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Sustainability Metrics and Optimization Techniques for Industrial Infrastructure

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Abstract*: An integral component of a sustainable urban transformation is the creation of sustainable infrastructure. Sustainable industrial infrastructure is essential for promoting long-term economic growth with the least amount of environmental damage and the greatest amount of social well-being. The conventional infrastructure development methods have been quite focused in most cases on productivity and cost effectiveness without considering the overall sustainability implications providing sustainability metrics and optimization in regards to industrial infrastructure systems. It focuses on the systematization of environmental, economic, and social indicators of sustainability into decision-making based on high-level optimization frameworks sustainable design and operation systems, such as energy-saving systems, waste energy reuse, integration of renewable energy, and digital technologies, Artificial Intelligence (AI), Internet of Things (IoT), and Digital Twins (DTs). The use of mathematical, heuristic, metaheuristic, and data-driven optimization methods as effective in contributing to multi-objective sustainability the role of Multi-Criteria Decision-Making (MCDM) methods in solving trade-offs between competing sustainability objectives. Optimization based on AI, energy-based evaluation, and hybrid models of industrial infrastructure. The results underline the fact that a connection between sustainability measures and optimization models can facilitate the creation of a system of resource-intensive, resilient, and environmentally-friendly industrial infrastructure, which will be able to sustain the industry transformation.*

Keywords: *Sustainable Industrial Infrastructure, Multi-Objective Optimization, Artificial Intelligence, Energy-Efficient Systems, Decision-Making Models.*

I. INTRODUCTION

Modern economies are largely based on industrial infrastructure, which allows large-scale manufacturing, energy production, transportation, and logistics infrastructure [1][2]. The productivity and stability of industrial infrastructure directly determine economic growth, as well as the competitiveness in the industry [3][4]. Traditional development of industrial infrastructure has been steered by productivity as well as cost efficiency at the cost of the long-term effects on the environment and society. This method has led to higher energy use, resource overuse and environmental destruction, thus the need to make a paradigm shift to more sustainable industrial systems.

Sustainable industrial infrastructure is an enhancement of traditional infrastructure ideas incorporating environmental protection, economic viability and social responsibility in the lifecycle of infrastructure [5]. This combined outlook focuses on designing with energy conservation, saving resources, cutting emissions and enhancing occupational safety [6]. Through embracing the concept of sustainability, industrial infrastructure able to limit the negative effects on the environment without reducing service stability and cost efficiency [7]. Nevertheless, in an endeavor to make industrial infrastructure sustainable, the evaluation approaches should be systematic and able to capture multiple dimensions of sustainability at the same time [8].

Sustainable industrial infrastructure implementation needs strong procedures for the sustainability performance evaluation. The sustainability measures offer a quantitative and methodological foundation behind the measurement of environmental, economic, and social effects related to industrial infrastructure [9][10]. Energy intensity, carbon emissions, water consumption, lifecycle cost, and productivity as well as safety indicators are metrics that allow an objective performance evaluation of alternative design and operation strategies and benchmarking [11]. Nevertheless, sustainability metrics appear to be inadequate in many instances since the industrial infrastructure systems comprise complicated interactions and trade-offs of various and even contradictory goals, and, therefore, it becomes extremely difficult to make decisions.

Optimization methods are important in connecting the sustainability measures and the feasible decision-making [12][13]. The optimization techniques convert sustainability measures into objective functions and constraints allowing finding optimum or nearly optimal solutions while taking into account operational and environmental restrictions in the real world, and regulation [14][15][16]. Multi-objective decision-making and trade-off analysis are aided with the help of mathematical optimization, heuristic and metaheuristic methods, as well as data-driven and artificial intelligence-based methods. By incorporating sustainability metrics with optimization methods, the decision-makers are able to create industrial infrastructural systems that are economically viable, yet environmentally accountable, socially acceptable, and resilient to help in the long-term sustainable industrial development.

A. Structure of the Paper

This paper is organized as follows: Section II provides an sustainable design and operation of industrial infrastructure. Section III Optimization technique for industrial infrastructure Section IV. Linking sustainability with optimization metrics in Section V Literature review, Section VI Conclusions and future work.

II. SUSTAINABLE DESIGN AND OPERATION OF INDUSTRIAL INFRASTRUCTURE

Sustainable infrastructure has little effect on the environment. The amount of energy, water, and pollutants is significantly reduced. Innovation and recycling are used to guarantee maximum use of resources [17]. Stakeholder participation ensures the highest level of acceptance. These infrastructures are considered to be the nation's vital infrastructures because they provide uninterrupted or minimal downtime serviceability amid natural disasters. Green efforts and the use of green materials and processes guarantee the least amount of environmental impact possible during the building and demolition phases.

A. Sustainable Industrial Ecological Framework

To capture the interconnections between industrial operations and surrounding ecosystems, the framework incorporates spatial resource flow models, as shown in the figure. 1 below:

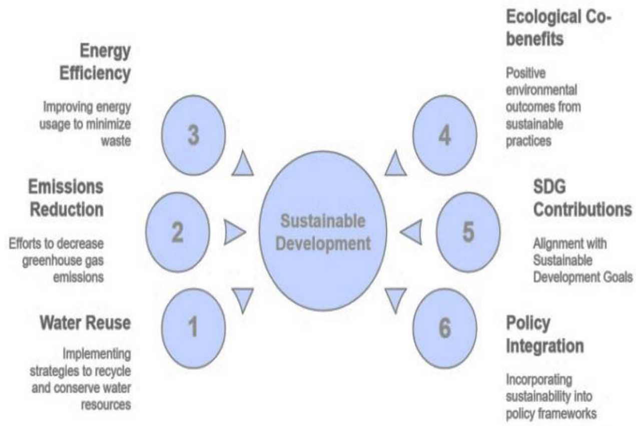

Figure 1 : Industrial–Ecological Symbiosis Framework in Sustainable Development

This enables industrial processes to actively encourage the ecosystem services that the surrounding natural green infrastructure provides by integrating AI-optimized dynamic operations [18]. In contrast to traditional static formulations that are unable to adapt to operational disturbances or real-time climatic variability, this framework integrates spatial awareness into its design to guarantee that improvements in industrial efficiency significantly enhance ecological resilience.

B. Components of Sustainability in Industrial Infrastructure

Manufacturing companies' sustainability components are based on the three primary economic, social, and environmental foundations or aspects [19]. The triple bottom line (TBL) is the term for them. The multi-objective optimization of the TBL concept of sustainability is complex. The key features and problems in each of the sustainability pillars are shown in Table I. These problems or elements reflect what any manufacturing company requires to be able to survive and be sustainable.

Table 1 : Components of Sustainability in Industrial Infrastructure

Economic Sustainability	Social Sustainability	Environmental Sustainability
Globalization impacts	Workforce management	Environmental management systems
Innovation and technological development	Human rights and labor standards	Efficient use of natural resources
Infrastructure reconfiguration and flexibility	Social responsibility and ethical conduct	Pollution prevention and control
Competitive strategies	Customer health and safety	Hazardous material management
Performance evaluation and productivity	Responsible business practices	Ecosystem and biodiversity protection
Flexible organizational and management structures	Stakeholder engagement	Climate change and emissions reduction

a) Sustainability Cost

The minimisation sustainability index is advised as the standard for maximising both time and cost in order to achieve sustainability.

i) Infrastructure Cost

The cost of infrastructure is determined by the amount of resources initially sought or purchased in order to meet and complete the necessary infrastructure. Actually, there are two primary components to the cost of sustainable infrastructure: both a variable and a fixed component [20]. The expenditure required when the system is upgraded and enhanced in terms of sustainability is known as the sustainability cost component, which is a variable and is represented by the s_c. K is incurred independently depending on the infrastructure's size and nature. As a function of the fixed (set up) cost, the cost is incurred exponentially. As a result, the cost of infrastructure sustainability is represented by $C(s)$, as follows Equation (1):

$$C(s_c) = Ke^{-sc} \qquad (1)$$

Where: K= Infrastructure capital investment, s_c = sustainability cost as the basis for the sustainability index.

ii) Development Cost

The costs of development related to sustainability or sustainable development comprise all expenses proportionate to the sustainability index, and as development is being updated and upgraded, sustainable development. The issues and elements listed below are some of the development costs for sustainability in Equation (2)

It is evident that, in contrast to economic sustainability has the highest criteria, followed by social and environmental sustainability, the sustainable index Ds_c and the cost of sustainability development:

$$D(s_c) = \{\sum_{i=1}^{n} c_i\}s_c = (c_1 + c_2 + c_3 + \ldots\ldots + c_n)s_c = Ds_c \quad (2)$$

Where: D = total development cost for sustainability.

b) Sustainability Time

i) Infrastructure Time

The exponential equation for sustainability is used to determine the sustainability-related infrastructure time requirements, which rely on the initial infrastructure time requirements. Consequently, Ts_t and the subsequent Equation (3) determines the time of infrastructure sustainability:

$$T(s_t) = T_0 e^{-st} \qquad (3)$$

Where; T_0 = time required for initial infrastructures, s_t = sustainable time-based sustainability index.

ii) Development Time

The development periods encompass all periods that correspond to the sustainability index. The total of these periods is related to the sustainability index at any given moment, as the developmental periods are the carrying times connected to the development.

The sustainability development time and any time sustainable index, ts_t is expressed as the following Equation (4):

$$t(s_t) = \{\sum_{i=1}^{n} t_i\}s_t = (t_1 + t_2 + t_3 + \cdots .. + t_n)S = ts_t \qquad (4)$$

Where: t = total development time for sustainability.

C. Energy-Efficient Design and Operations

The main pillars of sustainability in industrial infrastructure are design and operations that are energy-efficient, as energy use contributes significantly to operating costs and the environmental impact. The introduction of energy efficiency during the design phase and operation phase helps industries to save carbon emissions, increase productivity and improve performance in the long term.

- Energy-Efficient Design Strategies: Energy-saving design is concerned with reducing the energy requirements at the early stages [21]. This involves the choice of high-efficiency machinery and equipment, optimization of the plant layout to minimize the energy loss and the use of process integration methods including heat integration and pinch analysis.
- Operational Energy Management: Energy management activities are necessary for maintaining energy efficiency. Systems Energy management systems (EMS) allow the energy consumption in industrial processes to be continuously monitored, analyzed, and controlled.
- Waste Energy Recovery and Reuse: Reusing and recovering waste energy is one energy-efficient method. Industries can employ excess energy thanks to technology like energy cascade technologies, cogeneration (combined heat and electricity) and waste heat recovery systems.
- High technological trends are very vital in improving energy efficiency [22][23]. Real-time information about the energy Digital Technologies and Smart Energy Operations: consumption is available through sensors, automation, and Internet

of Things (IoT) platforms [24], which can be used to forecast maintenance and optimize data. Artificial intelligence and digital twins [25].

- Integration of Renewable Energy Sources: mobilization of renewable sources of energy [26], Carbon emissions and fossil fuel use are decreased when solar, wind, and biomass are integrated into industrial infrastructure.

III. OPTIMIZATION TECHNIQUES FOR SUSTAINABLE INDUSTRIAL INFRASTRUCTURE

Optimization methods are very important in attaining sustainability in industrial infrastructure through efficient utilization of the resources, lessening the environmental effects and enhancing economic results. These methods help in decision-making through the determination of the best solution when the sustainability goals are numerous and competing.

A. Mathematical Optimization Techniques

Decision-making tools on sustainable industrial infrastructures are based on mathematical optimization methods, which offer systematic and quantitative procedures for finding the ideal solution to a problem with a set of constraints. The methods are popular to increase the efficiency of the resources, decrease the environmental effects, and promote the economic performance:

- Linear Programming (LP): Linear programming is used when both the restrictions and the objective functions are linear. In energy management, production planning, and optimization of logistics, LP techniques are often applied to minimize cost or energy consumption under operational constraints. LP models can be applied to large-scale industrial systems because they are computationally efficient.
- Nonlinear Programming (NLP): The optimization of problems with nonlinear connections is the focus of NLP, which is typical in industrial processes like energy conversion, modeling of emissions and flow systems of materials.
- Mixed-Integer Programming (MIP): Mixed-integer programming is a type of modeling that enables the modeling of decisions that entail the selection of equipment, location of facilities, and operating online or offline, which are common in sustainable infrastructure planning and design.
- Constraint-Based Optimization: Constraint-based models guarantee that the sustainability requirements are met because the environmental limits, safety standards and policy regulations are taken directly into the optimization model.

B. Heuristic and Metaheuristic Optimization Methods

For large-scale and complex industrial infrastructure systems, exact optimization methods may become computationally infeasible [27]. Effective near-optimal solutions are produced by heuristic and metaheuristic algorithms, such as particle swarm optimization and genetic algorithms. These methods are particularly effective for infrastructure layout design, energy system optimization, and scheduling problems:

a) Genetic Algorithm (GA)

It is a refined metaheuristic method. Search and optimisation issues are addressed with GA [28]. The subsequent mutation involves adding new strings to the population and selecting the ones with the highest fitness.

b) Particle Swarm Optimization (PSO)

Social animal behaviour serves as the inspiration for particle swarm optimization (PSO), a population-based optimization technique based on swarm intelligence. Similar to genetic algorithms, PSO generates a population of potential solutions at random and applies them through random mutation while taking into account user experience and the best solutions available worldwide. PSO has been widely employed in energy systems and industrial infrastructure to fulfill sustainability and performance standards while optimizing resource utilization, system performance, and system cost. Infrastructure planning and optimization issues of considerable industry size benefit greatly from PSO's capacity to seek multi-dimensional, complicated solution spaces efficiently.

c) Artificial Bee Colony (ABC)

An expanded version of the swarm-based optimization method ABC is used to solve limited optimization situations. ABC uses food sources as the answer and operates on the same concept as bee behaviour. The program mimics the bees' foraging behaviour. The colony includes scout, worker, and observer bees. The source of the meal represents a potential fix for the issue. The suitability of the solution is reflected in the quality of the food supply.

d) Ant Colony Optimization (Aco)

ACO is a metaheuristic method that may be used to solve a variety of issues. It operates on the idea of finding the quickest path between the colonies and the food sources. The pseudocode for ant colony optimization (ACO) in environmental management and water resources issues for both continuous and discrete domains.

C. Data-Driven and Artificial Intelligence (AI)-Based Optimization

These methods use historical and real-time data to help in making intelligent decisions that would enhance energy efficiency, emissions, efficient use of resources, and operational performance [29]. Data-driven optimization can be used to control complex industrial systems adaptively and predictively and in real-time by bringing together ML, reinforcement learning, digital twins, and IoT-enabled analytics [30][31]. Some of the primary methodologies, data needs, optimization, environmental effects to sustainability of the industrial systems with their data needs [32], to the deliverance of environmental accountable, economically viable, and sustainable industrial infrastructural systems are underscored in the table 2.

Table 2 : Data-Driven and Artificial Intelligence-Based Optimization Techniques for Sustainable Industrial Infrastructure

Technique	Description	Data Requirements	Optimization	Impact of Sustainability	Industrial Applications
Machine Learning (ML)	Uses historical and real-time data to learn system behaviour	Historical process data, sensor data	Minimize energy use, emissions, and costs	Improves energy efficiency and resource utilization	Energy forecasting, predictive maintenance
Supervised Learning	Learns relationships from labeled datasets	Labelled operational and performance data	Predict sustainability indicators	Enhances accuracy of energy and emission predictions	Quality control, fault detection
Unsupervised Learning	Identifies patterns in unlabelled data	Unlabelled sensor and operational data	Detect inefficiencies and anomalies	Reduces energy waste and resource losses	Pattern recognition, anomaly detection
Reinforcement Learning (RL)	Learns optimal actions via interaction	Real-time operational data	Real-time adaptive optimization	Enables dynamic energy and process optimization	Smart grids, autonomous process control
Artificial Neural Networks (ANN)	Models complex nonlinear relationships	Large-scale numerical datasets	Optimize nonlinear system behaviour	Improves prediction accuracy for complex systems	Emissions modeling, process optimization
Digital Twins	Virtual representation of physical systems	Real-time and historical system data	Simulation-based optimization	Supports lifecycle sustainability improvement	Smart factories, asset management
Big Data Analytics	Analyses large, diverse datasets	Structured and unstructured big data	Strategic sustainability optimization	Enhances long-term planning and decision-making	Supply chain sustainability
IoT-Enabled Optimization	Uses sensor networks for monitoring and control	Real-time sensor data	Continuous operational optimization	Reduces energy and water consumption	Energy and water management

D. Optimization Applications in Industrial Infrastructure Systems

The industrial infrastructure systems have been extensively utilized to achieve sustainability, efficiency and operational performance through optimization techniques. They are important in five major areas of application as follows:

a) Energy Management and Optimization

The optimization is employed in order to reduce the energy and operational expenses as well as to satisfy the production needs. These have been used in optimal scheduling of energy, demand side management, optimization of waste heat recovery, and renewable energy integration.

b) Production Planning and Scheduling

Production planning and scheduling in industrial establishment involves the use of optimization techniques that help in efficient planning and scheduling the production process in the industry by balancing between the availability of resources, processing time, and sustainability.

c) Resource and Material Flow Optimization

The Optimization is used to control flow of materials, water as well as other resources within the industrial infrastructure, through minimizing resource wastage, enhancing recycling and reuse and better supply chain.

d) Infrastructure Design and Capacity Planning

Optimization methods are used to help design industrial infrastructure systems, such as the layout of the facilities, equipment selection, and capacity expansion planning. The optimization approach that is sustainable in nature ensures economic viability of infrastructure investments in the long term.

e) Maintenance and Asset Management

Predictive and optimization-based maintenance schemes enhance the reliability and life of the asset. With the help of optimized maintenance schedules and allocation of resources, industries can minimize downtimes, increase life of the infrastructure, and decrease environmental and economic expenses of equipment failure.

IV. LINKING SUSTAINABILITY METRICS WITH OPTIMIZATION MODELS

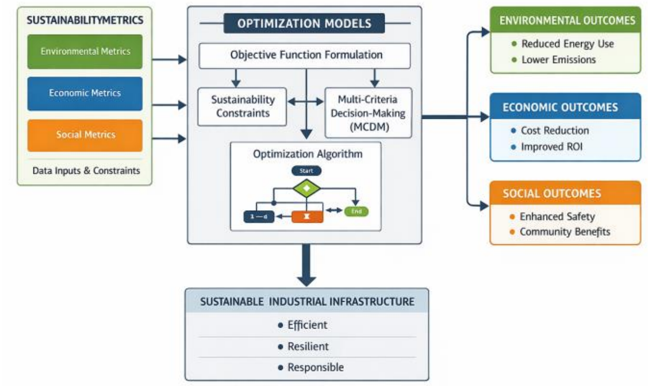

Figure 2 : Linking Sustainability Metric with Optimization Model

Sustainability into practical and measurable decision-making procedures in industrial infrastructure systems, it is important to connect sustainability indicators with optimization models. Sustainability measurements are the quantitative indicators of environmental, economic and social performance, and optimization models are the ones that optimize the solutions based on the available set of indicators given set constraints in Figure 2:

A conceptual framework used to depict sustainability measures that are systematically incorporated into optimization models to aid in the creation of sustainable industrial infrastructure.

- Environmental indicators, including power usage and emissions.
- Economic indicators, such as cost and ROI.
- Social measures, including safety and community impact.

Objective formulation of functions is the mathematical definition of sustainability objectives, including minimization of energy use, reduction of greenhouse gas emissions or minimization of lifecycle cost [33]. These objectives give a quantitative foundation to the optimization process in order to achieve sustainability.

- Sustainability constraints: Sustainability constraints are also added to make sure that optimized solutions not violate the environmental laws, resource constraints, safety standards, or even the policy requirements. These constraints may be embedded by embedding them.
- Multi-Criteria Decision-Making (MCDM): Trade-offs between rival sustainability goals are considered by Multi-Criteria Decision-Making (MCDM) techniques when sustainability goals of the environment, economics, and social objectives clash. MCDM methods empower transparency.
- Optimization algorithm: The optimization algorithm unites the objective functions, constraints, and MCDM evaluation with of exploring the solution space in a systematic manner and finding the optimal or near-optimal solutions the development of efficient, resilient, and responsible industrial infrastructure systems.

A. Role of Sustainability Metrics in Optimization

Sustainability metrics are vital in the area of optimization as they convert the generative sustainability objectives into specific and quantitative aspects that can be incorporated by the decision-making models in an organized manner. Under the industrial infrastructure, such metrics are used to make sure that optimization results are in line with environmental protection, economic efficiency, and social responsibility as explained in Table 3 below:

Table 3 : Sustainable Metric Parameters in Optimization

Sustainability Dimension	Primary Focus	Key Metrics	Use in Optimization
Environmental	Resource efficiency and environmental impact	Energy use, emissions, water consumption, waste, recycling	Objective functions and environmental constraints
Economic	Cost efficiency and system performance	Capital cost, operating cost, LCC, ROI, productivity	Cost minimization and profitability optimization
Social	Safety, compliance, and social well-being	Occupational safety, health impact, employment quality, stakeholder satisfaction	Social performance constraints and ranking criteria

B. Constraints Based on Sustainability Requirements

The optimization solutions are required to operate within constraints that are based on the sustainability requirements converted regulatory requirements, resource supply, safety requirements, and policy targets into mathematical limits including emission limits, energy efficiency limits, budget limits and safety requirements. With the inclusion of sustainability constraints, optimization models allow making sure that solutions are not only optimal in their performance but also feasible, compliant, and socially acceptable. The method helps to avoid the environmental damage or economically not feasible results and to make responsible decisions in the implementation of sustainable industrial infrastructure systems.

C. Multi-Criteria Decision-Making Integration

MCDM techniques are integrated to optimize with sustainability orientation by means of the systematic assessment of numerous [34], often conflicting criteria Key points include:

- Balanced Evaluation of Sustainability Dimensions: MCDM allows considering environmental, economic, and social aspects at the same time, and none of them dominates the decision-making process.
- Trade-Off Analysis: MCDM methods aid in open trade-off analysis of conflicting goals, including cost reduction and emission reduction.
- Incorporation of Stakeholder Preferences: The methods of weighing and ranking allow the decision-makers to take into account the policy objectives and priorities of the many stakeholders involved in the decision-making process.
- Decision Transparency and Robustness: MCDM enhances transparency, consistency, and confidence in decisions relating to sustainability by defining the criteria and weights used to make decisions.

V. LITERATURE REVIEW

This section reviews previous studies on sustainability for industrial infrastructure in optimization techniques. It summarizes key frameworks, algorithms, and decision-making approaches used to integrate environmental in table IV economic, and social sustainability objectives, while highlighting major challenges and future research direction:

Sanad et al. (2025) a social effect sub model and an environmental impact sub model. Every sub model measures a different aspect of project sustainability. Pareto-optimal solutions that balance project time, cost, environmental effects, and social costs are created using the nondominated sorting genetic algorithm-II. The best alternative is appraised and chosen using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), which uses Shannon entropy to objectively calculate the weights of each goal based on their variability [35].

Wang, Si and Zhang (2025) To conduct a comprehensive assessment of mechanical manufacturing systems' sustainability, this study develops an emergent assessment framework that incorporates the four aspects of economic, social, ecological, and sustainability. The relatively low Net Energy Yield Ratio (NEYR), Energy Investment Ratio (EIR) of 2.27, and Improved Energy Sustainable Index (IESI) of 0.44 for the balancing shaft housing manufacturing system, according to empirical research, all indicate insufficient long-term sustainability and poor social benefits. However, completion and casting process optimisation resulted in a decrease in the emergency waste rate (EWR) from 12.96% to 9.86%, significantly improving overall sustainability [36].

Boussetta et al. (2025) enhancing corporate performance and promoting sustainable industrial practices via smart digital infrastructures. Enhancing operational efficiency, supply chain transparency, and data-driven decision-making in business and business environments can be achieved by combining AI with big data analytics, blockchain, the IoT, and new applications in resource optimisation, predictive maintenance, and real-time environmental monitoring. This promotes environmental responsibility, progress, and resilience. This analysis offers insightful information on how AI, digital infrastructure, and sustainability interact, outlining future research avenues to develop reliable and effective solutions [37].

Table 4 : Comparative Analysis of Sustainable for Industrial Infrastructure in Optimization Technique

Author(s) & Year	Focus	Key Findings	Challenges	Future Work
Sanad et al., 2025	Sustainability-oriented project scheduling using multi-objective optimization and MCDM	Developed environmental and social impact submodels integrated with NSGA-II generate Pareto-optimal solutions that balance social, environmental, financial, and temporal objectives. Shannon entropy objectively determined weights, and TOPSIS successfully ranked optimal solutions.	High computational complexity; results sensitive to objective definition and data quality	Apply the framework to real-life large-scale projects; incorporate uncertainty and dynamic weighting; integrate additional sustainability indicators.
Wang, Si & Zhang, 2025	Emergy-based sustainability evaluation of machinery manufacturing systems	Proposed a four-dimensional emergy framework (economic, social, ecological, sustainability) poor sustainability (IESI = 0.44), but process optimization reduced emergy waste rate from 12.96% to 9.86%, improving sustainability.	Emergy analysis requires extensive data and expert judgment;	Extend energy evaluation to different manufacturing sectors; integrate energy analysis with AI-based optimization and real-time monitoring systems.
Boussetta et al., 2025	AI-enabled digital infrastructures for sustainable industrial practices	Demonstrated that integrating AI with IoT, big data, and blockchain enhances resource optimization, predictive maintenance, environmental monitoring, and supply chain transparency, improving sustainability and business performance.	High implementation costs; data security and interoperability issues; lack of standardized frameworks.	Develop standardized AI-driven sustainability frameworks; empirical validation across industries; address ethical and governance challenges of AI adoption.
Ruiz-Vélez et al., 2024	Sustainable design of reinforced concrete precast modular frames (RCPMF)	Proposed a hybrid MOO–MCDM framework using customized NSGA-II and LCA. Different MCDM methods produced highly correlated rankings (correlation = 0.9816), confirming robustness of decision-making.	Focus limited to specific structural systems; high computational demand; social dimension less emphasized.	Expand framework to other infrastructure systems; incorporate social sustainability indicators; include uncertainty and resilience considerations.
Singh & Ru, 2023	Digitalization and Sustainable Development Goals (SDGs)	Identified key indicators such as internet penetration, logistics performance, industrial reforms, clean fuel adoption, and rural connectivity as drivers of sustainable development and digital justice.	Macro-level analysis lacks project-level applicability; difficulty in quantifying social equity impacts.	Develop micro-level assessment models; link digital indicators with environmental performance; explore causal relationships using empirical data.
Hosny, Ibrahim & Eldars, 2022	Sustainability-based infrastructure project portfolio selection	Developed a genetic algorithm-based optimization model to rank and select infrastructure projects under budget constraints while meeting minimum sustainability scores across economic, environmental, and social pillars.	Sustainability scores depend on expert judgment; static model does not consider long-term uncertainty.	Incorporate dynamic and stochastic elements; integrate AI-based prediction of sustainability performance; apply model to national infrastructure planning.

Ruiz-Vélez et al. (2024) In order to ensure that transport infrastructure is socially, economically, and environmentally responsible, it is acknowledged that sustainability principles must be incorporated into the decision-making and structural design procedures, especially with regard to reinforced concrete precast modular frames (RCPMF). This highlights the importance of sustainable development. This blends multi-criteria decision-making (MCDM) and multi-objective optimisation (MOO) approaches and is specifically made for the design and selection of RCPMF. A thorough life cycle analysis (LCA) and a customised Non-dominated Sorting Genetic method II (NSGA-II) method enable the efficiency of three repair operators—statistical, random, and proximity-based—in optimising economic and environmental aspects. Similar rankings were obtained using MCDM approaches, with minor score differences and a significant correlation of 0.9816 [38].

Singh and Ru (2023) Addressing the digital divide and ensuring digital justice and equality via sustainable growth, and improve internet and mobile broadband subscriptions with fewer negative effects, the following metrics are being used: quality and ranking, development initiatives, industrial reforms and emission control, Subscription rates for mobile and internet broadband, logistic performance index, and connectivity to rural areas. Technology integration, industrial policy changes, and logistic sector reforms enhance quality and sustainability, boost financing and assistance, and enhance rural connection [8].

Hosny, Ibrahim and Eldars (2022) predicted that sustainability performance is prioritised according to a nation's infrastructure, which is the engine of its economic development. A sustainability score optimisation model was created with certain criteria in mind, as meeting the minimal score needed to meet each of the three sustainability standards and rigorously adhering to a budget cap. Based on the projected sustainability performance of the projects, decision-makers can then evaluate, rank, and prioritise them. This optimisation model was implemented using the Genetic Algorithm Technique [39].

VI. CONCLUSION AND FUTURE WORK

Optimization methods in sustainability metrics to inform decision-making in the development and operation of industrial infrastructure. Along with environmental, economic and social signals, by using mathematical, heuristic and artificial intelligence-based optimization models, there are possibilities of designing sustainable industrial systems to achieve a balance between efficiency, resilience, and responsibility. The energy-efficient design, digital technologies, and data-driven optimization methods can greatly optimize the use of resources, decrease emissions, and enhance long-term infrastructure performance. Moreover, the multi-criteria-based decision-making methods are critical towards balancing trade-offs between conflicting sustainability goals and including stakeholder preferences openly. However, there are still some challenges, such as large data demands, computational load, uncertainty in sustainability metrics, and little application in practice at large scale. Future studies can standardize sustainability indicators, incorporate uncertainty and dynamic decision-making into optimization models, and scale AI-based real-time optimization frameworks. Additional empirical studies in different sectors of the industry should be done to increase the robustness and application of such models' social indicators of sustainability, policy integration, and ethics related to the digital technologies should also be given priority. The development of these spheres will reinforce the implementation of sustainable optimization structures in practice and help to migrate to resilient and sustainable systems of industrial infrastructure.

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