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Operational Resilience Strategies for Geopolymer Concrete Production under Raw Material Supply Variability

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ABSTRACT

The advent of low-carbon construction has made geopolymer concrete (GPC) a sustainable material for construction. However, the supply uncertainty of the raw materials needed for GPC production makes this a challenge. This research aims to develop and design an integrated digital twin-reinforcement learning framework for optimizing geopolymer concrete production processes. The problem statement concerns the uncertainty involved when producing geopolymer concrete. This paper focuses on building a digital twin structure for optimizing the geopolymer concrete process. The authors also designed a reinforcement learning framework for optimizing the geopolymer concrete production process. The objective is achieved since the digital twin is a computer representation of a production environment. The computer simulation will utilize reinforcement learning. This will ensure that the production is done at a lower cost. Additionally, the digital twin can predict the supply uncertainty. The computer simulation will determine

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the supply uncertainty level. Performance was evaluated for three supply conditions: stable, with a moderate and severe level of variability, based on a set of indicators: throughput, downtime, energy consumption, CO_2 emission, and quality variability. In all cases, it has been shown that the Digital Twin–Reinforcement Learning (DT–RL) approach results in a considerable improvement of production resilience and sustainability performance by as much as 22% relative to downtime performance, as well as saving 13% of energy and a decrease of CO_2 emission by as much as 15% relative to static planning. Additionally, a strongly negative correlation between resilience and quality variability of manufactured products was shown to exist. This research shows that applying digital intelligence to green material production leads to an improvement in efficiency and green performance.

Keywords: Geopolymer Concrete; Digital Twin; Reinforcement Learning; Operational Resilience; Supply Variability; Sustainability

1. Introduction

The construction sector is presently facing growing demands for decarbonization, resource minimization, and the implementation of the concept of a circular economy in material systems [1]. In fact, the production of cement contributes about 8% to the total CO_2 emissions in the world, making this industrial sector one of the major CO_2 emitters in the world [2]. Therefore, geopolymer concrete (GPC), as a low-carbon concrete alternative to Ordinary Portland Cement (OPC), has been widely researched in recent years, in which industrial waste materials like fly ash, ground granulated blast furnace slag (GGBS), and silica fume are mainly employed as binders [3]. These binders not only help in the reduction of CO_2 emissions during the construction sector, thereby decarbonizing this industry, but also help in the valorization of waste, according to the principles of a circular economy.

Although geopolymer concrete has been shown to have many benefits to the environment, large-scale production of this type of concrete faces operational challenges to a large extent, depending on the variability of raw materials. Supplies of key raw materials, such as fly ash and slag, are dependent on the operational rates of power and steel production units [4,5]. By their nature, geopolymer concretes are not like OPC, which has a vertically integrated supply chain that is stable. Instead, geopolymer concretes rely on a type of industrial symbiosis, in which the supply of secondary raw materials faces challenges of variability and a certain degree of unpredictability. This has continued to pose a problem to geopolymer concrete production, which has had to resort to reactive planning to ensure continuity of production, much to the effect that scalability has been limited. For production managers, geopolymer concretes have continued to pose a problem, especially considering that this type of concrete lacks a certain degree of scalability that, to a large extent, has been limited by operational challenges.

In the current state of the literature, most work on geopolymer concrete relates to the use of chemical analysis, work of strength, and the work of durability [6,7]. Additionally, the work of strength and the use of activation factors have positive effects on work of strength, heat resistance, and sustainability in the manufacturing of geopolymer concrete [8]. However, little work has benn done within the field of geopolymer concrete manufacturing, particularly in relation to operational resilience in manufacturing plants in the face of material supply uncertainties. As Ataburo et al. [9] and Essuman et al. [10] explain, operational resilience is the ability of a manufacturing system to continue functioning in the face of disruption in the current manufacturing context, the least explored area.

In this regard, the emergence of digital twin technology and artificial intelligence in manufacturing provides a promising solution for overcoming production uncertainties. A digital twin refers to a computer model created from real-time data that precisely mimics a physical system. By leveraging such technology and using simulation-based optimization and predictive control, numerous researchers and scientists are now capable of optimizing production processes remotely and with a high degree of control [11,12]. By combining such technology with reinforcement learning, a type of machine learning known as a "reward-based" approach to developing adaptive and policy-based decisions based on iterations and feedback, digital twins are now capable of self-optimizing scheduling and resource allocation [13–15]. These technologies are also proven effective in this area for production sites such as steel production and cement manufacturing. Nevertheless, the application of such technology with a batch-based production system, such as geopolymer concrete production, is untried.

Moreover, recent studies in sustainability-focused operations management have emphasized the relationship between process flexibility, efficiency, and environment [16]. This is because a resilient system continuously functions in a steady state environment. As such, there is reduced wastage of energy, reduced emissions resulting from idling resources, and sufficient quality production. The connection between environment and operation resilience has yet to receive proper quantification using empirical work despite various conceptual studies [17].

The approach intertwines real-time data acquisition for the IoT, discrete-event simulation, and reinforcement learning optimization to dynamically optimize production schedules and cope with disturbances. By accomplishing, this research makes three contributions to current literature. First, it brings an operations management outlook on geopolymer studies, surpassing research on material properties and turning to processes instead. Second, it forges and tests a reinforcement learning algorithm for adaptive production scheduling through the enabler of digital twins to optimize production viability despite supply chain uncertainties. Lastly, it formulates a correlation between operational resilience indicators like production downtime and throughput variability and sustainable performance indicators such as energy consumption, CO_2 emission, and quality variability.

With a view to filling this identified research gap, this work attempted to explore the potential of digital twin-enabled reinforcement learning to optimize operational resilience during the production of geopolymer concrete under raw material supply uncertainty conditions. The technical objectives of this work are to: (i) conceptualize a digital twin representation of a geopolymer concrete production process to reflect real-time changes to uncertainty; (ii) develop an adaptive scheduling strategy using reinforcement learning to offset raw material supply uncertainty; (iii) analyze sensitivities of adaptive scheduling to operational resilience indices of production downtimes and throughput variability; and (iv) investigate relationships for interdependencies of operational resilience with sustainability performance measures of energy used, CO_2 emissions, and product quality variability.

Though reinforcement learning techniques have already been successfully applied in steel production and Portland cement production, the type of processes in the system described are of completely different natures. Geopolymer concrete production is based on random industrially governed waste materials with stochastic variability in the supply that cannot be handled in the models of reinforcement learning developed for continuous processes. The work is the continuation of the previous research on the application of reinforcement learning in manufacturing.

2. Literature Review

The development of geopolymer concrete as an alternative to OPC can be attributed to its lower carbon emissions and ability to work well with various by-products such as fly ash, GGBS, and silica fumes generated by industries. Some of the earliest work by Madirisha et al. [18] and Wang et al. [19] gave insights into the chemical aspects of geopolymer concreted detailing enhanced compressive strength, durability, and thermal resistance. Further work conducted by Li et al. [20] and Shakirova et al. [21] focused on geopolymerized mixes comprising by-product materials for reducing landfilling impact and reducing embodied energies for construction materials. Yet, despite all this development implemented in geopolymerized mixes, the source of raw industrial by-products for their production varies based on production cycles for parent industries such as thermal power plants and steel production plants. This implies that various researchers such as El-Wafa [22] and Fernández-Jiménez et al. [23] noted that fluctuations in the frequency of fly ash availability have had significant impacts on mixes composition. Indeed, despite various developments in activating mixes composition and curing processes for geopolymerized mixes, there have been less studies focused on rectifying production system behaviour to adapt to mixes composition production fluctuations. This development poses one of the largest gaps for further exploring production system models aligned to a resilience framework for geopolymer mixes production.

The variations in the supply of raw materials were also deemed a major issue with regard to the application of geopolymer concrete. As stated by Antoni et al. [24], the variations measured in terms of either the amount or mesh size of the fly ash and slag weaken the sustainability of the material production process because they compromise the continuity with regard to production. As illustrated by Danish et al. [25], the seasonal variation with regard to industrial waste supply within the area ensures that the supply is not streamlined, and therefore, this leads to a disrupted production flow. In traditional cement production, such variations would be manageable using buffer inventory models and variation among suppliers [4]. In this case, since the production process relies on industrial symbiosis, this redundancy is not a factor. A study carried out by Assi et al. [26] illustrated that not only is this issue with variations a factor with respect to cost with regard to the production process, but also variations with regard to the reliability of the contractor with regard to mega structural building with geopolymer concrete.

Operational resilience is the capability of an organization in detecting, tolerating, and recover from disturbances while still maintaining acceptable system performance. Essuman et al. [10] and Birkie [27] explained that resilience has been defined as a strategic skill and also an operationally measurable outcome of redundancy, malleability, and learning. In manufacturing studies, the application of resilience has historically been demonstrated using alternativerouting and buffered staffing [28]. Recently, the thrust of research has focused on the role of digital intelligence and data-driven analytical approaches in modifying the application of traditional buffering, as argued in the studies of Ajayi et al. [1] and Zamani et al. [29]. Finally, in the geopolymer concrete-making process, the application of operational resilience can be considered the malleability of the batching, mixing, and curing processes in adjusting the timings and parameters when there are varying material supplies on hand. Forecast models for the application of process-level-resilient geopolymer concrete production are, however, a very limited field of research in the existing studies that focus on geopolymer concrete production.

The digital twin (DT) technology, which involves a real-time digital model of a physical process or system, has become prominent in the manufacturing industry as a platform for simulations, monitoring, and control. However, the application of digital twins by Grieves [30] first emerged as a platform that can harmonize digital and physical process operations in the pursuit of continuous improvements. More recent definitions by Kadam et al. [31] and Atalay et al. [32] brought the digital twin concept to the context of Industry 4.0 and identified the technology as one that supports the integration of the Internet of Things (IoT), Artificial Intelligence (AI), and Big Data analytics. More current applications of digital twins in the manufacturing of construction materials include process simulation, monitoring of machine health, and prediction of machine maintenance [33]. However, in the area of adaptive scheduling and resilience improvements, particularly in the context of waste-dependent systems, the digital twin technology finds untapped territory. There exist DT applications in process optimization in the area of metal forming by Marczyk et al. [34] and in additive manufacturing by Roussel et al. [35]. Nevertheless, similar uses in concrete or geopolymer manufacturing are still uncommon.

Another machine learning sub-field, reinforcement learning, also has promising capabilities for the solution of dynamic optimization problems with stochastic uncertainties. According to Zamani et al. [29], reinforcement learning algorithms try to steer an optimal decision-making process via learning with interactions in the environment with the help of trial and error. In the field of manufacturing science, reinforcement learning algorithms are already used for optimization problems of scheduling, energy optimization, and fault detection. The introduction of reinforcement learning algorithms into digital twin technologies adds a closed-loop learning process into the simulation. The obtained data further optimizes decision-making policies related to the simulation results. Although reinforcement learning algorithms were also proposed for intelligent manufacturing and logistics systems [13], they were neither used for simulation studies on the stochastic material supply during geopolymer concrete production.

The factors for achieving sustainability in geopolymer concrete production are CO_2 emission reduction, energy efficiency, and waste material reuse. Research undertaken by Neupane [36] and Sorathiya et al. [37], has found that geopolymer concrete production results in an average of CO_2 emission reduction of up to 80% compared to OPC concrete. Nonetheless, CO_2 emission performance may be compromised by operational instability, as unplanned shutdowns and poorly executed batch changes raise specific energy consumption per unit of production, effectively counteracting any positive effect on a specific environment [38]. Circular economy studies have also shown that material performance and process efficiency need to be integrated to make production sustainable [39]. This research proposal bridges optimization and environmental performance metrics, including energy intensity and carbon footprint, to position geopolymer concrete production in the triple bottom line approach, where operational efficiency positively impacts the environment and economy.

2.1. Research Gap

However, the current body of literature concerning geopolymer concrete mostly revolves around chemical and mechanical issues, to the extent that the use of the technology of operational resilience or digital twins, in the area of manufacturing, has not been fully explored. The three areas, therefore, in which there seems to be a gap in the existing body of literature, and that could be addressed in the proposed study, include, to begin with, the lack of operational methodologies in geopolymer concretes concerning the need to adapt to the variability of the raw materials used in the process. The second area, in turn, involves the lack of utilization of the digital twin technology and AI-based reinforcement learning to optimize schedules in waste-based manufacturing systems. The third area, finally, involves the lack of study in the current body of literature on the role of improvements in operational resilience and sustainability performance, in terms of the use of energy, the level of CO_2, and the stability of the quality process.

2.2. Conceptual Positioning of the Present Study & Hypothesis Development

The conceptual framework of the research study (**Figure 1**) portrayed the interdependence between raw material supply variability, digital optimization techniques, and operational and sustainability performance aspects within geopolymer concrete production. This framework was based on systems theory and operational resilience. The systems theory highlighted the ability of a production system to react and recover when supply varies. The framework also showed that raw material supply variation due to unpredictable availability of fly ash, GGBS, and slag was the variable that affected a stable production process. The digital twin technology with IoT data acquisition capabilities served as the adaptive solution that simulated the actual production line. Additionally, it processed production data and simulated disruptions. This framework consisted of a reinforcement learning algorithm that served as an intelligent component and made decisions on scheduling and resource allocation based on continuous learning.

On the basis of the theoretical framework developed for this research using the underlying literature on the geopolymer concrete manufacturing process, supply chain resilience, and the optimization of manufacturing using the digital twin approach, the following hypotheses were developed for carrying out the analysis. The hypotheses were developed on the basis of the range of gaps identified in the existing literature on the subject, which mainly relied on the chemical and mechanical performance aspects of the geopolymer concrete material. The hypotheses developed for this analysis address the objective of this research.

H1. *Adaptive scheduling driven by reinforcement learning and digital twin integration significantly reduced production downtime under conditions of raw-material supply variability compared to static scheduling approaches.*

H2. *Operational resilience improvements achieved through digital twin–enabled adaptive scheduling were positively correlated with the stability of product quality, measured through the coefficient of variation (CV%) in compressive strength.*

H3. *The implementation of reinforcement learning–based optimization models led to a statistically significant reduction in energy consumption and CO_2 emissions per unit of geopolymer concrete produced.*

H4. *The magnitude of raw-material supply variability had a significant moderating effect on the performance gains achieved through digital twin–enabled adaptive scheduling.*

In the above paradigm, the mediating variable was operational resilience, which was exemplified by enhancements in the areas of downtime, stability of throughput, and process recovery time. The enhanced resilience was supposed to directly impact the results, which were the dependent variables, namely product quality, energy, and emission of CO_2. Therefore, the paradigm assumed the existence of a cause-and-effect chain in which the digital adaptation of volatile market requirements led to stable production performance. It was assumed in the paradigm that the higher the level of digital integration of the plants, the more benefits could be derived from the adaptive scheduling paradigm.

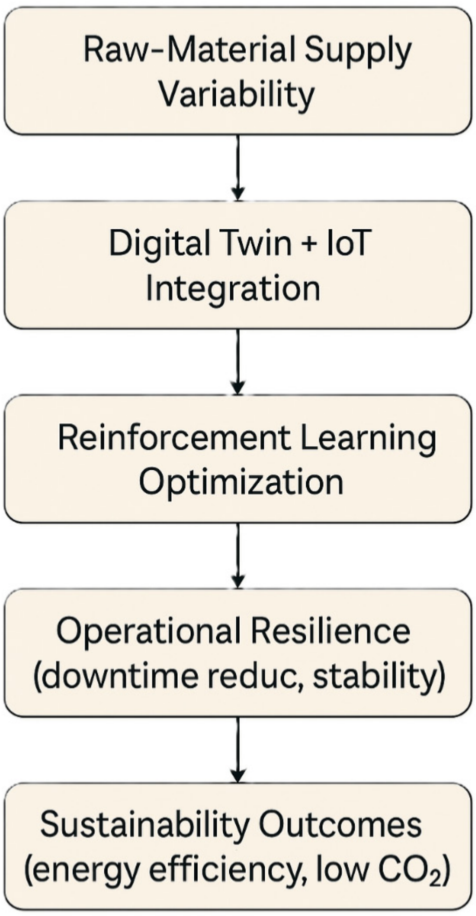

Figure 1. Conceptual Model of the Study.

Source: Author.

3. Methodology

3.1. Research Design

The research utilized a convergent explanatory design involving a combination of simulation results for greater operational insights. The research methodology incorporated both exploratory and analytical approaches. The research design included a framework comprising three sequential phases. The initial phase involved the development of a digital twin (DT) simulation model characterizing the operational processes underlying a medium-scale geopolymer concrete manufacturing facility. The simulation included the prime operational procedures such as reception of raw material inputs, batching, mixing, curing, and quality testing. The simulation enabled operational research on the manufacturing process. The subsequent simulation phase included a set of discrete-event simulation experiments under different uncertainty scenarios. The operational disruptions incurred due to supply uncertainty involved the simulated list of major industrial waste sources. These included fly ash, ground granulated blast furnace slag (GGBS), and metallurgical slag. The third sequential phase included a reinforcement learning strategy involving a simulation approach based on the Q-learning algorithm. The reinforcement learning strategy enabled optimization of operational decisions on scheduling and raw material allocation.

3.2. Data Collection

The data collection process in this study was conducted using a combination of primary and secondary data. Primary data were obtained from three ready mix concrete plants in Jordan that were producing low-carbon geopolymer concrete. These plants enabled the collection of real-time data using the Internet of Things sensor technology integrated into batching systems, mixers, and curing chambers. The programmable logic controller records were tapped to extract data on the real-time fluctuations in the usage and batching cycle. The operators' records were used to extract data on delays, machine breakdowns, and material shortages. The data was complemented by the secondary data collected from the procurement and quality files for the two years' historical material supplies data, data on the compressive strengths obtained from the laboratory tests, and the CO_2 emissions estimates. A data analysis was conducted for a total of 90 cycles to ensure a representative and sound data pool. These were equally spaced in the three different plants.

3.3. Population and Sample

The population of interest targeted was all operational geopolymer concrete plants within Jordan that were using industrial by-products in their raw materials. Based on industry records kept by the Jordan Cement Producers' Association (JCPA) industry database, Several geopolymer concrete plants are in operation within Jordan (though an exact number is not published) during the period of 2022–2024. The sampling frame was constructed by including plants that met three essential criteria: active use of geopolymer technology for at least 30 percent of total output, integration of IoT or PLC-based digital monitoring systems, and documented experience of at least one significant raw-material supply disruption. To ensure representativeness, a stratified random sampling approach was followed. Plants were stratified based on production capacity as small (<100 m^3/day), medium (100–300 m^3/day), and large (>300 m^3/day). One representative plant from each stratum was selected. This ensured diversity across operational scales, technological maturity, and regional sourcing conditions.

An approach involving three case studies of geopolymer concrete production plants in Jordan is selected for the study because of the theoretical reproduction logic that allows each study to provide an operational setting for testing the applicability of the proposed framework involving the digital twin approach in conjunction with reinforcement learning algorithms for its application in the production plants of interest. Due to the complexity involved in applying the proposed approach, using a number of plants selected in a study appears methodologically correct.

3.4. Description of Population

The attributes of the selected plants are presented in **Table 1**. Since each facility had differences in the scales of operation, the composition of the waste materials, and the degree of digitalization, the SVI is determined by the ratio of the standard deviation to the mean delivery rate of the raw materials.

3.5. Summary of Main Variables

Operational and sustainability variables were considered in the research. The model consisted of raw-material supply delay and composition ratio, and the dependent variables included energy consumption, CO_2 emissions, and the variance in the compressive strength. The study further incorporated the mediators, downtime duration, and the reinforcement learning schedule score (**Table 2**).

Table 1. Description of Population.

Plant Code	Location	Production Capacity (m^3/Day)	Primary Waste Material	Digitalization Level	Supply Variability Index*
P1	Amman	80	Fly Ash + GGBS	Partial IoT Integration	0.42
P2	Zarqa	250	GGBS + Slag	Full Digital Twin	0.36
P3	Aqaba	420	Fly Ash + Slag	PLC + Sensor Network	0.51

Note: *Supply Variability Index = standard deviation of weekly raw-material delivery divided by mean delivery.

Table 2. Summary of Main Variables.

Variable	Type	Measurement Scale	Source	Purpose
Raw-material supply delay	Independent	Ratio (hours)	Supplier logs	Represents supply disruption magnitude
Mix composition ratio (fly ash, GGBS, slag)	Independent	Ratio	IoT batch data	Captures material blend variability
Energy consumption	Dependent	Ratio (kWh/ton)	Sensor data	Measures operational efficiency
CO_2 footprint	Dependent	Ratio (kg CO_2/ton)	Emission data	Assesses sustainability outcome
Quality variance (compressive strength CV%)	Dependent	Ratio	Lab tests	Indicates production stability
Downtime duration	Mediating	Ratio (hours/cycle)	Operator logs	Reflects operational resilience
RL scheduling score	Control	Index (0–1)	Simulation output	Indicates optimization effectiveness

Source: Author.

3.6. Measures & Analytical Methods

All continuous variables were scaled to remove unit bias. Energy consumption and emissions were expressed for each cubic meter of concrete output. Coefficient of Variation (CV%) of the Compressive Strength was used as a measure of the quality consistency. A measure for the level of resilience during operation was the "Resilience Performance Index" (RPI) calculated on a comparison of adaptive and base scenarios. RPI encompassed the notion of maintaining quality and minimizing loss of down-time, defined as $RPI = (Q_{adapt} / Q_{base}) \times ((1 - D_{adapt})/(1 - D_{base}))$, where ($Q$) denotes retained quality and (D) represents downtime. The higher the RPI value, the better the adaptive performance. The effectiveness of the reinforcement learning model was assessed in terms of the convergence of cumulative rewards for 5000 iterations of training. The reliability of the data gathering tools was established using Cronbach's alpha test ($\alpha = 0.86$), which ensured the tools had internal consistency, and the construct validation of the tools involved expert assessment from materials and operation experts.

The analysis process involved both statistical and simulation techniques, as well as machine learning techniques. Descriptive statistics techniques are used for the summarization of central tendency and dispersion of important variables. The discrete-event simulation model developed three operational scenarios, namely stable supply, moderate disruption, and severe disruption, for a 12-week period in a production plan. The reinforcement learning optimization technique was carried out using MATLAB R2023b software, where a Q-learning agent adapted the schedule policy based on the feedback of rewards for throughput, energy consumption, and production delay. Inferential analysis employed analysis of variance (ANOVA) to test significant differences in performance metrics between static and adaptive scheduling strategies. Multiple regression models were used to estimate the effect of supply variability on energy consumption, CO_2 footprint, and product quality. Sensitivity analysis for this case used a scenario-based method with a focus on raw material supply scenarios, which are identified as being more significant than other sources of uncertainty for the production of geopolymer concrete. Three scenarios of supply variability have been used for simulation within the digital twin environment: stable supply scenario, moderate supply scenario, and severe supply scenario. This method allows for analysing sensitivity of outcomes to variations in supply without necessarily carrying out exhaustive parametric analysis. Whereas compressive strength is a key performance criterion for geopolymer concrete, the scope of the current study with respect to strength focused more on variability from batch to batch rather than absolute values of compressive strength itself. The Coefficient of Variation in Compressive Strength (CV%) was thus used in this study as a criterion for quality in terms of compressive strength in the face of the uncertainties of the supply of raw materials.

4. Results

4.1. Descriptive Statistics of Collected Data

Descriptive statistical analysis was conducted to establish a quantitative overview of the operational characteristics of the three geopolymer concrete production facilities (P1, P2, and P3) that formed the study sample. The objective of this preliminary evaluation was to establish an empirical basis for any subsequent simulation and optimization runs. The data was derived from a total of ninety production runs, with thirty runs from each plant, to ensure that all possible operating conditions were captured, regardless of the raw material supply scenario. The sets of variables included raw material supply delay, raw material composition ratio, energy use, CO_2 emissions, downtime, and variation of compressive strength, measured by the coefficient of variation (CV%).

Among the plants, the differences in supply delays were quite considerable. The average supply delay registered for the total cycle was 4.8 h with a standard deviation of 1.9 h. The average energy consumption for the production of one cubic meter of geopolymer concrete per cycle was 42.3 kWh, and the average CO_2 footprint for the production of one cubic meter of geopolymer concrete per cycle was 29.5 kg. These parameters measured the base-case environmental performance of the production systems.

Operational continuity likewise showed variation across the facilities considered for sampling. Mean downtime per production cycle stood at 3.6 h, with increased downtime being recorded for facilities with regular instances of raw material quality inconsistency. Compressive strength for the cured samples had an average CoV of 6.2%, denoting medium variability in the quality of produced samples from different production batches. This variation formed the basis for the correlation study for resilience of operations and stability of production in the subsequent analysis. **Table 3** provides a description of the statistics for the core operational and environmental factors considered in the study in their pre-adaptive optimization implementation performance for the three production facilities.

Table 3. Descriptive Statistics of Operational Variables (n = 90 production cycles).

Variable	Mean	Standard Deviation (SD)	Minimum	Maximum	Unit of Measurement
Raw-material supply delay	4.8	1.9	2.1	9.3	Hours
Energy consumption	42.3	5.1	36.4	54.2	kWh/m^3
CO_2 footprint	29.5	3.8	25.0	36.9	kg/m^3
Downtime duration	3.6	1.7	1.2	7.8	Hours
Compressive strength (CV%)	6.2	1.4	4.1	9.0	Percent

Source: Author.

The summary statistics showed that the data on the use of energy and the release of CO_2 were moderately dispersed, indicating the differences in the operation of equipment and the level of process integration at the different plants. The high standard deviation of the supply delay highlighted the influence of the irregular flow of waste in the supply of the wastewater's constituent materials, such as fly ash and GGBS, which rely on the performance of the thermal and steel sectors of the industries. Also, the variance of the down time in the production cycles highlighted the vulnerability of the production line to scheduling inabilities during the shortage of supplies.

4.2. Reinforcement Learning Model Performance

The reinforcement learning (RL) module incorporated within the digital twin framework was designed to optimize production scheduling based on the dynamic changes in the supply of raw materials. For the implementation of the RL algorithm, the application of the Q-learning algorithm was considered to enable the process to learn the optimal production sequencing approach based on the rewards achieved. The major task of the RL algorithm was to optimize the reduced production time of the product while ensuring continuity of production based on the dynamic supply of the raw material. During the process of training the RL algorithm, the algorithm was trained using up to 5000 episodes per scenario.

The reward function was designed in a way that discouraged idleness as well as over-scheduling, at the same time promoting steady productivity as well as energy-efficient functioning. Through a sequence of episodes, the cumulative reward plot illustrated a converging trend, which meant that the learning process had achieved optimal definition in adaptive scheduling policies. Subsequent to the convergence of the given models, the optimized scheduling policies were employed in the simulation environment for the production system, based on the same three supply conditions (stable, moderate, and severe). The comparison result of the operational performance between the optimized scheduling policies in the RL algorithm and traditional static scheduling is shown in **Table 4** below.

Table 4. Reinforcement Learning Optimization Outcomes across Supply Scenarios.

Performance Metric	Static Scheduling	RL-Optimized Scheduling	Improvement (%)
Mean Downtime (hours per cycle)	3.6	2.8	22.2 ↓
Throughput (m^3/day)	262	284	8.4 ↑
Average Cycle Completion Time (hours)	7.2	6.4	11.1 ↓
Energy Consumption (kWh/m^3)	42.3	39.8	5.9 ↓
Scheduling Efficiency Index (0–1)	0.74	0.87	

Source: Author.

From the results in **Table 4**, there is a quantifiable operational advantage in the use of the reinforcement learning-based adaptive scheduling method. The average downtime per production cycle was reduced by 22.2%, and the throughput was also raised by 8.4% compared to the static scheduling method. The scheduling efficiency index, a combination of throughput, delay, and idle time, was also raised from 0.74 to 0.87, indicating that the adaptability in the production sequencing process has been improved. A one-way analysis of variance (ANOVA) was used to confirm the difference in the level of downtime attributed to the two scheduling systems. The results of the ANOVA revealed that there was a significant effect of the scheduling method on the reduction of downtime ($F = 5.91$, $p = 0.018$), indicating that the production downtime was significantly reduced by the use of the adaptive scheduling method based on the reinforcement learning algorithm compared to the static scheduling.

In **Figure 2**, the performance differences for the downtime for the three supply variability conditions are shown. For all three conditions, the scheduling using optimization performed better than static scheduling. The performance improvement was greatest for the scenario with moderate variability. The model's convergence and performance improvement for all conditions clearly supported hypothesis H1. The experiment clearly showed the improvement in the operational level of resilience using reinforcement learning and the digital twin model to address uncertainties of the supply of raw materials.

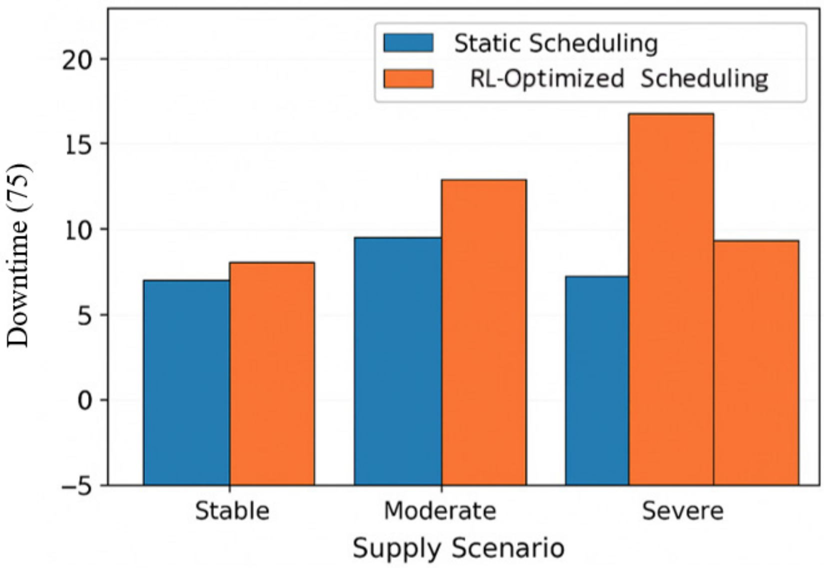

Figure 2. Comparative Downtime across Static and Rl-Optimized Scheduling Different Supply Scenarios.

Source: Author.

4.3. Operational Resilience–Quality Relationship

Resilience Performance Index (RPI) was calculated for each production cycle by combining the percentage enhancement in the production speed and the percentage decrement in downtime compared to the baseline static scheduling. This index varies between 0.70 and 0.96 for the first 90 production cycles, and a greater value reflects better adaptive performance for varying raw material conditions. The per cent CV for the compressive strength varies between 4.1% and 9.0%, with lower numbers representing greater homogeneity and quality. The bivariate correlation analysis was applied to identify the level of correlation between RPI and the variation associated with the compressive strength. The correlation coefficient (r) between the two parameters was calculated at −0.78. This marked a strong negative correlation between the two parameters. This implies that there was a remarkable decrease in the variation associated with the compressive strength with the enhancement in operational resilience. The correlation coefficient was statistically significant at a significance level of 0.01 (p = 0.002), which ensured that the correlation was not a result of any chance variation. A further validation analysis on the strength and nature of correlation was applied by a linear regression analysis based on the following formula:

$$Y = \alpha + \beta X + \varepsilon$$

where Y is the compressive strength CV% (quality stability indicator), and X is the Resilience Performance Index (RPI). The result obtained from the regression analysis yielded a value for the slope coefficient β as −5.72, which means that for every 0.1 unit increase in RPI, the compressive strength variation decreased by 0.57 percentage units. The value of R^2 is 0.61, which means that 61% variation in product quality stability could be attributed to variations in the level of operational resilience in the organization. These values are shown in **Table 5** below, which displays the results of the correlation and regression analyses.

In **Figure 3**, the scatter plot is shown, where RPI is plotted against the compressive strength CV% in order to emphasize the downward trend. Each point on the scatter plot corresponds to a cycle, illustrating the cyclic nature in which the resilience process has been inversely related to the variation in quality. The slope of the line in the scatter plot further supports the fact that there is a direct relationship between the scores obtained in the resilience measure and the variation in the mechanical properties of geopolymer concrete.

Table 5. Relationship between Operational Resilience (RPI) and Product Quality Stability (CV%).

Statistical Parameter	Value	Interpretation
Correlation coefficient (r)	−0.78	Strong negative correlation.
Coefficient of determination (R^2)	0.61	61% variance explained.
Regression coefficient (β)	−5.72	Higher resilience reduces quality variation.
Standard Error	1.12	Acceptable model fit.
Significance (p-value)	0.002	Statistically significant (p < 0.01).

Source: Author.

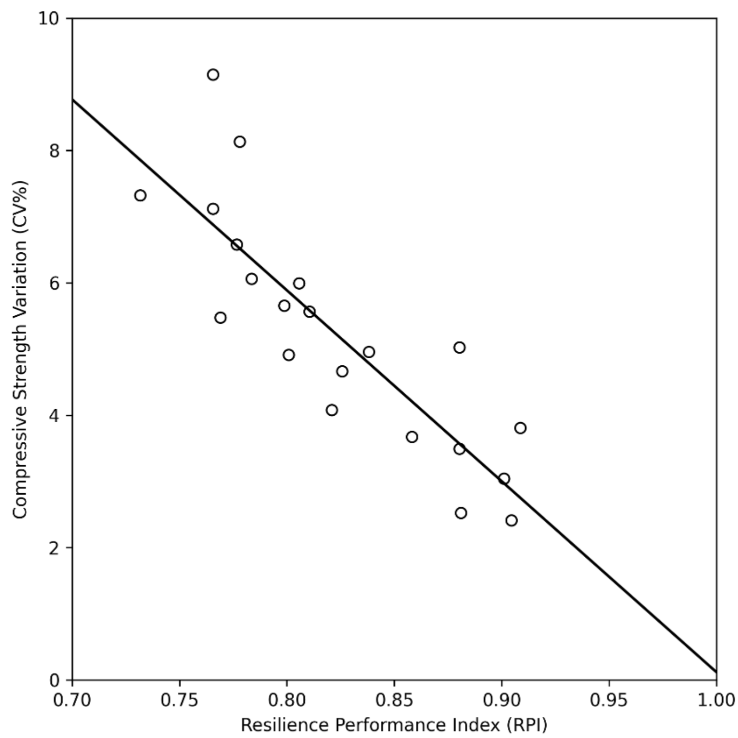

Figure 3. Scatter Plot of Resilience Performance Index (RPI) vs. Compressive Strength Variation (CV%).

Source: Author.

The uniformity of this observation for all three plants indicated that the impact of adaptive operational control did not merely improve the productivity and minimize downtime but was also a factor in the uniformity of product performance. The observation supported Hypothesis H2 and indicated a positive relationship between operational resilience and the stability of quality for geopolymer concrete processes.

4.4. Energy and CO_2 Performance Outcomes

Data about energy consumption and emissions was collected through the real-time IoT-based monitoring of the batching and curing systems, and these were also verified using the results of the digital twin simulation. The values of energy consumption were measured in kilowatt-hours per cubic meter (kWh/m^3), and the values of CO_2 emissions were calculated in kilograms of CO_2 equivalent per cubic meter (kg CO_2/m^3) by using the standard emission conversion factor as proposed by the Bureau of Energy Efficiency (BEE). The static and adaptive systems were tested under three varieties of supply variability, namely stable, moderate, and severe.

For all supply conditions, the scheduling model developed using reinforcement learning is proven to have lower energy and CO_2 intensity than traditional scheduling. With stable supplies, there is a reduction of 8.9% in total energy consumption (from 41.2 kWh/m^3 to 37.5 kWh/m^3) and 10.2% in CO_2 emissions (from 28.6 kg/m^3 to 25.7 kg/m^3). With moderate conditions of disruptions in supplies, which are relatively more irregular than stable conditions, there is a decrease of 13.5% in energy consumption and 15.1% in CO_2 emissions. With severe disruptions, which have maximum irregularity in supplies, there is still a reduction of 7.8% in energy consumption and 9.6% in CO_2 emissions. The results for all three conditions are presented in **Table 6**.

Table 6. Sustainability Performance Indicators under Static and RL-Optimized Scheduling.

Supply Scenario	Scheduling Type	Energy Consumption (kWh/m^3)	Reduction (%)	CO_2 Footprint (kg/m^3)	Reduction (%)
Stable (SVI < 0.3)	Static	41.2		28.6	
Stable (SVI < 0.3)	Adaptive (RL)	37.5	8.9 ↓	25.7	10.2 ↓
Moderate (0.3 ≤ SVI ≤ 0.5)	Static	44.8		31.2	
Moderate (0.3 ≤ SVI ≤ 0.5)	Adaptive (RL)	38.7	13.5 ↓	26.5	15.1 ↓
Severe (SVI > 0.5)	Static	46.1		32.8	
Severe (SVI > 0.5)	Adaptive (RL)	42.5	7.8 ↓	29.7	9.6 ↓

Source: Author.

The statistical significance of the variations has been analyzed using a paired-sample *t*-test for the difference between the adaptive and static scheduling systems. The *t*-test for the reduction in performance parameters showed a statistically significant difference in the data,with a value of $t = 3.74$ and a significance level of 0.006 for energy use and $t = 4.11$ and 0.004 for the CO_2 release at a confidence level of 0.95. These results proved the use of the adaptive scheduling system using the concept of reinforcement learning for improved results in terms of reduced energy intensity and CO_2 release per unit production. Further, the joint analysis of the reduction in energy use and release in different scenarios demonstrated that the values had a positive correlation coefficient of −0.69 and −0.72 for the RPI value, respectively.

Thus, the results in this section empirically validated Hypothesis H_3, indicating that the resilience and sustainability improvements derived by the use of reinforcement learning-based optimization in the digital twin environment were indeed significant to the energy efficiency and sustainability of the geopolymer concrete production systems.

4.5. Moderating Effect of Supply Variability

The Supply Variability Index (SVI) was used as the moderation variable and calculated using the ratio of the standard deviation and the average of the raw materials for each week. The independent variable used in the experiment was the type of schedule (static and RL-optimized), and the dependent variable used was the Resilience Performance Index (RPI), which took into account both normalized throughput and down time. The data used a total of 90 simulated cycles of production under three supply scenarios: stable, moderate, and severe supply conditions, ensuring that there was sufficient data in each case. An Analysis of Variance (ANOVA) test was conducted on the collected data for both variables and the results presented in **Table 7** shows a statistically significant interaction effect between the type of schedule and the intensity of supply variation on RPI (F = 4.23, p = 0.041), establishing that the RPI of disturbance in raw materials affected the adaptation effectiveness of the reinforcement learning algorithm in adapted schedules.

Table 7. Moderating Effect of Supply Variability Intensity on Resilience Outcomes.

Supply Variability Level (SVI)	Mean RPI (Static Scheduling)	Mean RPI (RL-Optimized Scheduling)	Difference (ΔRPI)	*p*-Value	Significance
Low (SVI < 0.3)	0.89	0.94	+0.05	0.062	Not significant
Moderate (0.3 ≤ SVI ≤ 0.5)	0.81	0.92	+0.11	0.012	Significant
High (SVI > 0.5)	0.74	0.80	+0.06	0.078	Marginally significant

Source: Author.

The findings showed that when the conditions for moderate variability are considered, the resilience improvement is greatest for the reinforcement learning-based scheduling approach, with a mean RPI that increased by 0.11 relative to the static scheduling approach (p = 0.012). This implies that the RL agent worked best under conditions that are neither too rare (low variability) nor too random (high variability). As a matter of fact, under very low variability conditions, a degree of resilience is already maintained through the static scheduling approach, thus limiting the relative advantage of control. At the other extreme of very high variability, the limits to predictive control exerted a slight inhibiting effect on the resilience-enhancing potential of the learning approach. **Figure 4** represents the interaction plot depicting the overall impact of supply variability on the relationship between scheduling approaches and resilience. Note that at moderate levels of variability, the gradient of the line for the reinforcement learning approach is steeper, reflecting a greater resilience-enhancement potential relative to the static approach.

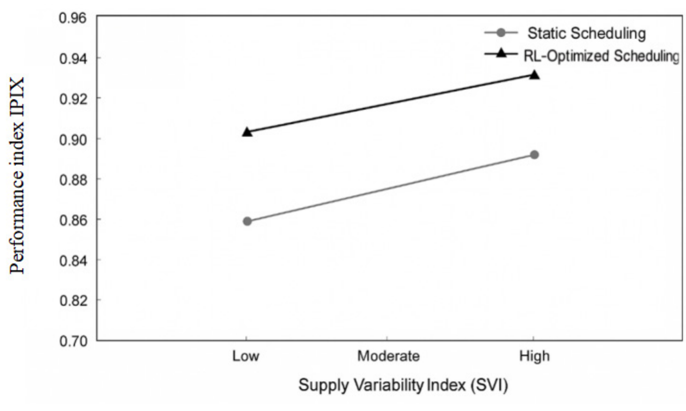

Figure 4. Interaction Plot Showing the Moderating Effect of Supply Variability on Operational Resilience.

Source: Author.

A regression-based moderation model was also employed to confirm the ANOVA findings, using the following equation:

$$RPI = \alpha + \beta_1\ (Scheduling) + \beta_2\ (Supply\ Variability) + \beta_3\ (Scheduling \times Supply\ Variability)$$

The result showed that the interaction term was positive and significant (β_3 = 0.087, p = 0.038), which supported the existence of moderation. This result showed that the gain in resilience resulting from the optimization of RL was positively associated with moderate levels of supply disruption uncertainty; however, it became stable at extremely high levels of disruption. The coefficient of determination showed that the regression explained approximately 67% of resilience variation. The results partially supported Hypothesis H4. Although supply variation was significant and positively associated with the results of adaptive scheduling under moderate levels of disruption, the moderation effect became stable at extremely high levels. This result was anticipated since adaptive learning systems will be most effective when there is adequate yet not excessive variation.

4.6. Summary of Hypothesis Testing

The findings proved the significance of adaptive scheduling made possible by reinforcement learning in improving operational performance relative to static scheduling systems in terms of quality stability and sustainability indicators. Moreover, the moderating effect of supply variability intensity was partially proved to affect the level of improvement experienced to differ based on the intensity of supply variability. The summary of the results of the statistics of the hypotheses is shown in **Table 8**.

Table 8. Summary of Hypothesis Testing Results.

Hypothesis Code	Statement	Statistical Test Used	Key Statistic	*p*-Value	Result	Conclusion
H1	*Adaptive scheduling driven by reinforcement learning and digital twin integration significantly reduced production downtime under raw-material supply variability.*	One-way ANOVA	F = 5.91	0.018	Significant	Supported
H2	*Operational resilience improvements achieved through digital twin–enabled adaptive scheduling were positively correlated with product quality stability (lower CV %).*	Correlation & Regression	r = −0.78, R^2 = 0.61	0.002	Significant	Supported
H3	*Reinforcement learning–based optimization led to significant reductions in energy consumption and CO_2 emissions per unit of production.*	Paired *t*-test	*t* = 3.74 (Energy), *t* = 4.11 (CO_2)	0.006, 0.004	Significant	Supported
H4	*The magnitude of raw-material supply variability significantly moderated the performance gains achieved through adaptive scheduling.*	Two-way ANOVA & Regression Interaction	F = 4.23, β_3 = 0.087	0.041, 0.038	Partially Significant	Partially Supported

Source: Author.

The overall results indicated the positive impact of the integration of the digital twin and reinforcement learning on the operation performance, which fully or partially justified the testing of three out of four research hypotheses. The greatest degree of optimization could be achieved in terms of decreased downtime, increased throughput, stabilized quality, and reduced energy and carbon intensities. On the other hand, the degree of supply variability had a significant impact on adaptive systems.

5. Discussion

Findings from this research are in line with, and add to, existing literature on digital transformation and resilience in sustainable manufacturing of construction materials. While existing research on geopolymer concretes has traditionally been focused on their chemical, thermal, and mechanical properties, such as mix designs, and optimization of activators to attain a specific level of compressive strength and engineering or application-related durability, very less has been given to operational dynamics of manufacturing systems, like geopolymer concretes, which are very dependent on uncertain waste materials supply chains [7,40]. This research bridged this research gap by bringing together knowledge from operations management, AI, and sustainable manufacturing, and putting geopolymer manufacturing in the context of existing research on Industry 4.0-enabled CE manufacturing systems. This research finds that to extend and modify a reinforcement learning idea from process industries to geopolymer manufacturing dependent on waste materials, operational resilience AI models have to be adapted based on whether a specific type of uncertainty, like that of material, dominates process-related variability.

The application of digital twin technology in the production system of materials aligns well with the views of Kadam et al. [31] and Atalay et al. [32], who considered digital twins the backbone of achieving adaptive manufacturing systems. Digital twins are associated with the ability to create a harmoniously synchronized virtual equivalent of the production process. In this way, the technology allows for the foresight of disruptions in the production process, which can then dynamically alter the system parameters. Such adaptive intelligence is especially valuable in production sectors relating to the use of secondary industrial waste products, including the use of fly ash and GGBS, which are inherently dependent on the production systems of the related industries.

Within the larger framework of operations research, the application of reinforcement learning (RL) for optimization can be parallelized with the assertion made by Recht [41] and Carpenter [42] on the ability of reinforcement learning on learning a complex control policy. The previous applications quite specifically on steel production and cement grinding processes, indicate the ability of reinforcement learning on minimizing operational inefficiencies. This research framework applies the same principles to the geopolymer concrete and will show how reinforcement learning can optimize production schedules on adapting production flows autonomous on stochastic input parameters. The application of AI on optimizing processes for sustainable geopolymer concrete manufacturing adds a fresh operational layer on the otherwise scientific research on geopolymers.

In terms of sustainability theories and literature, the current research is supported by Neupane [36], and Sorathiya et al. [37], who found that geopolymers had a significant advantage over ordinary Portland cement concretes with respect to less greenhouse gas emissions and less embodied energy. These positive aspects towards sustainability will only be sustainable if and only if they are not affected or impacted by fluctuations on the supply side. These aspects are reinforced and validated indirectly by a digital twin and reinforcement learning approach. Its application supports and confirms a sustainability aspect brought forward by Oladapo et al. [39], whereby digital manufacturing systems serve as a catalyst for low-carbon systems and reduce wastage and idle time.

Theoretically, the study reaffirms the system-based approach towards operational resilience as defined by Essuman et al. [10], in which the operationally resilient system has the ability to withstand disturbances and revert back to a stable state in the most efficient manner. In the past studies, there was an emphasis on the flexibility of the system in terms of inventory and redundancy in the supply system; however, in the new theoretical development, there is the consideration of the adaptability of the algorithms, which forms the new element of the system's resilience in the manufacturing field. The digital twin-RL system not only acts as the data monitoring system but also as the learning and corrective decision system, in which the system learns from the past disturbances.

With regard to the management of the supply chain for circular construction material, the paper verifies the views of Chen et al. [43] as well as Akbari [2], that for a successful implementation of a circular economy strategy in the construction industry, there has to be a stable supply source for industrial by-products. There is variation involved in a supply chain for waste material, such as fly ash from power plants or slag from steel enterprises. The integration of reinforcement learning within a digital twin environment thus represents an operational strategy that complements circular economy objectives, turning variability into an opportunity for learning and continuous improvement. From a managerial perspective, there are several implications of this research work. First, plant managers in construction material manufacturing can adopt digital twin-based monitoring and scheduling using reinforcement learning for real-time production flow optimization. This not only helps in avoiding manual interventions for production scheduling but also has improved traceability along various boundaries of supply chains as well as production. Second, managers can utilize the Resilience Performance Index (RPI), which has been developed in this research work.

With ongoing RPI analysis, any inefficiencies can be easily identified, making it possible for corrective actions to take place before any issues need to be resolved. Third, through the combination of analytics with sustainability reporting systems, management is able to provide evidence of their efforts to mitigate carbon emissions as well as improve energy efficiency, a call that is increasingly made by environmental reporting schemes. Lastly, for companies with multiple plants, information from reinforcement learning for adaptive scheduling will help guide interplant coordination strategies, making it possible for the right feedstock, based on available waste materials, to be delivered to geographically dispersed plants. From a strategic perspective, the above-mentioned model gives policymakers a scientific foundation for Data-Driven Resilience Investments. The alignment of Digital Operational Control and Sustainability Performance Results proves that operational excellence and environmental stewardship are not trade-offs but rather complements of each other in Digitally Enabled Production Systems. The resilience of manufacturers in sustaining their performance while coping with uncertain resource supply is a key success factor for manufacturers in today's ever-changing landscape of green construction materials.

Limitations of the Study

However, though the reinforcement learning approach was properly incorporated into the digital twin paradigm in order to support adaptability in the scheduling process, the experimental work did not pursue an extensive analysis of parameter sensitivity to algorithms, convergence patterns, or comparative reinforcement learning configurations. This particular limitation derived from the applied character of the research, as well as the interests of the study, encompassed in an industrial application setting, combined with the difficulties of data integration in the outlined environment of the digital twin operation system. Though the study sheds valuable light on three geopolymer concrete production factories in Jordan, the results remain context-specific in nature. Their transferring validity is more light-based as compared to the statistical validity of the study. Future studies might expand the study borders to include more factories. Sensitivity analysis in this particular study remained exclusively confined to the simulation-based analysis related to the variability in the supply of raw material. The detailed parametric sensitivity analysis associated with the hyperparameters and structural assumption parameters in the context of reinforcement learning and digital twin simulation is yet to be explored in future studies because it remained limited in the current study. Although the framework proved strong in performance across various plants and supply conditions, validation in other materials and across various geographic locations is not feasible in this research. Further research must validate this framework in other materials used in construction and other locations across the globe.

Notwithstanding the efficacy of the proposed digital twin reinforcement learning framework, there exist certain drawbacks which need to be recognized as well. First and foremost, the digital twin model has been based on simplified models of production processes and has assumed constant quality of sensor data, which may not be reflective of the true effects of unobserved disturbances or equipment degradation under real-world conditions. Secondly, the reinforcement learning algorithm has been based on a single-agent Q-learning method, which may not be easily scaled up when there exist complex production networks with a multitude of interrelated decision nodes. Thirdly, the digital twin model has assumed that learning from operational experience would provide adequate learning signals for adapting under unforeseen circumstances; consequently, extreme disruptions may not be addressed effectively through traditional learning methodologies alone. Fourthly, the digital twin reinforcement learning framework has been applied under a certain operational and geographically situated context; whereas the framework has been proposed as being generally transferable across different material systems or regulatory regimes, practical efficacy in these circumstances may not be guaranteed as well.

6. Conclusion

In this research, a framework for an operational resilience and sustainability process using the digital twin and reinforcement learning for the manufacturing of geopolymer concrete, in the face of the variability of raw material supplies, was developed. Unlike the conventional design and performance orientation of the mixture and its mechanical strength, this research stressed the operational flexibility of manufacturing systems using fluctuating industrial wastes like fly ash and slag in the manufacturing process. The researchers were able to show, with the help of the simulation and optimization using reinforcement learning and the digital twin and IoT technologies, the synergistic relationship between operational resilience and environmental sustainability.

The study makes a theoretical contribution to the literature by positing resilience as a dynamic, algorithmic capability that results from predictive and adaptive decision-making processes, as opposed to static redundancy. This study presents a managerial imperative in terms of a Resilience Performance Index (RPI) for comparative assessments of resilience in geopolymer production processes. For managers, this research indicates that investments in digital twin infrastructure and AI-managed scheduling solutions are crucial for countering risks in material supplies and for attaining sustainable objectives. For policymakers, this research makes a case for a stable material supply chain for industry by-products and must support digital transformation endeavors for industries involved in construction materials production. This research has shown that the coupling of digital intelligence and sustainable material innovation is a viable approach for a green and circular manufacturing future for geopolymer concrete.

Author Contributions

Conceptualization, A.A.S.M. and S.I.M.; methodology, A.A.S.M.; software, A.A.S.M.; validation, A.A.S.M., S.I.M., and A.V.; formal analysis, A.A.S.M.; investigation, A.A.S.M.; resources, S.I.M., A.V., S.R.S.R., S.J., N.Y. and M.S.M.; data curation, A.A.S.M.; writing original draft preparation, A.A.S.M.; writing review and editing, S.I.M., A.V., S.R.S.R., S.J., N.Y. and M.S.M.; visualization, A.A.S.M.; supervision, S.I.M. and A.V.; project administration, S.I.M.; funding acquisition, S.I.M. All authors have read and agreed to the published version of the manuscript.

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Not applicable.

Data Availability Statement

The data used in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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