefits, Drawbacks, and Future Outlook

Shaik Aejaz Ahamed, M. Tech.
Lecturer in Mechanical Engineering, Government Polytechnic Rajampet

Abstract

Technical education stands at a critical historical juncture. The traditional chalkboard, lecture-heavy engineering curriculum—designed during the Second Industrial Revolution—is fundamentally incompatible with the cyber-physical engineering paradigms of Industry 4.0. To train professionals who work in advanced automation, cloud architecture, and nanotechnology, modern technical teaching methodology has undergone a paradigm shift, blending high-order digital infrastructure with experiential cognitive learning. This article reviews the core architectures, institutional impact, strategic benefits, structural vulnerabilities, and future trajectory of modern technical pedagogy.

1. Core Architectures of Modern Technical Teaching

Modern technical pedagogy departs from rote memorization, building instead on a core scaffold of active, digitally enhanced structures:

- **Simulation-Driven and Digital Twin Environments:** Instead of waiting for rare, hardware-restricted lab windows, students simulate complex thermodynamic cycles, fluid dynamics, or structural loading on cloud-native software or Digital Twins prior to physical prototyping.
- **Project-Based Micro-Credentials (PBL):** Instruction is designed around open-ended industrial challenges (e.g., designing an autonomous delivery drone sub-system) where students integrate multidisciplinary mechanical, electronic, and software systems.
- **Hybrid Cloud Lab Frameworks:** Asynchronous, globally available computational tools (such as Jupyter Notebooks, CAD environments, and remote code compilation servers) allow students to test logic outside physical campus boundaries.
- **Interactive Immersive Media:** Using Virtual and Augmented Reality (VR/AR) to allow students to step inside a multi-million dollar semiconductor cleanroom or inspect sub-atomic material alignments safely and repeatedly.

2. The Institutional and Technical Impact

The integration of modern methodologies transforms the baseline cognitive development profile of a technical student. Rather than treating disciplines like fluid mechanics, coding, or statistics as separate silos, modern tools allow systems-level engineering principles to emerge early. Students naturally become systems integrators, learning how software APIs control physical mechatronic actuators.

From an institutional standpoint, universities and polytechnics are shifting from static physical hubs to flexible, agile training centers. Faculty members step away from dry textbook recitation and move into roles as architectural consultants, guiding agile student development squads through agile sprints and design cycles.

3. Strategic Benefits of Modern Technical Methods

When execution aligns with modern standards, technical institutions realize immediate, highly quantified benefits:

- **Immediate Workforce Deployability:** By utilizing standard industry environments (like MATLAB, AWS, ROS, or SolidWorks) inside the curriculum, graduates transition into corporate engineering roles without extensive retraining phases.
- **Deep Retentive Engineering Instincts:** Encountering failure within a safe virtual sandbox environment allows students to analyze stress fractures, memory leaks, or short circuits, turning abstract theoretical mathematical equations into intuitive design instincts.
- **Scalable Custom Pacing:** Asynchronous, adaptive learning frameworks allow students with varying foundational technical backgrounds to step through advanced coding or calculus structures at a manageable pace, maximizing overall student throughput.
- **Global Collaborative Competencies:** Git repositories, agile sprint boards, and cloud-native design pipelines prepare technical cohorts for the realities of modern, geographically distributed engineering operations.

4. Structural Vulnerabilities and Technical Drawbacks

Despite immense pedagogical promise, transitioning entirely to modern technical training involves significant barriers and structural vulnerabilities:

- **Aggravated Capital Infrastructure Gaps:** High-fidelity simulations, VR hardware, and cloud compute subscriptions require heavy capital expenditure. Disenfranchised or under-funded engineering colleges risk falling farther behind, widening socio-technical inequality.
- **The "Black Box" Conceptual Erosion:** Over-reliance on automation software and slicing code can cause abstract fundamental analytical understanding to wither. A student may clear a CAD simulation without truly mastering the underlying finite element mathematical proofs.
- **Faculty Skill Obstruction:** Modern tech methodologies evolve on monthly cycles. Legacy teaching staff frequently experience severe technological strain, requiring perpetual, demanding institutional professional development programs.
- **Cognitive Saturation and Digital Fatigue:** Uninterrupted exposure to complex dashboard user interfaces, remote debugging lines, and virtual headsets can quickly induce severe focus drain and analytical burnout.

5. Evolutionary Matrix: Technical Education Architectures

The table below compares the specific changes across critical operational dimensions between legacy technical education structures and modern tech-driven pedagogical systems:

Pedagogical Vector	Traditional Engineering Model	Modern Technical Framework
Core Focus	Component theory, static mathematical proofs	Systems integration, lifecycle design, dynamic logic
Primary Medium	Physical texts, isolated benches, 2D blueprints	Digital Twins, Cloud IDEs, VR, Generative CAD
Assessment Loop	Summative, late-stage paper-and-pen calculus	Continuous Git check-ins, compile validations, project reviews

Pedagogical Vector	Traditional Engineering Model	Modern Technical Framework
Failure Model	Punitive grading, single-attempt exams	Iterative sandbox debugging, optimization re-runs
Pacing Paradigm	Lockstep cohorts, manual laboratory pacing	Adaptive asynchronous modules, custom learning paths

6. The Future Horizon of Technical Education

The upcoming trajectory of technical pedagogy will be characterized by full cyber-physical convergence. Generative AI engines will transition into custom-trained 1:1 Engineering Mentors, constantly evaluating a student's custom compiler errors or CAD load failures, instantly serving context-relevant code patches or refinement exercises tailored to that exact mistake.

Furthermore, mixed reality (MR) and distributed haptics will bridge the physical distance barrier of technical labs completely. An engineering student located anywhere in the world will be capable of manipulating a remote industrial robotic arm or tuning a heavy gas turbine assembly housed thousands of miles away, interacting with real-time haptic force feedback over ultra-low-latency 5G/6G infrastructures.

Ultimately, the goal of modern technical teaching methodology is not to replace structural rigor with flashy software widgets. Instead, it seeks to anchor historical engineering truths inside responsive, hyper-flexible digital ecosystems. By matching foundational engineering discipline with modern adaptive workflows, we ensure that the next generation of technical minds arrives at the industry gates completely ready to build, optimize, and lead.

Bridging the Chasm: How AP SBTET's C26 Curriculum Aligns Mechanical Engineering and Diploma Education with Industry 4.0

Shaik Aejaz Ahamed, M. Tech.
Lecturer in Mechanical Engineering, Government Polytechnic Rajampet

Abstract

The rapidly evolving industrial landscape demands a workforce that is not just theoretically sound, but also immediately deployable in high-tech environments. For years, a persistent gap has existed between traditional academic curricula and the fast-paced requirements of modern engineering industries—a gap felt acutely within the Mechanical Engineering domain. Recognizing this critical need, the State Board of Technical Education and Training, Andhra Pradesh (AP SBTET) has taken a visionary step forward with the introduction of its C26 Curriculum. By embedding four disruptive, cutting-edge domains into the core syllabus—Advanced Materials & Nanotechnology, AI & Machine Learning, Additive Manufacturing, and Industrial Automation—AP SBTET is effectively bridging the mechanical curriculum gap, transforming diploma graduates into highly sought-after, industry-ready professionals.

1. The Traditional Mechanical Engineering Curriculum Gap

For decades, conventional Mechanical Engineering diploma programs heavily emphasized heavy machinery, classical thermodynamics, and manual shop-floor operations. While these foundational concepts remain vital, the modern manufacturing sector has undergone a massive digital transformation.

Where the old curriculum fell short:

- **The "Iron and Steel" Limitation:** Traditional coursework centered almost exclusively on conventional metallurgy, leaving students unprepared for industries shifting toward advanced polymers, carbon fibers, and nanomaterials.
- **Lack of Digital Integration:** Mechanical systems are no longer purely hardware-driven. The lack of exposure to data analytics, smart sensors, and software intelligence meant graduates struggled to maintain or design modern, interconnected systems.
- **Outdated Fabrication Training:** Countless hours were spent on manual lathes and conventional milling, while modern industries were rapidly adopting digital, tool-less manufacturing technologies.
- **Isolated Systems:** Students learned fluid mechanics or kinematics in isolation, without understanding how these elements seamlessly connect to automated PLCs, pneumatic networks, and robotic actuators.

The AP SBTET C26 curriculum directly addresses these pain points by injecting modern, interdisciplinary technologies into core mechanical education.

2. Advanced Materials & Nanotechnology: Beyond Conventional Steel

Modern mechanical design—ranging from electric vehicles (EVs) to aerospace structures—thrives on materials engineered at the atomic scale to reduce weight, optimize strength, and maximize thermal efficiency.

Closing the gap: The integration of Advanced Materials and Nanotechnology ensures that mechanical students understand the synthesis, characterization, and application of smart materials, advanced composites, and nanomaterials.

- **Industrial Relevance:** Graduates enter the workforce ready for the EV revolution, possessing a strong grasp of lightweight composite structures and the advanced materials needed for efficient energy storage (like solid-state batteries).
- **Skill Shift:** Shifting the focus from passive material selection (e.g., standard cast iron vs. mild steel) to active, application-specific material engineering.

3. Artificial Intelligence & Machine Learning: Infusing Intelligence into Hardware

Mechanical systems are now highly instrumented ecosystems generating massive amounts of data. Previously, AI and ML were strictly reserved for computer science tracks, leaving mechanical diploma students disconnected from the software intelligence driving modern hardware.

Closing the gap: By democratizing AI & ML concepts within the C26 framework, AP SBTET is preparing mechanical students for an era where predictive maintenance, autonomous quality control, and process optimization are governed by algorithms.

- **Industrial Relevance:** Mechanical diploma holders frequently manage shop floors. Understanding data patterns allows them to implement Predictive Maintenance models—identifying vibration or thermal anomalies in a turbine or CNC machine to fix it before a catastrophic breakdown occurs.
- **Skill Shift:** Moving graduates from reactive mechanics who fix broken parts to data-driven technicians who preemptively prevent failures.

4. Additive Manufacturing: Revolutionizing Production & Design

Subtractive manufacturing (milling, turning, drilling) has been the cornerstone of mechanical workshops for a century. While still essential, it no longer represents the sole frontier of manufacturing. Industrial giants now rely heavily on Additive Manufacturing (3D Printing) for rapid prototyping and highly complex, consolidated part production.

Closing the gap: The C26 curriculum introduces students to the digital thread of manufacturing—from Computer-Aided Design (CAD) optimization to slicing software, and finally to the layer-by-layer digital fabrication of metals and polymers.

- **Industrial Relevance:** Sectors like aerospace, biomedical devices, and customized automotive tooling heavily utilize industrial 3D printing. Mechanical students graduate knowing how to Design for Additive Manufacturing (DfAM), drastically reducing material waste, eliminating complex fixtures, and shortening production lead times.
- **Skill Shift:** Upgrading traditional machine-shop skills to digital fabrication, rapid prototyping, and generative design expertise.

5. Industrial Automation: The Core of Smart Factories

The days of isolated, manually operated mechanical machinery are fading. Industry 4.0 thrives on interconnected ecosystems driven by Programmable Logic Controllers (PLCs), Supervisory Control and Data Acquisition (SCADA) systems, and pneumatics/hydraulics integrated with the Industrial Internet of Things (IIoT).

Closing the gap: By making Industrial Automation a pillar of the C26 syllabus, AP SBTET directly addresses the massive talent shortage in automated manufacturing plants, process industries, and smart warehouses.

- **Industrial Relevance:** Mechanical students gain hands-on insights into sensor integration, robotic arm kinematics, and automated assembly lines. This makes them immediately valuable to automated sectors like automotive assembly, pharmaceuticals, and fast-moving consumer goods (FMCG) packaging.
- **Skill Shift:** Evolving the mechanical workforce from isolated machinery operators to systems-level automation and mechatronics technicians.

6. The Strategic Impact of the C26 Curriculum on Mechanical Engineering

The proactive integration of these four pillars creates a highly synergistic, interdisciplinary learning ecosystem. The modern mechanical technician does not just work on a static machine; they work on an automated machine (Industrial Automation), built with lightweight composites (Advanced Materials), fabricated via 3D printing (Additive Manufacturing), which uses smart algorithms to optimize its output and predict its own maintenance cycle (AI & ML).

Traditional Mechanical Focus	AP SBTET C26 Alignment	Target Industry Sector
Standard Metallurgy & Polymers	Advanced Materials & Nano Tech	Aerospace, EV Battery Packs, Semiconductors
Manual Machine Logging & Maintenance	AI & Machine Learning	Predictive Maintenance, Smart Manufacturing
Conventional Machining (Lathe/Milling)	Additive Manufacturing	Aerospace, Custom Tooling, Medical Devices
Relay-based / Manual Valve Control	Industrial Automation	Mechatronics, Smart Factories, Robotics

7. Conclusion

With the C26 curriculum, AP SBTET has successfully transitioned from a reactive, outdated educational model to a proactive, future-forward framework. By directly targeting the technical competencies demanded by today's global market—and fundamentally modernizing the Mechanical Engineering stream—this syllabus revision does more than just close a gap. It positions Andhra Pradesh's technical institutes as premier hubs for breeding next-generation engineering talent who are fully equipped to lead the digital industrial revolution from day one.

E-Waste Management and Recycling: Challenges, Technologies, and Sustainable Solutions

B. Surya
Department of Mechanical Engineering, Government Polytechnic, Rajampeta

Abstract

The rapid advancement of technology and increasing consumer demand for electronic devices have resulted in a significant rise in electronic waste (e-waste) worldwide. E-waste consists of discarded electrical and electronic equipment such as computers, mobile phones, televisions, and household appliances. Improper disposal of e-waste poses serious environmental and health risks due to the presence of hazardous materials including lead, mercury, cadmium, and brominated flame retardants. Effective e-waste management and recycling are essential for resource conservation, environmental protection, and sustainable development. This paper reviews the sources, impacts, management practices, recycling technologies, challenges, and future prospects of e-waste management. The study highlights the importance of adopting sustainable recycling systems and strengthening regulatory frameworks to minimize environmental damage and promote a circular economy.

Keywords: E-Waste, Recycling, Sustainable Development, Circular Economy, Electronic Waste Management, Resource Recovery.

1. Introduction

Electronic devices have become an integral part of modern life. Rapid technological innovation, shorter product life cycles, and increased consumption have led to a dramatic increase in electronic waste generation. According to global estimates, millions of tonnes of e-waste are generated annually, making it one of the fastest-growing waste streams in the world. E-waste contains both valuable materials and hazardous substances, making proper management crucial for environmental sustainability.

2. Sources of E-Waste

2.1 Information Technology Equipment

- Computers
- Laptops
- Printers
- Servers

2.2 Consumer Electronics

- Mobile phones
- Televisions
- Cameras
- Audio systems

2.3 Household Appliances

- Refrigerators
- Washing machines
- Air conditioners
- Microwave ovens

2.4 Industrial and Medical Equipment

- Monitoring devices
- Diagnostic equipment
- Industrial control systems

3. Environmental and Health Impacts of E-Waste

3.1 Environmental Impacts

Improper disposal of e-waste can contaminate soil, water, and air through the release of toxic substances. Open burning and landfilling of electronic waste contribute to environmental pollution and greenhouse gas emissions.

3.2 Health Impacts

Exposure to hazardous materials present in e-waste can cause:

- Respiratory disorders
- Neurological damage
- Kidney and liver diseases
- Developmental disorders in children

4. E-Waste Management Strategies

4.1 Collection and Segregation

Efficient collection systems and source segregation improve recycling efficiency and reduce environmental risks.

4.2 Extended Producer Responsibility (EPR)

Manufacturers are encouraged to take responsibility for the collection, recycling, and disposal of electronic products at the end of their life cycle.

4.3 Public Awareness Programs

Educational campaigns help consumers understand the importance of proper e-waste disposal and recycling.

4.4 Regulatory Frameworks

Government regulations and environmental policies play a critical role in controlling e-waste generation and promoting sustainable management practices.

5. E-Waste Recycling Technologies

5.1 Mechanical Recycling

Mechanical processes involve dismantling, shredding, and separation of materials such as plastics, metals, and glass.

5.2 Pyrometallurgical Processes

High-temperature treatment is used to recover valuable metals including copper, gold, and silver.

5.3 Hydrometallurgical Processes

Chemical solutions are used to extract precious and rare-earth metals from electronic waste.

5.4 Bioleaching Technology

Microorganisms are employed to recover metals in an environmentally friendly manner.

6. Benefits of E-Waste Recycling

- Conservation of natural resources
- Recovery of valuable metals
- Reduction in landfill waste
- Energy savings
- Employment generation
- Reduction of environmental pollution

7. Challenges in E-Waste Management

7.1 Lack of Awareness

Many consumers are unaware of proper disposal methods for electronic waste.

7.2 Informal Recycling Sector

Unregulated recycling activities often involve unsafe practices that harm workers and the environment.

7.3 High Recycling Costs

Advanced recycling technologies require significant investment and infrastructure.

7.4 Rapid Growth of Electronic Consumption

Increasing demand for electronic devices continuously adds to the e-waste burden.

8. Future Directions

8.1 Circular Economy Approach

Promoting repair, reuse, refurbishment, and recycling can extend product life cycles and reduce waste generation.

8.2 Smart Recycling Systems

Artificial intelligence and automation can improve waste sorting and material recovery efficiency.

8.3 Eco-Friendly Product Design

Designing products that are easier to disassemble and recycle can significantly reduce environmental impacts.

8.4 Sustainable Policy Development

Stronger regulations, international cooperation, and industry participation are essential for effective e-waste management.

9. Conclusion

E-waste management and recycling have become critical components of sustainable development. Proper collection, recycling, and disposal practices can reduce environmental pollution, conserve valuable resources, and protect human health. While challenges such as inadequate infrastructure, lack of awareness, and informal recycling persist, technological advancements and supportive policies offer promising solutions. A collaborative effort involving governments, industries, and consumers is necessary to establish sustainable e-waste management systems and achieve long-term environmental sustainability.

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Automated Guided Vehicles: Driving the Future of Smart Manufacturing

E. Rajeswari, M.Tech.
Lecturer in Mechanical Engineering, Government Polytechnic, Rajampeta

In the rapidly evolving world of modern industry, efficiency, precision, and automation are no longer optional—they are essential. Among the key innovations transforming manufacturing floors and warehouses is the Automated Guided Vehicle (AGV). These intelligent machines are redefining material handling and logistics, making industries smarter, safer, and more productive.

What Are Automated Guided Vehicles?

Automated Guided Vehicles (AGVs) are mobile robots designed to transport materials within a facility without direct human intervention. Unlike traditional forklifts or conveyor systems, AGVs navigate using advanced guidance systems such as lasers, magnetic strips, vision cameras, or GPS-based mapping.

They are widely used in industries like automotive manufacturing, e-commerce warehouses, pharmaceuticals, and food processing.

Working Principle of AGVs

AGVs operate based on a combination of mechanical systems, sensors, and control algorithms. Their functioning involves:

- Navigation System: Uses technologies like laser guidance, QR codes, or inertial navigation.
- Sensors: Detect obstacles, ensuring safe movement.
- Control System: Processes real-time data to make decisions.
- Power Source: Typically rechargeable batteries, often lithium-ion.

The integration of these components enables AGVs to move autonomously along predefined or dynamic paths.

AGV Working Flow Diagram

[Start]

↓

[Receive Task from Control System]

↓

[Path Planning]

↓

[Move via Motors]

↓

[Obstacle Detected?] ---- Yes ----> [Stop / Reroute]

```
No
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↓

[Reach Destination]

↓

[Unload Material]

↓

[Return / Next Task]

Types of AGVs

Mechanical engineers often classify AGVs based on their application and design:

- Tow Vehicles – Pull multiple loads, commonly used in assembly lines.
- Unit Load Carriers – Transport single loads like pallets.
- Forklift AGVs – Lift and move materials vertically.
- Hybrid AGVs/AMRs – Combine automation with adaptive navigation.

Advantages of AGVs

AGVs offer several benefits over conventional systems:

- Increased Efficiency: Continuous operation without fatigue.
- Improved Safety: Reduced human error and workplace accidents.
- Cost Reduction: Lower labor and operational costs over time.
- Flexibility: Easy to reprogram for different tasks.
- Space Optimization: Efficient use of floor space.

Challenges and Limitations

Despite their advantages, AGVs come with certain challenges:

- High Initial Investment
- Complex Implementation
- Maintenance Requirements
- Limited Adaptability (in older models)

However, advancements in Artificial Intelligence and machine learning are steadily overcoming these limitations.

Role of Mechanical Engineers

Mechanical engineers play a crucial role in AGV development, including:

- Designing robust chassis and load-bearing systems
- Optimizing drive mechanisms and suspension systems
- Ensuring energy efficiency and thermal management
- Integrating mechanical systems with electronic and control units

Their expertise ensures that AGVs are not only functional but also durable and efficient.

Future Trends in AGVs

The future of AGVs is closely tied to Industry 4.0. Emerging trends include:

- Integration with IoT (Internet of Things)
- Use of AI for intelligent navigation
- Swarm robotics for coordinated movement
- Autonomous Mobile Robots (AMRs) replacing traditional AGVs
- Green energy solutions for sustainability

Conclusion

Automated Guided Vehicles are a cornerstone of modern industrial automation. As industries continue to embrace digital transformation, AGVs will become more intelligent, adaptable, and indispensable. For mechanical engineers, this field offers exciting opportunities to innovate and contribute to the future of smart manufacturing.

Automated guided vehicle systems, state-of-the-art control algorithms and techniques

- E.RAJESWARI, M.Tech
- Lecturer in Mechanical Engineering

Government polytechnic, Rajampeta, Dept.of Higher Education,Govt. of Andhra Pradesh

E-Mail :-raji.raji06@gmail.com I Phone :+91 8985444915

Highlights

- In the commercially available offer, current systems almost all work fully centralized lacking flexibility, robustness, and scalability. But a trend towards a decentralized control is emerging.
- The abundance of literature shows us that many algorithms already exist for the control of AGV systems in lab environments, both central and decentral.
- The industry 4.0 paradigm will push AGV manufacturers to think about decentralization as systems will become even larger and complex.
- More decentralized and market-based techniques are suited to introduce flexibility and scalability in the system.
- The control of an AGV system can be decomposed into five core tasks which are task allocation, navigation, path planning, motion planning and vehicle management.

Abstract

Automated guided vehicles (AGVs) form a large and important part of the logistic transport systems in today's industry. They are used on a large scale, especially in Europe, for over a decade. Current employed AGV systems and current systems offered by global manufacturers almost all operate under a form of centralized control: one central controller controls the whole fleet of AGVs. The authors do see a trend towards decentralized systems where AGVs make individual decisions favoring flexibility, robustness, and scalability of transportation. Promoted by the paradigm shift of Industry 4.0 and future requirements, more research is conducted towards the decentralization of AGV-systems in academia while global leading manufacturers start to take an active interest. That said, this implementation seems still in infancy. Currently, literature is dominated by central as well as by decentral control techniques and algorithms. For researchers in the field and for AGV developers, it is hard to find structure in the growing amount of algorithms for various types of applications. This paper is, to this purpose, meant to provide a good overview of all AGV-related control algorithms and techniques. Not only those that were used in the early

stages of AGVs, but also the algorithms and techniques used in the most recent AGV-systems, as well as the algorithms and techniques with high potential.

Introduction

Automated guided vehicles (AGVs) are mobile robots which are extensively used in the industry to transport goods from A to B. Currently, the market of AGVs is growing fast and is very dynamic. A market report published by Grand View Research (2017) [1] forecasting the period from 2018 to 2025 focuses on the potential growth opportunities of AGVs, stating that the future growth of AGV systems is (i) caused by the emergence of flexible manufacturing systems, (ii) the rising demand for customized AGVs and (iii) the adoption of industrial automation by SMEs. Current AGV-systems are well known and widely implemented in manufacturing, medicine, and logistics. In these systems, a fleet of AGVs is organized in a centralized way. Tasks like motion planning and allocation of tasks are done by a central entity, shown in Fig. 1a, for all the AGVs together.

Driven by future requirements like flexibility, robustness, and scalability, the current trend in AGV systems is decentralization. The authors define decentralization as the distribution of the total intelligence of a system to its components: each device gets a part of the total intelligence to be able to operate independently, striving for the same global goals as depicted in Fig. 1b.

The Grand View Research market report [1] states decentralization as one of the future technologies which will gain great attention. The most important reason why this trend is gaining attention, is the expansion of the AGV fleet. In future systems, larger and more complex systems will be needed to fulfill the transportation demand within a factory. This will not be feasible with currently employed systems because of memory, communication and computation limits. Academia and leading companies investigated decentralization resulting in rich publications which [2], [3] tried to review. This paper updates the state of the art and dedicates special attention to recent advances in practical applicable decentralization.

The authors decompose the AGV control into five distinct core tasks. Every core task is criticized in a decentral context. The remaining chapters are organized as follows. Section 2 starts with the Industry 4.0 context and how we see future AGVs fit in this context. In Section 3, a discussion on general decentralized control is provided as a prelude to decentralized control specific for AGVs. The main advantages and drawbacks of distributed control are discussed and the different paradigms to introduce decentralization in a system are described. In Section 4, the core tasks needed to control a whole AGV-system are described. In Sections 5–9, every core task is deepened out referencing the current existing state-of-the-art algorithms and techniques. To end each of these sections, a conclusion is made regarding which algorithms or techniques will be more prevalent in the future and thus, which will be more suitable for decentralized control of AGV systems. We complete the paper with a brief research discussion in Section 10 on how the AGV of the future looks like and how it will be controlled. Finally, we draw some general conclusions about every core AGV task in Section 11.

AGVs in an Industry 4.0 context

Industry 4.0 represents the fourth industrial revolution in manufacturing. The Industry 4.0 paradigm puts information central. The paradigm creates value from information extracted and refined from data. It is the paradigm by choice for our factories of the future which enable mass customization and allow further horizontal and vertical integration.

With the possibility of free flow of data between elements in the production or in the logistics ecosystem, there is no need to rely on central

Discussion on the adoption of a decentralized control architecture

Decentralized control is one of the main features of Industry 4.0 paradigm. Many research is already conducted towards decentralized algorithms and techniques to control manufacturing systems in a distributed way [5], [6], [7]. Some research is done to the benefits of this architecture comparing to currently central and hierarchical structures. Many researchers mention the future need for decentralization [5], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17] recognizing the limits of

Core AGV tasks

A complete AGV-system consists of multiple core tasks to be able to operate in complex environments. If an e-commerce warehouse is taken as a running example, then these core tasks can be easily distinguished. In such an e-commerce situation, there is a continuous stream of orders which enters the logistical warehouse system (ERP1 or WMS2). An order can be seen as an object somewhere in the warehouse that needs to be brought to the

Task Allocation

Task allocation is one of the most challenging AGV tasks. It assigns a set of tasks to a set of robots, which can be seen in Fig. 6.

This is a constrained optimization NP-hard problem [21] in which the cost of the total assignment needs to be as low as possible, which means that if there are a lot of tasks and robots, the number of solutions will be enormous. So there does not exist an efficient algorithm which can produce an exact solution to the problem in a finite amount of time. To solve

Localization

As for any vehicle moving inside, also in AGV control localization is one of the core tasks to consider. In contrast to the other tasks, this task is mostly already decentralized: all the localization equipment and software are onboard. Information about the location in the 2D-map of the environment can be communicated to a central computer or to neighboring devices for other control purposes. As this core task is independent on the control architecture, we will not discuss the suitability of

Path Planning

A next core AGV task is path planning [96], [97]. We interpret path planning as the static planning task of an AGV whereas motion planning, which is going to be handled in the next section, can be seen as dynamic path planning. Static planning means that a basic collision-free path is computed using known information. No dynamic time-dependent elements are considered, only the known map with obstacles is used. Using this map, the robot knows its free configuration space and the obstacle space.

Motion Planning

Section 7 describes static path planning where a basic path is constructed only considering static obstacles like walls and racks. But in reality, this static path is not collision-free. During the execution of the path, the AGV can face obstacles where the static path planner does not know about. These obstacles can be unforeseen static obstacles, people, and other moving AGVs. Obviously, also collision with these features has to be prevented. Besides collisions, also deadlocks [105] need to

Vehicle management

Vehicle management is the simplest core AGV task in that sense that it does not require complex algorithms or techniques. It monitors battery status, error status, and maintenance status. This status will cause constraints on the possibility to perform tasks and thus need to be considered at the task allocation level. Using a centralized control, the central controller takes all the vehicle management statuses into account. If it knows for example that the battery life of a vehicle is not

Discussion

In our paper, we clearly want to take some steps towards Industry 4.0 if it comes to AGV control. The current employed AGV fleets operate in a classical central and hierarchical architecture where all AGVs act as slave devices which are authorized by a fleet manager, which is further mastered by an order managing system. We strive for a more heierarchical architecture, where all AGVs have an equal role and have the intelligence to operate as master of their own actions. Recently published

Conclusions

This paper covers the current and future-potential state-of-the-art techniques and algorithms to control an AGV system for a central and decentral architecture. We decomposed the total AGV control into a set of five core tasks and reviewed for each of those core tasks the available algorithms and techniques available in literature. The review revealed that a lot of work is done to four out of the five core tasks. A lot of central as well as decentral algorithms and techniques are available in

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Effect of Various Curing Methods and Curing Ages on Compressive Strength of Plain Concrete

Sri M. L. Anoop Kumar, A. Nanda Kishore, A. Ajay Sai, C. Madhu Sai, D. Manasa Swetha, G. Lakshmi Thanusri, K. Nitheesh Kumar

Department of Civil Engineering, Government Polytechnic, Rajampeta

Abstract

Concrete is the most important and most consumed construction material in global construction industry. The properties of concrete are greatly influenced by properties of its constituents and curing methods utilized for preparation of specimens. This study is focused on investigating the influence of three common curing methods, i.e., ponding, sprinkling and wet cover curing on compressive strength behavior of concrete. In total, 45 cubes were casted and tested after curing for 3, 7, 14, 28 and 56 days. The obtained results suggest that ponding method of concrete curing is most effective among all the three methods of concrete curing considered in this study. After ponding, the performance of concrete cured with wet cover curing method was quite acceptable. Moreover, the study also suggested that sprinkling method of curing gives lowest compressive strength due to greater moisture movement which abates the hydration of binder in concrete. This study will be helpful for construction practitioners in deciding the best-suited curing method under given conditions and available methods of preparation of concrete.

Keywords—Concrete, Curing, Curing Methods, Compressive Strength

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1Introductiononcrete is being widely adopted as construction material since ages because of its availability, versatility and durability [1]. It is a man-made construction material composed of cement, fine aggregates, coarse aggregates and water [2][3]. The cement in concrete acts as a binder that sets and hardens other components of concrete together while the aggregates are employed for adequate bonding [2]. This process of setting and hardening of cement is a chemical process called as hydration which is caused and accelerated by water used for curing of concrete [4]. As the hydration of cement is an exothermic chemical reaction that emits considerable amount of heat, the curing temperature below 10◦C i.e. 50◦F is not acceptable [5]. The improper curing of concrete can result in loss of half of its strength and proper curing of concrete ensures 90% attainment of concrete strength [6]. For proper curing, adequate moisture and temperature should be provided to concrete [5].

Hence, the curing of concrete is of extreme importance as it ensures the attainment of design strength and decreases the occurrence of surface cracks [4].

Curing not only reduces the shrinkage and permeability loss, but it also protects it from strength and durability losses, essentially on early days of strength gain [5]. The prime purpose of concrete curing in early age is to provide concrete enough amount of water for strength gains [6]. Based on conditions and availability, various methods for concrete curing are employed such as curing with gunny bags, curing with potable water, air curing, polythene curing, steam curing, ponding, sprinkling, wet covering etc. [5][7][8].

The curing of concrete with potable water involves sprinkling and/or ponding methods. In sprinkling method, the concrete is sprayed by water and in ponding method, concrete specimens are kept immersed in water for certain curing regimes [5]. The gunny bags curing and/or polythene sheet curing fall under the category of curing with wet covering.

The concrete samples are kept under gunny bags, polythene sheets and/or wet burlaps for providing moisture to concrete matrix for hydration process [9]. Similarly, in air curing, the concrete units are placed in stacks at room temperature to allow free flow of ambient air for curing [8]. The claim has been made [8] that the concrete cured by air exhibits 10%-20% lesser strength than the concrete cured by water. The behavior of concrete incorporating recycled aggregates at replacement levels of 0%, 25%, 50% and 100% under different curing methods i.e. air curing, water curing and painted curing was studied [10]. The study concluded that curing with paint materials was beneficial for strength gain except in case of 100% replacement of aggregates. Moreover, the concrete cured by water showed greater strength than the concrete cured by air [10]. Similar results were obtained as the authors in [11] concluded that concrete cured by ponding (immersing in the water) showed greater compressive, tensile and flexural strength than the concrete cured by air and wet plastic film. For

Oxide	Percentage	Oxide	Percentage
*SiO*2	20.67%	*Fe2O*3	3.2%
CaO	59.63%	*SO*3	2.49%
MgO	3.66%	*K2O*	0.67%
Na2O	0.12%	*LOI*	8.44%
*Al2O*3	6.03%	-	-

TABLE 1: Chemical composition of ordinary portland cement

Curing Methods	Number of Cubes				
	3 Days	**7 Days**	**14 Days**	**28 Days**	**56 Days**
Ponding	3	3	3	3	3
Sprinkling	3	3	3	3	3
Wet Cover Curing	3	3	3	3	3
Total Cubes	3x3x5= 45				

TABLE 2: Details of concrete cubes prepared for com- pressive strength test

research. The chemical composition of OPC is detailed in Table 1. The initial and final setting time of cement

hot weather conditions, the wet burlap sheet covering

method was suggested [12]. This study also urged that a mini-mum of 3 days wet burlap curing should be ensured for rich concrete mixes and similarly,

7 days wet burlap curing for lean concrete mixes should be ensured [12]. It is very much necessary that the minimum curing period should be optimized in relation to the required proper-ties of concrete as the concrete mixtures prepared with pozzolanic admixtures are more sensitive than the plain concrete [13]. It is a well-established fact that curing of concrete provides

strength to concrete matrix. Moreover, the curing days also influence the strength development process in concrete units.

This study, therefore, aims at checking the influence of various curing methods and curing days on compressive strength of plain cement concrete. The study compared the influence of ponding, spraying and wet cover curing on compressive strength of un-reinforced concrete. The curing regimes were selected as 3, 7, 14, 28 and 56 days.

Materials and Methods

The materials utilized in this study are basic com- ponents of plain cement concrete, i.e., aggregates, cement and water. The potable water with pH value of 7.4, complying to requirements prescribed in [14] was utilized for preparation of concrete. The Ordinary Portland cement (OPC) of Grade 43 conforming to prescriptions set in [15] was used for conduct of this

was 50 minutes and 214 minutes respectively. The fine and coarse aggregates conforming to guidelines of

[16] were utilized. The water absorption and specific gravity of fine aggregates was 1.25% and 2.5. Similarly, the water absorption and specific gravity of coarse aggregates was 2.67% and 2.71.

× ×

The concrete mix ratio was maintained as 1:1.5:3 and the targeted strength was 25 MPa. For preparation of concrete specimens prepared for compressive strength test, the standards of [17] were strictly followed. In to- tal, 45 number of cubes of size 150 150 150 mm were casted for compressive strength testing as detailed in Table 2. The universal testing machine (UTM) was used for compressive strength testing of cubes at the end of the respective curing age in accordance with guidelines of [18]. For curing of concrete specimens, three methods i.e. ponding, sprinkling and wet cover curing were considered, and the results were compared. For curing of concrete specimens via ponding method, the concrete cubes were immersed completely in the water for respective curing ages. Throughout this pro-

Curing Method	Compressive Strength (MPa)	Percentage Difference		
	7 Days	**28 Days**	**7 Days**	**28 Days**
Ponding	16.83	25.93	-	-
Sprinkling	15.32	25.52	-8.97%	-1.58%
Wet Cover Curing	16.62	25.83	-1.25%	-0.39%

TABLE 3: Percentage difference of compressive strength values at 7 & 28 days of curing

Fig. 1: Demonstration of various curing methods involved.

cess, the average laboratory temperature equivalent to standard room temperature was maintained in order to avert the possible thermal stresses that could fur- ther lead towards development of cracks. As ponding ensures continuous supply of moisture and uniform temperature, it is considered to be an ideal method for curing. For curing via sprinkling method, the concrete specimens were periodically showered with potable wa- ter available in the laboratory. However, as sprinkling re-quires supply of ample amount of water and careful supervision, the cost and human resource involved in it can be a major point of concern. In addition, the wet cover curing method employed the wet sheets in order to maintain the presence of water on the outer surface of complete area of concrete cubes. The wet coverings were provided to the cubes soon after the acquirement of enough strength by concrete cubes in order to pre- vent the possible surface damage, especially on edges. Figure 1 shows these three methods of concrete curing, adopted in this study.

Results & Discussion

This study involved checking the influence of three common curing methods i.e. ponding, sprinkling and wet cover curing on compressive strength behavior of concrete cubes. The cubes were subjected to curing for 3, 7, 14, 28 and 56 days. The concrete cubes were tested for compressive strength and it was observed that the ponding method of curing provided more strength than the wet cover curing method of curing followed by sprinkling method. The results are detailed in Table

3 in terms of percentage difference of compressive strength values obtained at testing after 7 and 28 days of curing of concrete cubes.

It was also observed that role of curing regimes was very crucial and important for strength development in concrete cubes. The curing of concrete by ponding

Fig. 2: Relation between curing methods, curing ages and compressive strength of concrete cubes.

helps in balancing the heat of hydration and aids in adequate strength development phenomenon. The heat of hydration is basically balanced and maintained through low porosity behavior caused by hear of hy- dration which results in loss of moisture. Moreover, the strength loss in sprinkling method is because of increased moisture movement from concrete which re- sults in early drying of the concrete, ultimately abating the entire hydration process. The concrete cured by ponding method was helpful in achieving the design strength of structural concrete i.e. 25 MPa. These results are in agreement with those obtained in [4] and [5]. The results are graphically illustrated as under in Figure 2.

Conclusions & Future Recommendations

The present study investigated the effect of various curing methods i.e. ponding, sprinkling and wet cover curing and curing days i.e. 3, 7, 14, 28 and 56 days on compressive strength of concrete cubes.

- The results depicted that sprinkling provides low- est of compressive strengths ob-served in this study
- Although, the ponding method of concrete curing provided greater strength than that provided by sprinkling method, the performance of concrete cured with both methods was quite comparable.
- Considering the results, this study recommends ponding method for curing of concrete.

Moreover, the effects of other methods say as air curing, solar curing, wet hessian curing and polythene sheet curing, steam curing etc. on strength behavior of concrete should also be studied in detail. In addition, other properties such as tensile and flexural strength values, fire and abrasion resistance, cracking behavior, permeability and durability of concrete can be checked

for concrete subjected to different curing methods and curing days.

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