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16. Abstract

This report develops an integrated framework to optimize precast concrete supply logistics under uncertain demand, variable lead times, capacity limits, and quality requirements. Four major components are addressed: a cooperative procurement policy for perishable raw materials, a curing and yard-layout optimization model to reduce pallet cycles and energy use, a two-stage stochastic delivery model for multi-project distribution, and a physics-informed neural network linking material composition and curing conditions with compressive strength. Results show reduced total system cost, improved storage efficiency, lower curing expenses, and highly accurate strength prediction. The integrated approach enhances reliability, sustainability, and cost-effectiveness for transportation-related precast operations.

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Transportation Infrastructure Precast Innovation Center (TRANS-IPIC)

University Transportation Center (UTC)

Developing a cost-effective, reliable and sustainable PC supply system under price volatility and uncertain materials supply

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FINAL REPORT

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Executive Summary:

This research project develops an integrated framework that strengthens the reliability, efficiency, and long-term durability of transportation infrastructure constructed with precast concrete components. Current industry practice treats procurement, production, curing, yard storage, and delivery as separate activities. This separation leads to waste, curing delays, inefficient yard usage, late deliveries, and variable product quality. These issues repeatedly appear in facilities such as Premier Concrete, WASKEY, and Gainey's, revealing the need for coordinated management across the entire precast supply process.

The project introduces a cooperative procurement approach that allows vendors and manufacturers to plan ordering quantities of perishable materials in a way that reduces waste, prevents shortages, and stabilizes production. This ensures that materials arrive before quality loss occurs and supports more reliable strength development in the components used for bridges, highways, and similar structures. The project also develops an optimization model that improves the arrangement of precast components on pallets and in storage yards. Many facilities currently use curing chambers and yard areas inefficiently, which raises energy costs and slows production. The proposed model identifies compact placement patterns that reduce the number of curing cycles and limit unnecessary handling. Better organization during curing and storage creates a more consistent environment for strength development and improves the readiness of components for shipment.

The delivery component of the research provides a two-stage planning model that selects suitable transportation modes and shipment schedules under uncertain demand and travel times. The results show meaningful improvements in transport cost, arrival on time, and capacity utilization. Better delivery planning helps construction firms receive components when they are needed and reduces the risk of delay in field operations. The study also develops a physics informed neural network that predicts concrete strength with high accuracy while respecting known material behavior. This tool allows managers to understand how material quality and curing conditions influence final performance and supports better decision making across procurement, production, and quality assurance.

The combined results show that treating the precast supply chain as a connected system reduces cost, improves operational reliability, strengthens yard and curing efficiency, and produces more consistent material performance, which supports transportation infrastructure that is stronger, more durable, and more sustainable throughout its service life. These findings give precast manufacturers practical advantages by enabling informed decisions about which raw materials should be ordered according to demand, and which should be stockpiled to manage uncertainty, creating a balanced inventory cycle that lowers ordering, purchasing, and holding costs. Improved production schedules, better storage strategies, and stronger delivery planning help companies respond to demand changes, reduce financial waste, and prevent delays. The physics informed neural network adds further value by providing a reliable way to predict concrete strength from mixed proportions and curing conditions, allowing managers to understand how procurement and production choices affect final quality and offering early warnings when strength development may not meet required levels. This enhances quality control, reduces the risk of rework, and ensures that delivered components meet performance expectations, thereby strengthening the ability of precast manufacturers to supply dependable and high-quality products for transportation infrastructure projects.

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1. Problem Description

The reliability and sustainability for a cost-effective transportation infrastructure are crucial in its precast concrete (PC) manufacturing, usage, and supply operations, and they are highly dependent on proper combination of scheduling and routing of resources, which encompasses the shipping of PC products to construction sites (as experienced in companies like *Gainey's, WASKEY*, and *Premier Concrete Products* in Louisiana). Reliable transportation ensures that precast concrete elements are delivered optimally on time, reducing the risk of project delays and material degradation, which can lead to costly repairs or replacements. Sustainability is enhanced by optimizing delivery routes and schedules, minimizing fuel consumption, and improving system reliability which aligns with the goals and supports long-term economic viability of infrastructure. This *Trans-IPIC/USDOT* research project emphasizes on addressing the issues of developing a cost-effective construction methodology and strategy to improve reliability and sustainability of PC distribution systems.

1.1 Problem Statement

Precast concrete plays a central role in transportation infrastructure because it reduces project duration, improves construction quality, and enhances on-site efficiency. However, the end-to-end supply chain supporting precast production remains fragmented across several independent research domains. Existing studies separately examine procurement, production scheduling, yard management, curing practices, or delivery routing, but they do not address how these stages interact and influence each other in actual precast operations. There is a clear gap of research that captures the way poor procurement timing, improper handling of materials with limited shelf life, inefficient yard layout, and uncoordinated delivery planning collectively impacts the cost, reliability, and structural performance of precast components used in transportation projects. Facilities such as Premier Concrete Products and WASKEY experience delays and losses precisely because these interdependencies are not formally modeled. Furthermore, quality prediction of precast products has not been connected to upstream supply chain decisions, and advanced tools such as Physics Informed Neural Networks have not been applied to link material characteristics, curing conditions, and resulting compressive strength. There is therefore a clear need for an integrated modeling framework that captures procurement, production, inventory, curing, yard operations, and outbound delivery under uncertainty and aligns these decisions with the strength requirements and performance needs of precast transportation infrastructure.

1.2 Alignment to TRANS-IPIC/USDOT priorities:

Developing a scalable solution that not only reduces the logistics costs associated with PC supply but also enhances reliability and sustainability, is fully aligned with the *Trans-IPIC/USDOT* general objective. Different types of raw materials can require different manufacturing (processing) times which may eventually affect the required time to transport and deliver the PC elements to the construction sites. This variability in waiting and project completion times aligns directly with the concerns of *Trans-IPIC/USDOT*. By optimizing delivery routes and vehicle utilization, this research tackles variability in manufacturing times caused by different raw materials, ensuring timely project completion and minimizing delays, which directly affects companies like *Premier Concrete Products* that struggle with lateness or earliness in 30-40% of their cases, often leading to the overutilization of their yards as internal storage for their products. Moreover, this research will consider special features and limitations not typically encountered in standard vehicle routing and scheduling problems, due to the significant scale of operations in the precast concrete industry. Since this proposal will prescribe a methodology to address issues such as raw material procurement, production scheduling, and the logistics of transporting PC products, it will certainly serve the purpose and priority of the DOT research undertakings.

1.3 Potential Impact of Research:

The potential impact of this research is significant in advancing the efficiency and sustainability of transportation infrastructure projects. By minimizing the total time spent by vehicles through optimized delivery schedules and routes, the research can reduce overall logistics costs, and fuel consumption, contributing more to sustainable economic construction practices. Additionally, by accounting for variable demand and volatile market conditions, the research can provide a resilient and adaptable supply network that meets the evolving needs of construction projects, ultimately leading to more reliable, cost-effective, and environmentally friendly infrastructure development.

2. Background

Despite the clear need for optimizing yard layout, material flow, and resource utilization in PC manufacturing facilities like Premier Concrete Products (PPP) and WASKEY in Baton Rouge, LA, there is a noticeable lack of research focused on the most economical methods for moving trucks, managing stockpiles (handling inventory, lateness/earliness), and improving overall efficiency in these specific environments. Existing literatures and PC manufacturing companies often overlook the comprehensive design of yard layouts that incorporate traffic, product placement, and operational efficiency, leaving a gap in practical recommendations for addressing bottlenecks and enhancing throughput in such transportation construction settings. Such mismanagement of yard layout and stockpiling of products incur various costs to the eventually to construction firms and DOT indirectly.

Recent research has focused on developing vehicle routes in vehicle routing problems with additional constraints. Hertz et al. (2012) emphasize routing and vehicle constraints in their study of concrete delivery problem (CDP), proposing a mixed-integer programming (MIP) model and a heuristic decomposition into assignment and routing subproblems. Asbach et al. (2009) extended this work by defining the problem as NP-Hard (Non-deterministically polynomial Hard) through reduction to the Euclidean travelling salesman problem (TSP) and suggesting a heuristic solution. Silva et al. (2005) shifted the focus to production centers, using a Genetic Algorithm to assign customer orders, while Naso et al. (2007) add more constraints. The challenge arises with multiple orders in a single day (Tzanetos and Blondin, 2023). In the light of logistics, very a few research have addressed minimization of routing costs, handling, and pickup costs near the vehicle at several places, late and early arrival costs with penalty costs for customers whose demand is not fully satisfied with the required number of vehicles used to make deliveries of precast concrete in single study.

There are other recent studies that have increasingly focused on enhancing scheduling strategies for precast concrete production by addressing uncertainty, demand variability, and real-time disruptions through advanced modeling and optimization techniques. Wang et al. (2018), and Wang and Hu (2018) addressed uncertainties and demand variability in precast production environments using simulation and dynamic rescheduling models. Their work demonstrated significant improvements in scheduling responsiveness, particularly under real-world disturbances. Similarly, Du et al. (2020) and Kim et al. (2020) developed dynamic models to accommodate fluctuations in order volume and due dates.

Other researchers have also made notable contributions to the field. To mention a few, Kong et al. (2017) optimized single-machine batch scheduling for precast construction, demonstrating that minimizing setup times and aligning workflows with due dates reduces delays. Ma et al. (2018) addressed rescheduling challenges in multi-line production of precast components, showing that stability in production lines enhances workflow continuity. Demiralp et al. (2012) analyzed the benefits of RFID technology in construction supply chains, highlighting its role in improving transparency and reducing coordination costs. Anvari et al. (2016) developed a multi-objective genetic algorithm for optimizing manufacturing, transportation, and assembly in precast construction, balancing trade-offs to reduce lead times and costs. Du et al. (2019) developed an innovative ontology and multi-agent framework for optimizing decision-making in prefabricated component supply chains, validated through a real-world case study. Altaf et al. (2018) designed a production planning system for panelized homes using RFID and simulation-based optimization, demonstrating that real-time data integration improves scheduling accuracy. Hsu et al. (2018) proposed a multi-stage stochastic programming model for modular construction logistics, showing that proactive planning for uncertainties minimizes costs. Wang and Hu (2017) improved precast production scheduling by integrating supply chain stages, reducing idle times, and improving on-time delivery. These studies collectively advance the field by addressing key challenges in construction and off-site manufacturing through innovative methodologies and optimization techniques.

Most studies address production scheduling, routing, or inventory separately and do not consider how procurement timing, material quality, yard layout, curing, and delivery collectively affect cost, timelines, and structural performance. Evidence from facilities such as Premier Concrete Products and WASKEY shows that inefficiencies in purchasing, storage, yard operations, and scheduling often accumulate across stages. The perishability of raw materials and their impact on concrete strength is also overlooked in existing models. Outbound delivery studies remain fragmented, with little work integrating penalties, uncertainty, load assignment, and vehicle constraints. No research applies Physics Informed Neural Networks to link material properties and curing with strength outcomes. Therefore, a major gap remains in understanding the interconnected and time-sensitive nature of precast concrete supply chains for transportation infrastructures. Existing studies do not integrate procurement, production, curing, yard operations, storage, and delivery into one comprehensive optimization framework, even though these stages strongly influence one another. Current research also does not consider perishable raw materials or examine how procurement timing affects the ultimate strength and quality of the manufactured precast components. Yard storage, crane accessibility, and internal truck movement within precast facilities are largely ignored, despite their significant effect on loading time, product flow, and delivery readiness in real facilities. Outbound delivery models rarely combine early and late penalties, demand shortfalls, travel time uncertainty, load assignment, and vehicle capacity constraints, which limit their relevance for transportation projects. Moreover, there is no application of Physics Informed Neural Networks to connect procured material quality and curing conditions with concrete compressive strength, leaving prediction disconnected from supply chain decisions.

3. Research Scope and Objectives

This research will address five major areas that remain unexamined in the existing precast concrete literature. It will first integrate procurement, production, curing, yard operations, storage, and outbound delivery into a single framework to capture how decisions in one stage affect all others. It will also examine the role of perishable raw materials by incorporating their limited shelf life into procurement planning and evaluating how timing influences the final strength of precast components. In addition, the study will analyze yard layout, storage placement, crane accessibility, and internal vehicle movement to understand their impact on loading efficiency and product flow. The work will also combine early and late penalties, demand shortfalls, travel time variability, load assignment, and vehicle capacity constraints into a comprehensive delivery-planning approach. Finally, it will apply a Physics Informed Neural Network to connect procured material quality and curing conditions with resulting compressive strength so that predictive insights can guide decisions across the supply chain.

Research Goal 1: To incorporate the perishability of raw materials into procurement planning and evaluate how procurement timing affects the strength and quality of manufactured precast components.

Research Goal 2: To optimize yard storage, crane access, and internal vehicle movement to improve product flow, reduce delays, and support timely delivery of precast components.

Research Goal 3: To develop a delivery model that integrates early and late penalties, demand shortfalls, travel time uncertainty, load assignment, and vehicle capacities for improved delivery performance in transportation projects.

Research Goal 4: To develop a Physics Informed Neural Network that links procured material quality and curing conditions with compressive strength to support decision-making across the precast supply chain.

4. Research Description

Efficient logistics and delivery systems for PC components are critical for successful road and highway construction projects, significantly influencing overall project reliability, sustainability, and cost-efficiency. A proper process flow mapping approach is required to represent a systematic framework for analyzing logistical processes, spanning from procurement planning to the final delivery at construction sites.

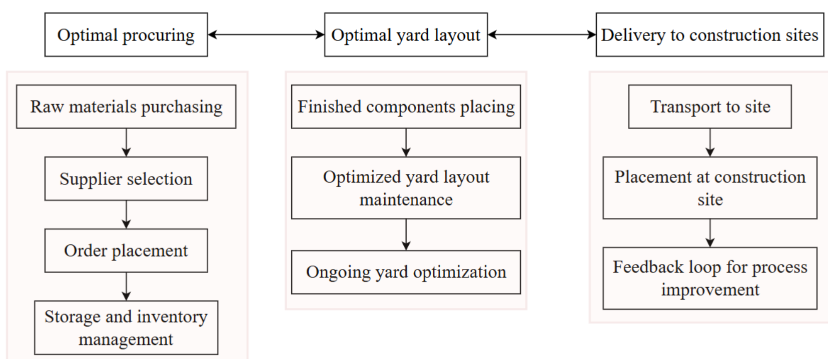


Figure 4.1. Activity flow for PC shipments to construction sites

Figure 1 highlights three stages, procurement, yard layout, and delivery where optimization ensures consistent material quality, proper curing, and timely placement. Consideration of these 3 signifucant factors can reduce delays and enhances the durability and long-term performance of precast roads and highways. However, according to the previously stated goals, this section will represent the detailed description of these research segments sequentially.

4.1 Research Goal (RG) 1:

This *research aims* at designing a penalty-based vendor-manufacturer contractual framework that optimizes perishability-conscious inventory policies under stochastic demand and lead times, models cost-risk trade-offs between parties and validates the system through real-world case studies to demonstrate joint cost savings and waste reduction in precast construction. Specifically, *the research objective* is to determine the optimal ordering quantities by developing an optimal vendor-manufacturer cooperative inventory policy for perishable precast raw materials under stochastic demand and variable lead times. By developing and implementing an optimal cooperative inventory policy, the vendor–manufacturer system can lower total costs, reduce waste, improve delivery reliability, and share operational risks, all while adapting to demand and lead time uncertainties leading to both economic and sustainability benefits in today's competitive precast concrete industry.

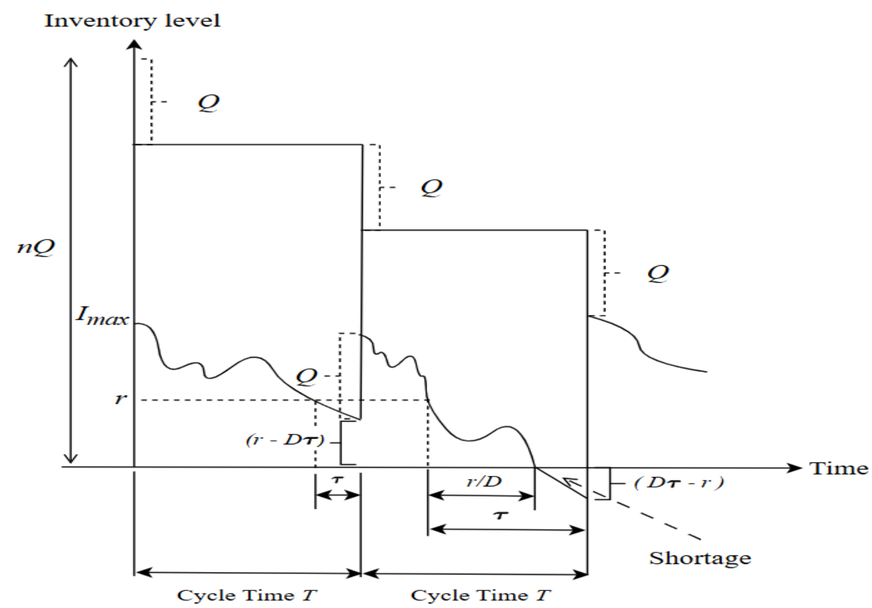


Figure 4.2. Integrated inventory system for a precast manufacturer and a material vendor

Figure 4.2 illustrates the operation of an integrated vendor–manufacturer inventory system for perishable precast raw materials when demand is probabilistic and follows a known distribution rather than being constant. The vertical axis represents the inventory level at the manufacturer, while the horizontal axis shows time across successive replenishment cycles. Each cycle begins with the arrival of an order quantity Q from the vendor, raising stock from the reorder point r up to Q, or from zero to nQ in the vendor's full lot. Because demand varies randomly over time, the inventory depletion curve is irregular, and shortages can occur during the lead time τ if actual demand exceeds the expected consumption between ordering and delivery. The current study integrates vendor and manufacturer decisions so that Q, r, and n are jointly optimized to minimize total system costs, including ordering, holding, perishability losses, shortage penalties, and late-delivery costs. This is particularly critical in precast manufacturing, where overstocking increases expiry risk for materials like admixtures, epoxies, and grouts, and understocking disrupts production schedules, making coordinated, data-driven ordering essential for both cost efficiency and service reliability.

If the precast material vendor and the manufacturer agree to cooperate with their inventory to minimize the total annual cost $TC_m(Q,r)$ and $TC_v(Q,n)$ respectively. The total annual cost for this integrated inventory policy, $TC(Q,r,n)$ as follows:

$TC(Q,r,n) = TC_m(Q,r) + TC_v(Q,n)$ which reduces to

$$\begin{aligned}
TC(Q,r,n) = {} & \frac{\int_{d_1}^{d_2} Dg(D)dD}{Q}\left(A_m + \frac{A_v}{n}\right) + \frac{(n-1)Qh_v}{2} \\
& + \frac{h_m}{Q}\int_a^{min(b,T_s)}\left[\int_{d_1}^{r/b} \tau\left(r - \frac{D\tau}{2}\right) g(D)dD\right] f(\tau)d\tau \\
& + \frac{r^2 h_m}{2Q}\int_a^{min(b,T_s)} f(\tau)d\tau + \frac{h_m}{2Q}\int_a^{min(b,T_s)}\left[\int_{d_1}^{d_2}(Q - D\tau)^2 g(D)dD\right] f(\tau)d\tau \\
& + \frac{rh_m}{Q}\int_a^{min(b,T_s)}\left[\int_{d_1}^{d_2}(Q - D\tau) g(D)dD\right] f(\tau)d\tau + \lambda\left[Q\int_{T_s}^{b} f(\tau)d\tau\right] \\
& + \frac{\pi}{2Q}\int_{min\left(b,\frac{r}{D}\right)}^{T_s}(D\tau - r)^2 f(\tau)d\tau + p_0\int_{d_1}^{d_2} D\, g(D)dD \int_0^{T_s}\left[1 - e^{-\beta t}\right]dt \\
& + \frac{c_p}{Q}\int_{d_1}^{d_2}\left[\int_{min(b,\alpha r/d_2)}^{min(b,T_s)}\left(\tau - \frac{\alpha r}{D}\right) f(\tau)d\tau\right. \\
& \left. + (1+k)\int_{max(\alpha r/d_1,T_s)}^{b}\left(\tau - \frac{\alpha r}{D}\right) f(\tau)d\tau\right] Dg(D)dD \qquad (4.1)
\end{aligned}$$

Multiple theorems have been developed to apply this cooperative policy and also to minimize the nonlinear total cost function $TC(Q,r,n)$ by proving its convexity and finding the optimal solutions for ordering quantity, safety stock and number of shipments. These algorithms are given following:

Theorem 4.1. If the delivery lot arrives beyond the shelf-life for a specific precast material, T_s, the material vendor, not the manufacturer, bears the maximum cost burden.

Theorem 4.2. If $b < T_s$, then

(i) $TC(Q,r,n)$ is strictly convex in n for given Q and r

(ii) $TC(Q,r,n)$ is strictly convex in Q and r for given n.

Theorem 4.3. If $T_s > b$, D is constant and $\beta = 0$ then, $TC(Q,r,n)$ in Equation (4.1) is reduced to the model described by Hossain *et al.* (2017).

Theorem 4.4. If Theorem 4.2 holds, then the optimal values of Q, r and n are obtained from the following equations:

(i) $$Q = \sqrt{\frac{2[N]}{(n-1)h_v + h_m \int_a^{min(b,T_s)} \int_{d_1}^{d_2} g(D)dDf(\tau)d\tau + 2\lambda \int_{T_s}^{b} f(\tau)d\tau}} \quad (4.2)$$

where,

$$N = \int_{d_1}^{d_2} D\, g(D)dD \left(A_m + \frac{A_v}{n}\right) + h_m \int_a^{min(b,T_s)} \left[\int_{d_1}^{r/b} \tau \left(r - \frac{D\tau}{2}\right) g(D)dD\right] f(\tau)d\tau$$
$$+ \frac{r^2 h_m}{2} \int_a^{min(b,T_s)} f(\tau)d\tau + \frac{h_m}{2} \int_a^{min(b,T_s)} \int_{d_1}^{d_2} D^2\tau^2 g(D)dD\, f(\tau)d\tau$$
$$- r h_m \int_a^{min(b,T_s)} \int_{d_1}^{d_2} D\tau g(D)dD\, f(\tau)d\tau + \frac{\pi}{2} \int_{min\left(b,\frac{r}{D}\right)}^{T_s} (D\tau - r)^2 f(\tau)d\tau$$
$$+ c_p \int_{d_1}^{d_2} \left[\int_{min(b,\alpha r/d_2)}^{min(b,T_s)} \left(\tau - \frac{\alpha r}{D}\right) f(\tau)d\tau + (1+k)\int_{max(\alpha r/d_1,T_s)}^{b} \left(\tau - \frac{\alpha r}{D}\right) f(\tau)d\tau\right] Dg(D)dD \quad (4.3)$$

(ii) $$r\left(h_m \int_a^{min(b,T_s)} f(\tau)d\tau + \int_{min\left(b,\frac{r}{D}\right)}^{T_s} f(\tau)d\tau\right) = -h_m \int_a^{min(b,T_s)} \int_{d_1}^{d_2} \tau g(D)dDf(\tau)d\tau +$$
$$h_m \int_a^{min(b,T_s)} \int_{d_1}^{d_2} D\tau g(D)dDf(\tau)d\tau$$
$$+ \lambda Q^2 \int_{T_s}^{b} \delta(Q - D\tau) g(D) f(\tau)dDd\tau + \pi \int_{min\left(b,\frac{r}{D}\right)}^{T_s} D\tau f(\tau)d\tau$$
$$+ \alpha c_p \int_{d_1}^{d_2} \left[\int_{min(b,\alpha r/d_2)}^{min(b,T_s)} f(\tau)d\tau + (1+k)\int_{max(\alpha r/d_1,T_s)}^{b} f(\tau)d\tau\right] Dg(D)dD \quad (4.4)$$

(iii) $$n = \frac{1}{Q}\sqrt{\frac{2A_v \int_{d_1}^{d_2} Dg(D)dD}{h_v}} \quad (4.5)$$

The Equations in Theorem 4.4 are intrinsic in Q, r and n and therefore it is impossible to derive a closed-form solution for each of them. Hence, to determine the optimal solutions, an iterative algorithm is followed below as a part of the solution methodology which was developed by Das Roy and Sarker (2021).

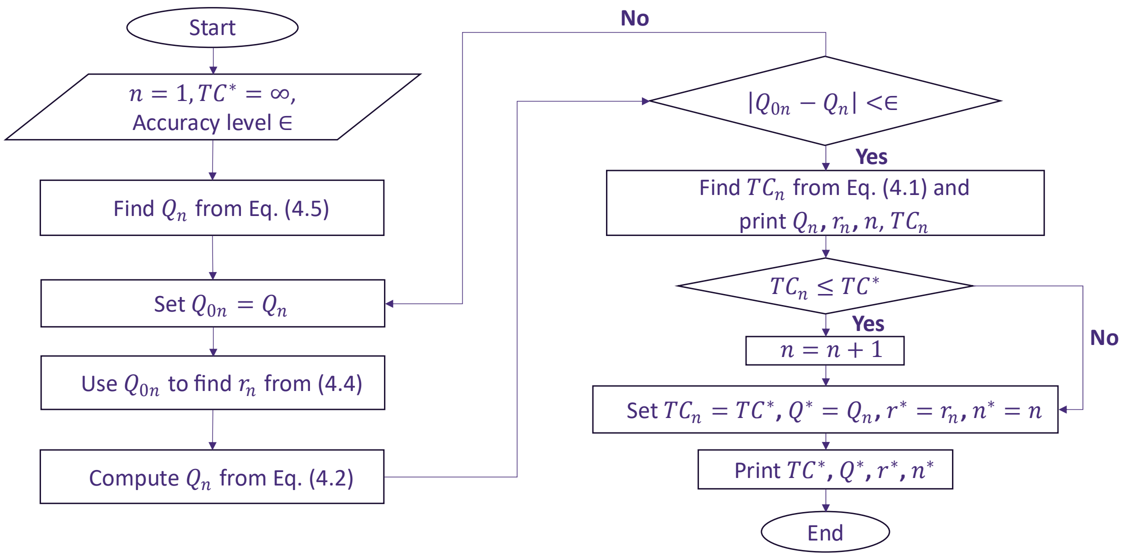


Figure 4.3. Iterative Algorithm

Here, (Q^*, r^*, n^*) is global optimum solution for the integrated precast inventory system. This theoretical solution approach presented here proves a general method to determine the optimal solution to the integrated problem of single precast material vendor and single precast manufacturer wherein the demand is probabilistically distributed, and shelf-life of the materials are also considered.

4.1.1 Application to Precast Material Inventory:

A precast manufacturing facility is considered which manufactures several types of components by using precast concrete (PC) for multiple construction projects of roads, highways, interstates, etc. in the US. To manufacture the components, this manufacturer orders PPC (Portland Pozzolana Cement) from a vendor for which the delivery lead time follows a uniform distribution such as $\tau \sim U(7{,}28)$ days. Moreover, the demand for this PPC follows an exponential distribution with scale θ, limited to values between 2500 and 4400 tons/year, based on the required manufacturing quantity of different PC components for multiple construction projects. Therefore, we have used a truncated exponential to model demand $g(D|\theta) = \frac{\frac{1}{50}e^{-(D-2500)/\theta}}{e^{-2500/\theta} - e^{-4400/\theta}}$ because in precast manufacturing small batch demands are far more common than very large orders and cutting off (truncating) at $[d_1, d_2]$ enforces the real minimum and maximum sizes the plant can handle while still keeping the formula eligible enough (Al-Athari, 2008). So, for $\theta = 50$,

$$g(D|50) = \begin{cases} \frac{1}{50} e^{-(D-2500)/50} \left(1 - e^{-(4400-2500)/50}\right)^{-1}, & 2500 \leq D \leq 4400 \\ 0, & \text{otherwise} \end{cases} \quad (4.6)$$

The mean of this truncated exponential distribution (4.14), say $\mu(50)$, can be found from the following equation:

$$\mu(50) = 2500 + 50 - \frac{(4400-2500)e^{-(4400-2500)/50}}{1-e^{-(4400-2500)/50}} \quad (4.7)$$

The other parametric values for this system are given in Table 4.1.

Table 4.1. Values for the system parameters

Parameter	**Description**	**Value**
A_m	Manufacturer ordering cost per cycle ($/order)	1000
A_v	Vendor ordering cost per cycle ($/order)	3400
h_m	Manufacturer's holding cost per unit per cycle ($/ton/year)	80
h_v	Vendor's holding cost per unit per cycle ($/ton/year)	40
λ	Perishability cost per unit i.e., shelf-life expiration ($/ton/year)	65
π	Back ordering cost per unit short ($/ton/year)	70
c_p	Penalty cost per unit for delayed or perished product	6190
α	Penalty time-scaling factor ($/year)	0.75
k	Additional penalty multiplier beyond shelf-life	0.80
p_0	Revenue loss per unit of unmet demand ($/ton)	500
β	Revenue decay rate due to delay (1/year)	0.03
d_1	Lower bound of demand distribution (ton/year)	2500
d_2	Upper bound of demand distribution (ton/year)	4400
a	Minimum lead time (year)	0.02≈7 days
b	Maximum lead time (year)	0.08≈28 days
T_s	Shelf-life of raw material (in years ≈ 5.5 months)	0.46≈5.5 months

Table 4.2 shows that $n = 2$ provides with the lower total cost for both the precast manufacturer and the vendor than for $n = 1$ and $n = 3$. Therefore, the global optimal solution was found at the point $(Q_n, r_n) = (Q_2, r_2)$. The global optimal values for ordering and reorder quantity with number of shipments are $Q^* = 364$ tons of PPC, $r^* = 284$ tons of PPC and $n^* = 2$, respectively.

Table 4.2. Local optimal solutions (Uniform lead time and Exponential demand)

n (Shipments)	Q_n (tons of PPC)	r_n (tons of PPC)	TC ($/year)
1	554	283	60,849.74
2	**364**	**284**	**60,186.94**
3	285	284	62,124.08

Here, if we calculate the value of the determinant of hessian matrix,

$H\langle Q,r\rangle = \begin{bmatrix} \frac{\partial^2 TC}{\partial Q^2} & \frac{\partial^2 TC}{\partial Q \partial r} \\ \frac{\partial^2 TC}{\partial r \partial Q} & \frac{\partial^2 TC}{\partial r^2} \end{bmatrix}$ then we find $\frac{\partial^2 TC}{\partial Q^2} =$ 0.74, $\frac{\partial^2 TC}{\partial r^2} =$ 0.11, $\frac{\partial^2 TC}{\partial Q \partial r} = \frac{\partial^2 TC}{\partial r \partial Q} =$ -0.17 at stationary point $({Q_2}^*, {r_2}^*)$. Therefore, $|H|_{({Q_2}^*,{r_2}^*)} = 0.74 \times 0.11 - 0.17^2 = 0.0525 > 0$. Hence, the hessian matrix is positive definite at this point, indicating the point with the lowest cost. This calculation was performed using Python on a computer with an 11th Gen *Intel(R) Core (TM) i7-11700 CPU@2.50 GHz* processor and 16 GB installed RAM with a CPU (Central Processing Unit) time 9.26s (approximately).

4.2 Research Goal (RG) 2:

The *goal of this research* is to develop a new layout optimization plan for arranging components on pallets during the curing process, which is crucial for the efficiency of precast production, by integrating adaptive elements that adjust to fluctuations in demand and resource constraints, ensuring a more efficient, reliable, and cost-effective manufacturing process. The *specific objective of this study* is to minimize the curing cost by maximizing the average utilization rate of pallet capacity e.g., area, space etc.

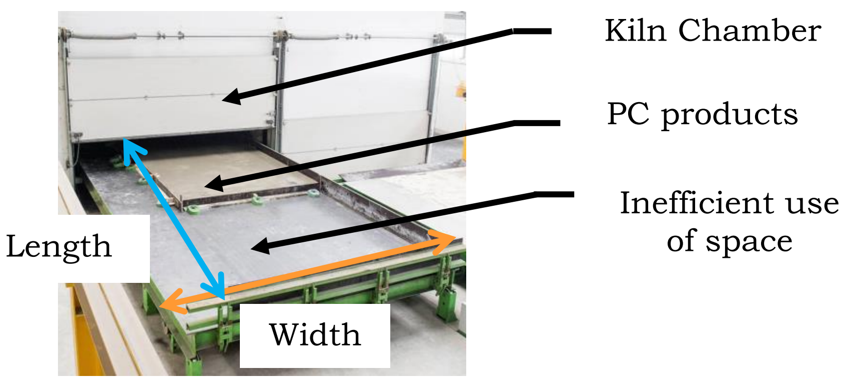


Figure 4.4. Mold placement on a pallet in curing process

The cost of precast concrete curing using pallets in the US varies widely depending on the project's complexity and the type of concrete used. A general estimate for precast concrete ranges from $375 to $1,300 per cubic yard, with simpler structures costing less. Pallet-based curing, which involves using pallets to raise precast concrete panels off the ground during the curing process, can add a cost of around $500 per pallet, depending on the size and material of the pallet. In projects related to transportation infrastructures, manufacturing PC components efficiently is crucial for constructing roads and bridges on time and within budget for which the curing process of PC components significantly affects the efficiency and cost of production.

In most PC production shops, a single component is placed on a pallet in the curing chamber which causes high energy consumption and labor costs during the curing stage and increases overall expenses. Thus, not using pallet space efficiently during this stage can lead to a higher number of pallets being used this situation will take longer to cure the products, resulting in delays and waste of resource time. Different layouts for PC component placements may yield different configurations on the pallet, resulting in different numbers of components being accommodated in a pallet. Therefore, by fitting more components on a pallet and subsequently into the kiln chamber once, costs and resource use per component can be reduced to boost production efficiency.

4.2.1 Model Formulation:

The objective function of this curing cost minimization (CCM) model is designed to minimize the total cost (Z_c) of placing precast concrete components on pallets for curing, while also satisfying various production and layout constraints. The cost function (4.8) being minimized includes the energy used for curing the concrete in kilns and the labor involved in loading and unloading these components.

CCM: $\boldsymbol{Min\, Z_c} = \sum_{o\in O}\sum_{j\in J}\left(\frac{T_c E^c}{b}\right) n_{jo} + \sum_{o\in O}\sum_{j\in J}\sum_{i\in I}\sum_{k\in K_i}(c_L t_L) z_{ikjo}$ (4.8)

$z_{ikjo} = n_{jo} x_{ikjo} \geq 0$

$\sum_{j\in J} n_{jo} \leq b$

$\sum_{i\in I}\sum_{k\in K_i} q_i x_{ikjo} \leq Q^{max} y_{jo}$

$\sum_{o\in O}\sum_{j\in J}\sum_{k\in K_i} z_{ikjo} \geq D_i$

For each pair $(p,q) \in \varepsilon_{jo}$,

$s^H_{ikjo} + s^V_{ikjo} = 1$

$X_{p,jo} + w_{p,jo} + d \leq X_{q,jo} + M^x_{pq}(1 - u_{pq,jo}) + M^x_{pq}(1 - s^H_{pq,jo}) + \bar{M}(2 - x_{p,jo} - x_{q,jo})$

$X_{q,jo} + w_{q,jo} + d \leq X_{p,jo} + M^x_{pq} u_{pq,jo} + M^x_{pq}(1 - s^H_{pq,jo}) + \bar{M}(2 - x_{p,jo} - x_{q,jo})$

$Y_{p,jo} + l_{p,jo} + d \leq Y_{q,jo} + M^y_{pq}(1 - s^V_{pq,jo}) + \bar{M}(2 - x_{p,jo} - x_{q,jo})$

$Y_{q,jo} + l_{q,jo} + d \leq Y_{p,jo} + M^y_{pq}(1 - s^V_{pq,jo}) + \bar{M}(2 - x_{p,jo} - x_{q,jo})$

The optimization procedure works by gradually building a library of feasible pallet layouts and letting the model choose how many times each layout should be used across production cycles. Each layout is treated as a pattern that contains a precise geometric arrangement of component copies. Every pattern respect pallet dimension, spacing, rotation options, non-overlap rules, knapsack weight limits, and per pallet mold limits. Because each pattern contains actual coordinates, selecting a pattern in the plan directly corresponds to a real pallet layout that can be produced on the shop floor. The model starts with a small set of simple seed patterns so that the master problem is always feasible. A linear program is then solved to decide how the current set of patterns should be allocated across production cycles. The LP includes slack variables for each component type, weighted by type specific penalties that become active whenever demand is not fully satisfied. These large penalties enforce the idea that unmet demand should be eliminated in later rounds. The LP also enforces per cycle kiln car limits and cycle level knapsack budgets, meaning each cycle can only hold a certain number of pallets and a certain total weight.

The dual values obtained from the LP solution play a key role in guiding the search for new layouts. They show which types are most expensive to leave unmet and which cycles have tight capacity or budget pressures. Using these duals, the algorithm ranks component types by their attractiveness for inclusion in new patterns. This ranking is adjusted so that items with large area or small impact do not dominate the layout generation process, and so that types with high slack are pulled forward. Several type orders are then constructed, some of which explicitly prioritize items that the LP is failing to cover. For each candidate order, a geometric placement routine attempts to build a new pallet layout. The placement follows a bottom left style rule and tests both orientations of each item while checking overlap and boundary feasibility. If a feasible layout is found, its reduced cost is computed by combining the cycle cost share, the labor term, the knapsack weight, and the dual contributions of the included component types. A layout with negatively reduced cost improves the LP objective and is added as a new pattern. In cases where a pattern helps serve highly underserved types, small positive reduced costs can also be accepted so that the master gains diversity where it needs it most. This loop between solving the master LP and generating new patterns continues until all component demands can be satisfied without using slack. At that point the model has discovered enough useful layouts to cover the entire demand within the operational limits. The last stage replaces the LP with an integer program that fixes the number of pallets of each pattern to be whole numbers. This integer solve uses the same constraints and slack penalties as the LP. Because all layouts have already been validated geometrically during generation, the integer solution directly corresponds to a practical and implementable production schedule.

4.2.2 Solution Approach:

The solution approach begins by preparing the initial data and creating a basic set of feasible pallet layouts called seed patterns. These seed patterns ensure that the optimization process starts with at least one valid way to place each component type on a pallet. Once the initial patterns are created, a restricted master problem is formed. This master problem decides how many times each known pattern should be used across production cycles while enforcing demand requirements, kiln limits, and weight budgets. At this stage, unmet demand is permitted but heavily penalized so that the model is driven to eliminate it in later steps.

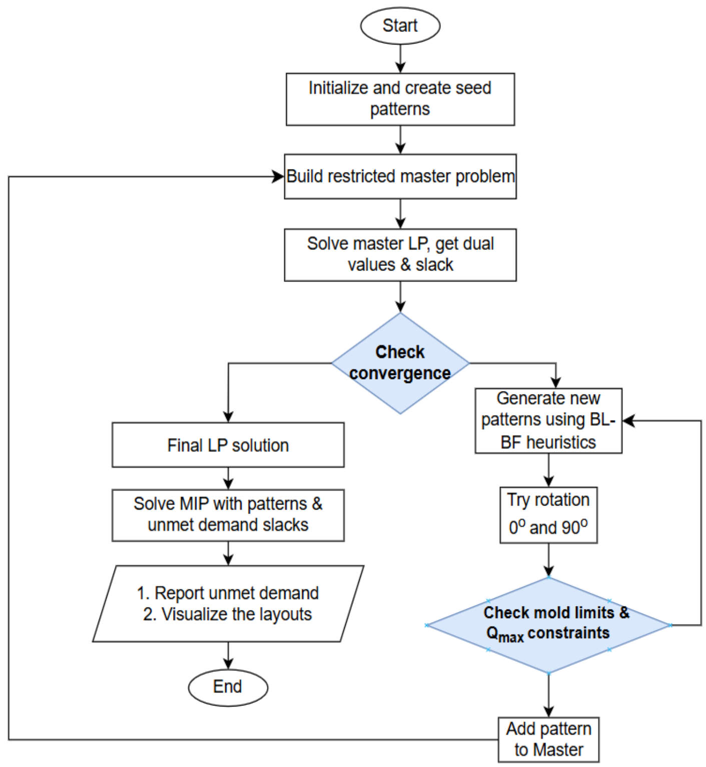


Figure 4.5. Algorithm CCM

The master linear program is then solved. From this solution, two pieces of information are extracted: dual values and slack. Dual values reveal which component types are most valuable to include in new layouts and which cycles are under pressure from capacity or budget constraints. Slack identifies which demand requirements are still not covered by the current set of patterns. These results are used to check whether the algorithm has converged. Convergence occurs when all demands can be satisfied without using slack, meaning the existing patterns are sufficient for a feasible solution. If convergence has not been reached, the algorithm generates new patterns using a bottom left and best fit placement heuristic. The heuristic tries to place items according to orders guided by the dual values. Each item is tested in both its original and rotated orientation to increase the chance of fitting efficiently in the pallet space. Every candidate layout is checked against mold limits and knapsack constraints to ensure it is physically and operationally valid. When a pattern meets all requirements, it is added to the master problem as a new column. The process then returns to the master LP step, allowing the expanded pattern library to improve the solution. Once the procedure identifies that no further slack remains, the final LP solution is accepted. At this point, a mixed integer program is solved using the full set of generated patterns. This step produces exact integer counts for how many times each pattern should be used, ensuring that the final plan is implementable in the actual production environment. The algorithm then reports any remaining unmet demand and provides visualizations of the selected pallet layouts. This final output enables planners to see both the quantitative results and the physical arrangement of components on each pallet.

4.3 Research Goal (RG) 3:

The *goal* of this section is to develop an optimal policy for precast concrete manufacturing companies that minimizes total costs including raw material procurement, mold usage and production, curing, and inbound/outbound transportation while meeting the diverse demands for multiple products to satisfy multiple customers. To achieve this broader goal, the specific *research objective* is to determine the optimal ordering quantity for multiple raw materials, the optimal manufacturing quantity, and the optimal quantity of precast products to be transported from the production area to internal and/or external storage, and subsequently to construction sites for a precast concrete manufacturing facility. A precast concrete (PC) manufacturing company is responsible for producing different types of PC products that are supplied to various construction sites. The manufacturing process begins with the procurement of multiple raw materials required for producing PC products. These raw materials may include cement, sand, gravel, additives, and other essential components. Upon procurement, they are stored in a raw materials inventory until they are needed for production. In the production stage, raw materials are combined in specific proportions to manufacture different types of precast concrete products. The composition and quantity of raw materials used depend on the type and structural requirements of the PC products.

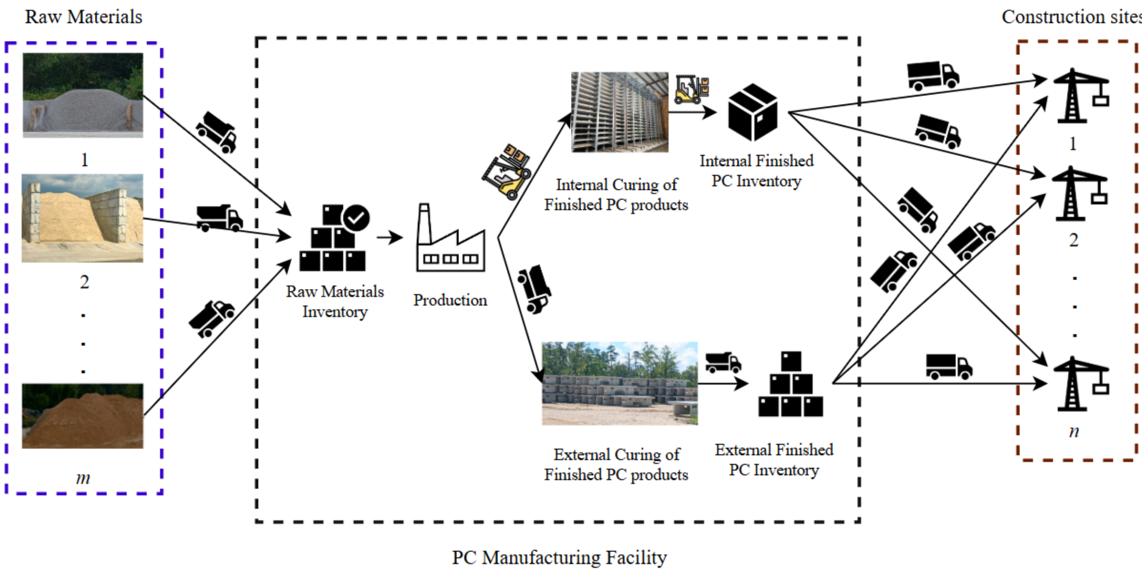


Figure 4.6. Overall production activities in PC manufacturing facility

Once manufactured, the curing process is a critical step to ensure the quality and durability of the precast elements. The curing process can be performed in two ways: Internal curing in which multiple PC products are cured in a controlled environment inside the manufacturing facility. This controlled curing process is necessary for certain products that require precise temperature and humidity conditions. Once the curing is complete, these products are moved to the internal finished PC products inventory, where they are stored before being transported to construction sites. External curing in which large PC products are cured in an open yard under natural environmental conditions. This curing method is applied to products that do not require strict temperature or humidity control. After the curing process, these products are transferred to the external finished PC products inventory for storage.

Once the curing and storage processes are completed, the finished PC products must be transported to multiple construction sites or customers. The delivery process involves selecting the appropriate inventory (internal or external) and determining the best transportation routes to ensure efficient and timely delivery. Each construction site may have different requirements in terms of the quantity, type, and timing of PC product deliveries. The entire supply chain of precast concrete production, from raw material procurement to the final delivery of products, involves several logistical and operational challenges. These challenges include optimizing inventory management, minimizing transportation costs, meeting delivery deadlines, and ensuring product quality throughout the process. Additionally, fluctuating market demands, supply chain disruptions, and environmental factors must be considered when designing an efficient distribution system. This research aims to develop an optimization model to improve the efficiency and cost-effectiveness of the PC manufacturing supply chain. The model will focus on optimizing raw material procurement, inventory management, production scheduling, curing process selection, and delivery route planning. By addressing these challenges, the research seeks to enhance the sustainability and reliability of precast concrete production and distribution while minimizing overall costs.

4.3.1 Model Formulation:

The mathematical formulation developed for the precast concrete delivery (PCD) model is given in Problem PCD below, wherein the optimal values of the number of vehicles contracted, the shipment quantities, the unmet demands, and the shipment starting times are determined as follows:

Problem PCD:

$$Min\ Z = f\left(y_m, z_r, x^s_{ijbm}, C^s_{ijbm}, u^s_{ijb}, S^s_{ijbm}\right)$$
$$= \sum_m F_m y_m + \sum_r G_r z_r + \sum_s p^s \left[\sum_{i,j,b,m}\left(c_m x^s_{ijbm}\right) + \sum_{i,j,b,m}\left[P_i max\{0, C^s_{ijbm} - L_i\} + \gamma_i u^s_{ijb}\right]\right]$$

First stage constraints:

$$F_m y_m \le F^c_m, \quad \forall m$$
$$z_r \le K_r, \qquad \forall r$$
$$y_m, z_r \ge 0 \text{ and } y_m, z_r \in \mathbb{Z}_+ \quad \forall m, r$$

Second stage constraints (for each scenario)

$$\sum_{m=1}^{\tau} x^s_{ijbm} + u^s_{ijb} \ge D^s_{ijb}, \quad \forall i, j, b$$
$$x^s_{ijbm} \le y_m D^s_{ijb}, \quad \forall i, j, b, m, s$$
$$\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{b=1}^{B} x^s_{ijbm} \le y_m C_m N_m, \quad \forall m$$
$$\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{b=1}^{B} v_j x^s_{ijbm} \le y_m V_m N_m, \quad \forall m$$
$$S^s_{ijbr} \le S^s_{ijbm}$$
$$C^s_{ijbr} \le C^s_{ijbm}$$
$$R^s_{ijbm} \ge \frac{v_j x^s_{ijbm}}{c_m}$$
$$C^s_{ijbm} \ge S^s_{ijbm} + \left\lceil R^s_{ijbm} \right\rceil T^s_m, \quad \forall i, j, b, m$$
$$C^s_{ijbm} \ge S^s_{ijbm} + \left\lceil R^s_{ijbm} \right\rceil T^s_m, \quad \forall i, j, b, m$$
$$S^s_{ijbm} \ge E_i, \ \forall i, j, b, m, s$$

$$S_{ijb(m+1)}^{s} \geq C_{ijbm}^{s}, \forall i, j, b, m < \tau, s$$

$$x_{ijbm}^{s},\ u_{ijb}^{s},\ S_{ijbm}^{s}, C_{ijbm}^{s} > 0,\ \ \forall i, j, b, m$$

This two-stage optimization model optimizes the delivery of precast concrete components for multiple construction projects under demand and travel time uncertainty. In the first stage, strategic decisions are made before uncertainty is realized, including determining the number of vehicles to contract for each transportation mode and allocating shared resources like cranes and loading equipment. These decisions involve fixed costs and are constrained by budget limits and resource availability. The second stage makes operational recourse decisions after scenario-specific demand and travel times are known. These include determining shipment quantities for each project-component-batch-mode combination, calculating unmet demand when necessary, and scheduling shipment start and completion times.

4.3.2 Solution Methodology:

The overall optimization problem is structured as a two-stage stochastic mixed-integer model for a multi-project, multi-component precast concrete distribution system. The first stage determines long-term contracting decisions, such as the number of vehicles engaged for each transportation mode and the number of resource units committed for the planning horizon. These first-stage decisions are chosen before uncertainty is realized. The second stage represents operational recourse decisions, where each scenario reveals a different realization of component demand and travel time conditions, and the system must dispatch the contracted capacity in the most efficient way.

The methodology integrates genetic algorithms, sample-average approximation, and a greedy recourse policy to obtain implementable and computationally tractable approximate solutions for a problem that would otherwise be too large for standard mixed-integer programming. The first portion of the methodology builds a search space consisting of integer decision vectors for the number of transportation vehicles across modes and the number of resources allocated. Each candidate solution is represented by a chromosome. A population is initialized with random feasible integer values within the upper bounds imposed by financial budgets and resource availability. The algorithm evolves this population over a series of generations using tournament selection, uniform crossover, and adaptive integer mutation. Elitism ensures that the best solutions found up to any iteration are fully retained so that the algorithm does not lose high-quality designs. The genetic algorithm evaluates each candidate decision vector by simulating operational performance under uncertainty. This simulation produces an approximate expected second-stage cost. The GA therefore drives the search toward first-stage solutions that minimize the combined fixed contracting cost and expected recourse penalties.

The uncertainty in demand and travel time is represented through a finite set of scenarios. Instead of evaluating all scenarios every time which would be computationally expensive the algorithm uses sample-average approximation. For each fitness evaluation, it draws a small subset of scenarios without replacement and computes the average second-stage outcome across them. This sample-based estimate serves as an approximation of the expected recourse cost. By repeating this sampling throughout the GA evolution, the algorithm approximates the true expectation while keeping the computation manageable.

For each sampled scenario, the second stage is solved through a purposely designed greedy dispatch rule. Once a particular realization of demand and travel time is observed, the system assigns batches to transportation modes in ascending order of per-ton cost. For each batch, the algorithm checks whether any mode with available capacity can accommodate the entire batch in terms of both weight and volume. If multiple modes are feasible, the least-cost mode is selected. If no mode can feasibly transport the batch, the batch is left unmet and is penalized. After assignment, the completion time of each project is updated by accumulating shipment durations, and any lateness beyond the deadline contributes delay penalties. Thus, each scenario produces a total recourse cost consisting of variable transport expenses, early/late delivery penalties, and unmet-demand penalties. This scenario cost is returned to the first-stage evaluation, completing the two-stage calculation loop. For a given first-stage vector, the algorithm combines the fixed contracting cost with the estimated expected recourse cost from the SAA process. This total cost becomes the fitness value that the GA minimizes. Generation after generation, the search moves toward first-stage decisions that minimize total expected system cost under uncertainty. The final portion of the model takes any selected first-stage plan typically the best GA solution and performs a full enumeration of all scenarios using the same recourse logic. It records unmet demand, project delays, mode-wise utilization, and service shares. The outputs include summary tables and distribution plots to help interpret the operational robustness of the chosen plan. This stage does not affect optimization but provides operational insights and diagnostic performance measures.

4.4 Research Goal (RG) 4:

Observing and predicting concrete strength is essential for maintaining durable transportation infrastructure because the ability of concrete to carry loads, resist cracking, and withstand harsh environmental conditions depends directly on how its strength develops over time. Transportation structures such as bridges, pavements, and precast components are exposed to heavy traffic, temperature changes, moisture, and chemical impacts, and any weakness in the concrete can accelerate deterioration and shorten service life. By monitoring strength during curing and using reliable prediction methods to estimate future performance, engineers can ensure safe handling, proper timing for construction operations, and timely opening to traffic. Strength prediction also helps identify potential quality issues early, supports preventive maintenance, and guides material and mix design choices that balance performance, cost, and sustainability, ultimately ensuring long term durability of transportation networks.

Therefore, in this section, the *research goal is* to develop a Physics-Informed Neural Network (PINN) framework that enforces material science laws as gradient-based constraints for concrete compressive strength classification and Implement systematic post-training validation to verify that the trained model respects material science principles beyond statistical accuracy metrics.

The Concrete Compressive Strength dataset originates from experimental work on high-performance concrete mixtures conducted by I.-C. Yeh in 1998 and is widely used for modeling and prediction studies in materials engineering. The dataset captures eight key input variables that collectively define the composition and curing condition of each concrete sample. Cement represents the primary binder in the mixture, responsible for the chemical hydration reactions that generate strength. Blast furnace slag and fly ash serve as supplementary cementitious materials that improve durability, long term strength, and environmental performance by partially replacing cement. Water governs both the hydration process and workability of the fresh mix, making its proportion critical for achieving the desired mechanical properties. Superplasticizer is included to improve fluidity without increasing water content, allowing for better compaction and higher strength. Coarse aggregate provides the load bearing skeleton of the concrete, while fine aggregate fills voids and enhances cohesion within the matrix. The age variable reflects the number of days between casting and testing, capturing the natural strength development that occurs as concrete cures. Together, these variables describe the physical, chemical, and temporal factors that influence compressive strength, making the dataset a valuable resource for understanding and predicting concrete performance.

4.4.1 PINN Model Development:

The model formulation process illustrated in Figure 4.9 follows a structured workflow that integrates data augmentation, machine learning, and physics-informed constraints to develop a reliable predictive model for concrete strength. The process begins with the original dataset, which contains measured concrete mix proportions and corresponding compressive strengths. Because the raw dataset may be limited in size or distribution, an augmentation step is applied to generate additional synthetic samples while preserving realistic physical relationships among variables. This expanded augmented dataset helps improve model generalization and robustness. After augmentation, the dataset is divided into training, validation, and test subsets to support unbiased learning and performance assessment. The core analytical engine in this workflow is the physics-informed neural network, which incorporates both traditional data-driven learning and physically grounded constraints. Inputs such as cement, water, slag, and age flow through the input and hidden layers to predict strength at the output. In addition to conventional data loss, the model computes a physics loss that enforces known monotonic relationships such as the non-increasing effect of water on strength and the non-negative effects of cementitious materials and curing age. By combining these two losses through a weighted objective function, the model is encouraged to learn patterns consistent with domain knowledge rather than solely relying on empirical correlations.

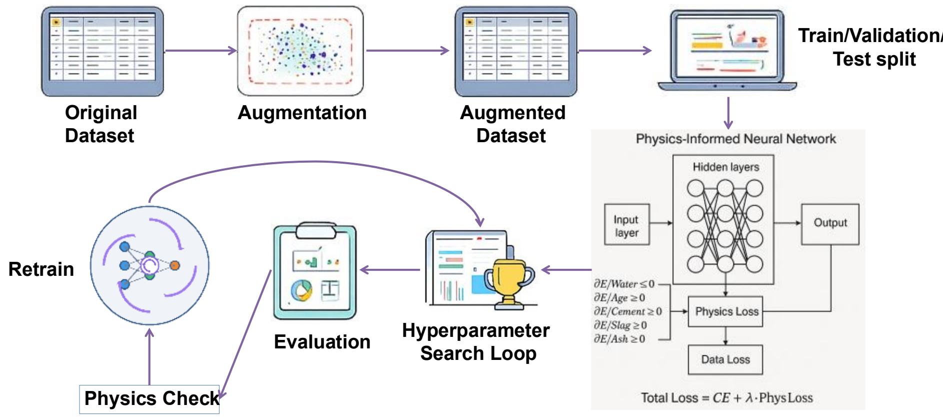


Figure 4.7. PINN Model Development Process

To refine model performance, a hyperparameter search loop evaluates multiple model configurations, including layer sizes, activation functions, learning rates, and physics loss weights. Each candidate model is trained and assessed through quantitative evaluation metrics and a physics check to verify whether predictions obey fundamental material behavior.

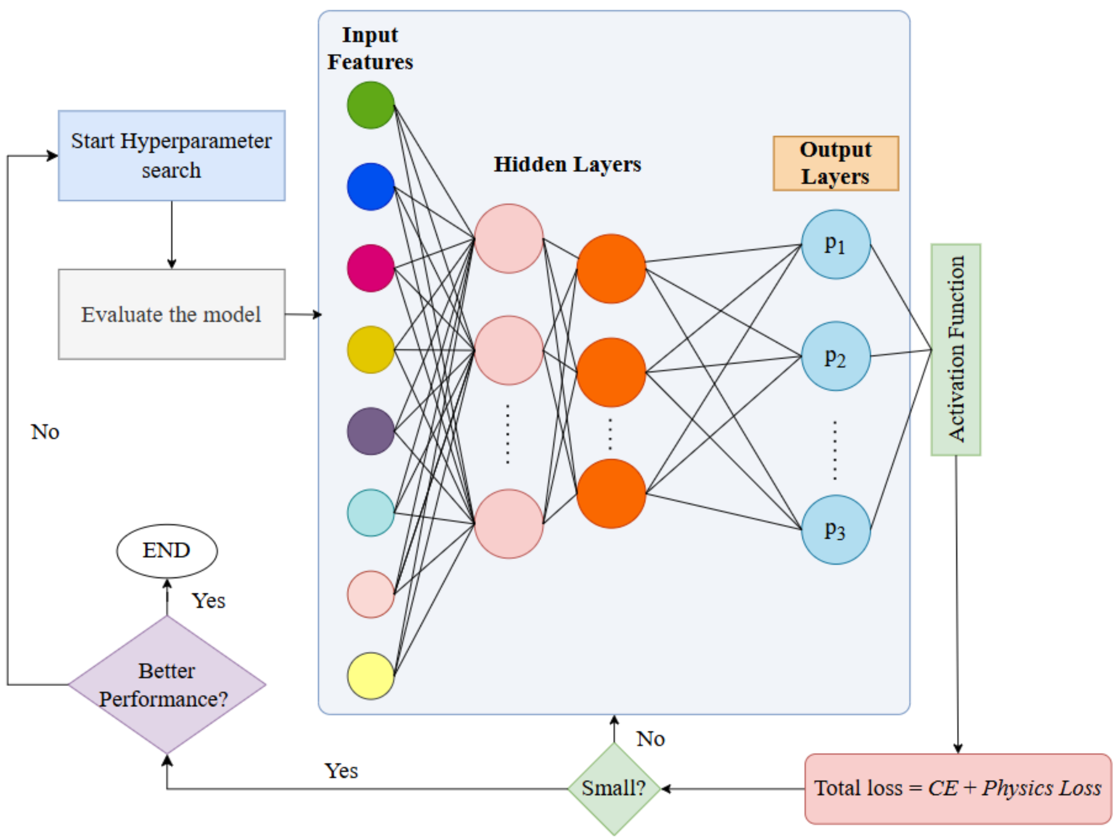


Figure 4.8. PINN Architecture with Hyperparameter Optimizing

If the physics constraints are violated, the model undergoes retraining with adjusted hyperparameters or loss weighting. This iterative cycle continues until a model satisfying both predictive accuracy and physical consistency is identified. The final outcome is a robust physics-informed neural network capable of producing reliable, interpretable predictions aligned with concrete science and practical engineering requirements. The proposed PINN structure in Figure 4.10 uses eight raw concrete mix features as inputs and passes them through a fully connected neural network with two to five hidden layers selected through hyperparameter search to identify the best architecture. The output layer performs a three-class classification of concrete compressive strength, categorizing samples into low strength, normal strength, and high strength based on established ranges from recent literature. The model combines traditional cross entropy loss with physics loss to ensure predictions align with known material behavior while still achieving strong classification performance. This structure allows the network to learn meaningful relationships within the data while remaining consistent with concrete science, resulting in a more robust and interpretable predictive model.

5. Project Results

This chapter presents the results obtained from the four major components of the study and demonstrates how each contributes to improving precast concrete supply chain performance for transportation infrastructure. The first section reports the findings related to incorporating raw material perishability into procurement decisions and shows how procurement timing affects the strength and quality of manufactured precast components. The second section provides the outcomes of the yard optimization analysis, including improvements in storage arrangement, crane accessibility, and internal vehicle movement that enhance product flow and reduce delays. The third section describes the results of the delivery model, which evaluates the combined effects of early and late penalties, demand shortfalls, travel time variability, load assignment practices, and vehicle capacity restrictions on delivery performance. The final section presents the performance of the Physics Informed Neural Network developed to link material composition and curing conditions with compressive strength and explains how this tool can support decision-making throughout the precast supply chain. Together, these results highlight the practical benefits of addressing perishability, yard operations, delivery planning, and strength prediction within an integrated research framework.

5.1 Results from RG 1:

The numerical analysis to implement the proposed Cooperative Procuring Policy, considered a precast manufacturing facility in the United States that produces various precast concrete components for infrastructure projects such as roads, bridges, and highways. To meet its production needs, the manufacturer purchases Portland Pozzolana Cement (PPC) from a vendor. The delivery time for these cement orders is uncertain and varies between 7 and 28 days, following a uniform distribution where the expected value of this lead time distribution is approximately 17.5 days. This means that any delivery time within this range is equally likely, which reflects the normal variability in transportation or supplier schedules. The manufacturer's annual demand for PPC is also uncertain and follows a truncated exponential distribution between 2,500 and 4,400 tons per year. Since smaller and more frequent orders are more common in precast production than large ones, the exponential distribution captures this natural tendency, while the truncation sets practical upper and lower limits for production capacity and storage space. Reference to Table 4.1, which lists the system parameters used in this example. It includes various cost factors such as the ordering costs of manufacturer and vendor, holding costs, perishability losses, and penalty costs for late or spoiled deliveries. The perishability cost and shelf-life account for material aging, while parameters like the penalty cost and revenue decay rate capture financial impacts due to late or missed deliveries. Together, these parameters define the complete cost structure and operational constraints of the vendor–manufacturer system for optimizing inventory and procurement decisions under uncertainty.

The optimal values of all the three decision variables are shown in Table 5.1 and Figure 5.1 represents the optimal number of shipments using the cooperative procurement policy between the precast material vendor and the PC manufacturer according to the results found in the numerical analysis.

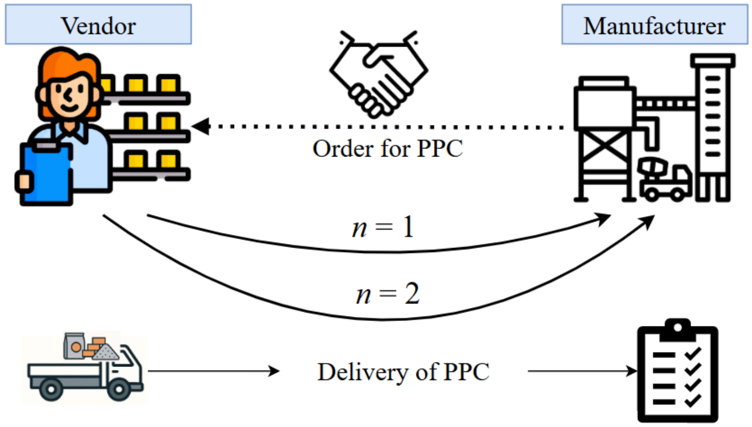


Figure 5.1. Optimal number of shipments using cooperative procurement policy.

Through iterative optimization, it was found that the total cost is lowest when the number of shipments is n = 2, indicating that making two deliveries per replenishment cycle provides the most cost-efficient balance between ordering, holding, and shortage-related expenses. At this optimal point, the ordering quantity, Q^* = 364 tons, and the reorder point r^* = 284 tons, meaning that a new order is placed whenever inventory drops to 284 tons, and each replenishment adds 364 tons to the stock whenever it arrives after shipment.

Table 5.1. Optimal solutions

Decision variables	Optimal value	Unit
n^* (Number of Shipments)	2	Number
$Q_n{}^*$ (Order quantity)	364	tons of PPC per order
$r_n{}^*$ (Reorder point)	284	tons of PPC Inventory level

Figure 5.1 visually represents this optimal inventory pattern over time. Since the lead time (τ) was uniformly distributed in between 7 and 28 days, shipment from the vendor arrives after an average time of 17.5 days, replenishing the stock to its maximum level. The demand was following a truncated exponential distribution within a range of 2500 and 4400 tons/year and $g(D|\theta) = \frac{\frac{1}{50}e^{-(D-2500)/\theta}}{e^{-2500/\theta} - e^{-4400/\theta}}$ based on the parameter θ. The mean of this truncated exponential distribution, say $\mu(\theta) = 2500 + \theta - \frac{(4400-2500)e^{-(4400-2500)/\theta}}{1-e^{-(4400-2500)/\theta}}$ (Al-Athari, 2008). For different values of θ, the demand for PPC will be exponentially distributed in between 2500 and 4400 tons/year.

Table 5.2. Cooperative cycles in inventory system

Cooperative cycle	Vendor's cycle	Mfg.'s cycle	θ	D (tons/year)	r (tons)	τ (days)	$r - D\tau$ (tons)
0	2	2	20	2520	284	17.50 days	166
1	1	1	50	2550	284	17.50 days	165
		2	245	2744	284	17.50 days	155
2	2	1	350	2841	284	17.50 days	150
		2	500	2957	284	17.50 days	145

According to Table 5.2, since the optimal number of shipments using the proposed cooperative policy for this example is n^* = 2, that means, 1 complete cycle of the material vendor will be equal to 2 individual cycles for the precast manufacturer. So, during the 1st cooperative cycle, vendor is sending 2 shipments to the manufacturer immediately after receiving the order from the manufacturer's end. In this case, each lot from vendor takes 17.50 days to reach the manufacturer and they utilize both of the shipments to satisfy their customers or demands. Here, the length of 1st cycle of manufacturer is about 52 days and the 2nd cycle takes 49 days and therefore the cycle for the vendor will be $T_{vendor} = 52 + 49 = 101$ days. It was also assumed that the vendor makes no delay between receiving the order and dispatching it for delivery. For every cycle of the precast manufacturer, the demands vary based on different parametric values of the truncated exponential distribution (Al-Athari, 2008). As a result, in each cycle of the manufacturer, the optimal cycle time ${T_{mfg}}^*$ is also changing since ${T_{mfg}}^* = \frac{Q^*}{E[g(D|\theta)]}$. The remaining inventory levels, $(r^* - D\tau)$, for the manufacturer in every cycle (Table 5.2), are also different for the same reason since $D \sim g(D|\theta)$. However, according to Figure 5.2, if both parties agree to participate in such cooperative policy, there is no chance of shortage even if the demand is changing as $\tau < r/D$ in all the cycles. This example clearly demonstrates the synchronization advantage achieved through the proposed cooperative policy between the vendor and the precast manufacturer. By aligning the vendor's complete cycle with two shorter manufacturer cycles, both parties maintain operational harmony and minimize delays. This coordination enables the manufacturer to meet fluctuating customer demands efficiently while optimizing inventory utilization and avoiding excess holding.

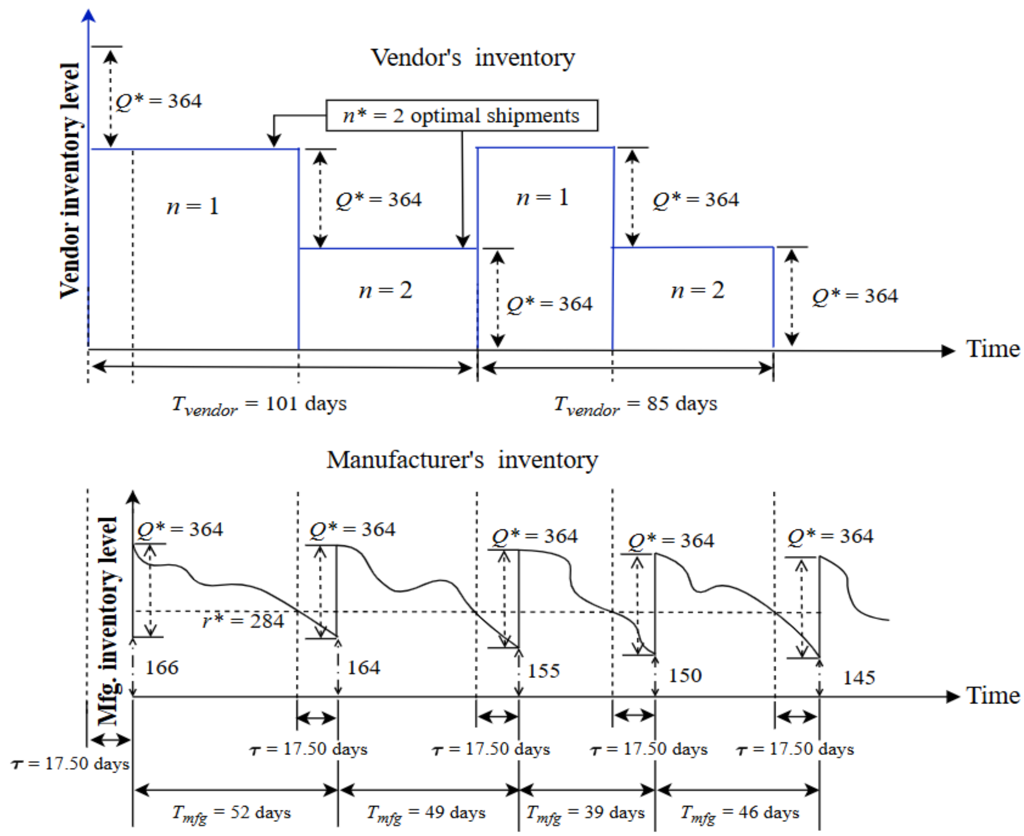


Figure 5.2. Integrated inventory system of vendor and manufacturer (see Tables 5.1 and 5.2)

Finally, these results demonstrate that the optimal policy balances delivery frequency and inventory risk. Fewer shipments (n = 1) cause higher holding costs for large stock accumulation, while more frequent shipments (n = 3) increase ordering and transportation costs. That means, both parties agreed with such cooperative procurement policy in this case, with n = 2 achieves the lowest total annual cost ($60,186.94/year), making it the most efficient strategy for managing the uncertain demand and variable lead time of perishable precast raw materials.

In conclusion, the proposed cooperative inventory policy effectively minimizes total system costs while maintaining an adequate and reliable flow of materials between vendors and manufacturers, even under uncertain demand and variable lead times. By optimizing key decision variables such as order quantity, reorder point, and number of shipments, the policy provides a structured approach to balance ordering, holding, and shortage costs. For precast concrete manufacturing systems, where raw materials such as cement, admixtures, or epoxy resins have limited shelf lives, this policy helps synchronize deliveries and consumption schedules, ensuring that materials are used within their shelf-life period while preventing costly shortages or overstocking.

5.2 Results from RG 2:

The methodology uses a curing cost minimization model (CCM) that arranges precast components on pallets while satisfying mold limits, weight limits, spacing rules, and demand requirements. The approach begins by creating a set of initial layout patterns and then uses an iterative algorithm to test, adjust, and improve these patterns. At each step, the master problem identifies a promising layout, and a subproblem checks whether the layout leads to unmet demand or violations of pallet capacity. If issues are found, new patterns are generated and added to the model. This cycle continues until the model reaches a stable solution where pallet layouts use space effectively, meet all constraints, and minimize the total curing cost.

The results show that the optimization model reduces curing cost by arranging precast components on pallets in patterns that use the pallet area more efficiently. Figure 5.3 showing unmet demand across rounds indicates that the algorithm quickly reduces the number of unassigned components as it progresses. This means the model learns how to improve layout quality with each iteration and becomes more effective at placing mixed component types on the same pallet.

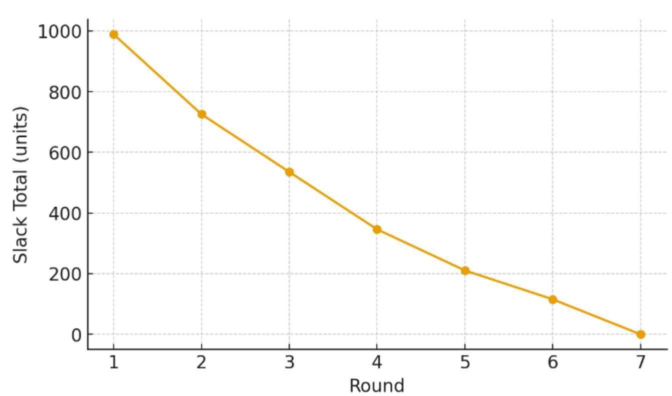


Figure 5.3. Total unmet demand of the whole project in every iteration

The bar chart of top layout patterns demonstrates that certain patterns appear more frequently because they fill the pallet space well without violating spacing or weight limits. These patterns provide consistent pallet utilization and reduce empty areas inside the curing chamber. The model does not generate patterns at random; instead, it selects patterns that improve cost performance and fit the size constraints of the curing chamber and pallets.

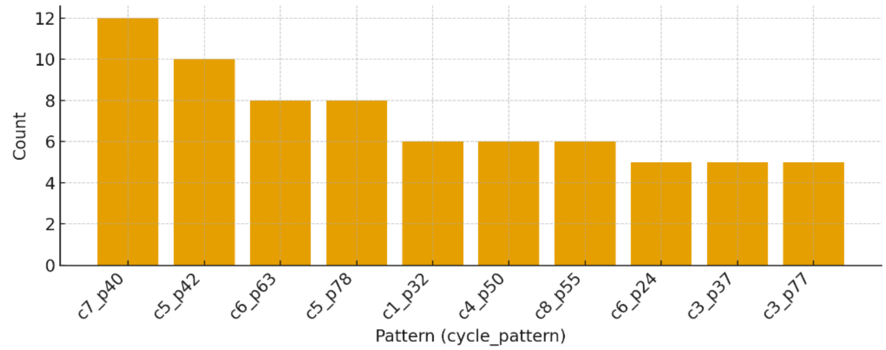


Figure 5.4. Usage frequency of patterns from different layouts

The optimal layout pattern diagrams illustrate several cycle and pattern combinations, showing how different components can be arranged together in a compact manner. Each layout shows that the algorithm can place PC components of different sizes while maintaining spacing rules. This leads to fewer pallet cycles during curing because more components can be cured at the same time.

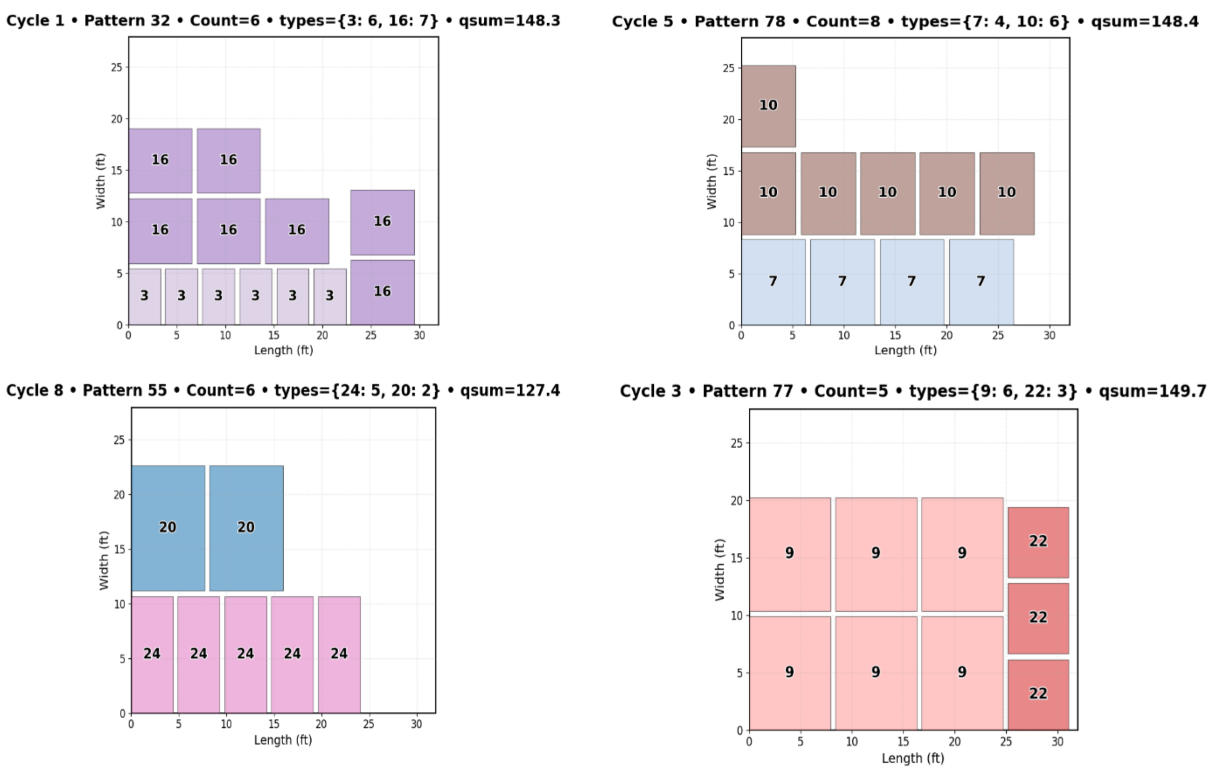


Figure 5.5. Optimal pallet layouts for multiple precast components from different projects

The key insights summarize that the algorithm improves efficiency as it runs and relies on adding only useful patterns that increase pallet utilization. The results confirm that mixed component placement is possible and that improved layouts reduce waste. Although the model is presented in the context of curing operations, the same layout optimization approach is also applicable to yard storage management. Precast manufacturers such as *WASKEY* and *Premier Concrete* (Baton Rouge, LA) face significant challenges in arranging large, irregular components in limited yard space, and the ability to form compact, non-overlapping patterns is essential for reducing handling time, shortening search time, and making better use of storage areas. Therefore, the findings support that optimized pallet layouts not only reduce curing costs but also help improve overall yard organization and space allocation for precast production facilities.

5.3 Results from RG 3:

Finished precast concrete products must be delivered to various construction sites with differing quantity, type, and timing requirements. This overall process involves selecting the right inventory and optimizing delivery routes. The overall supply chain from raw material procurement to final delivery faces logistical challenges such as minimizing transportation costs, meeting deadlines, and maintaining product quality.

The research objective illustrated Figure 5.6 is to develop and optimize a Precast Concrete Delivery (PCD) model that supports strategic and operational decision-making under uncertainty.

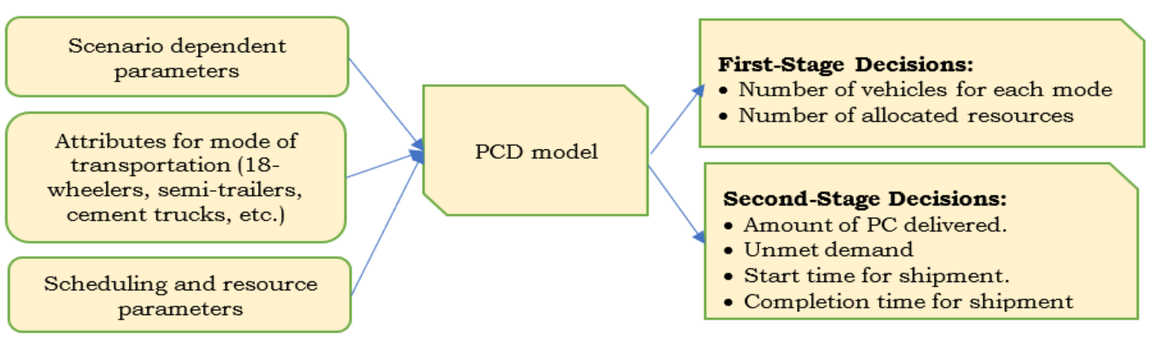


Figure 5.6. Model PCD

This PCD model was run by some collected data (Ref. [2],[4],[6],[14]-[15],[43],[45],[59]-[60]) to check its validity, and Figure 5.7 summarizes key parameters such as project deadlines, and the range of batch demands that the model must satisfy.

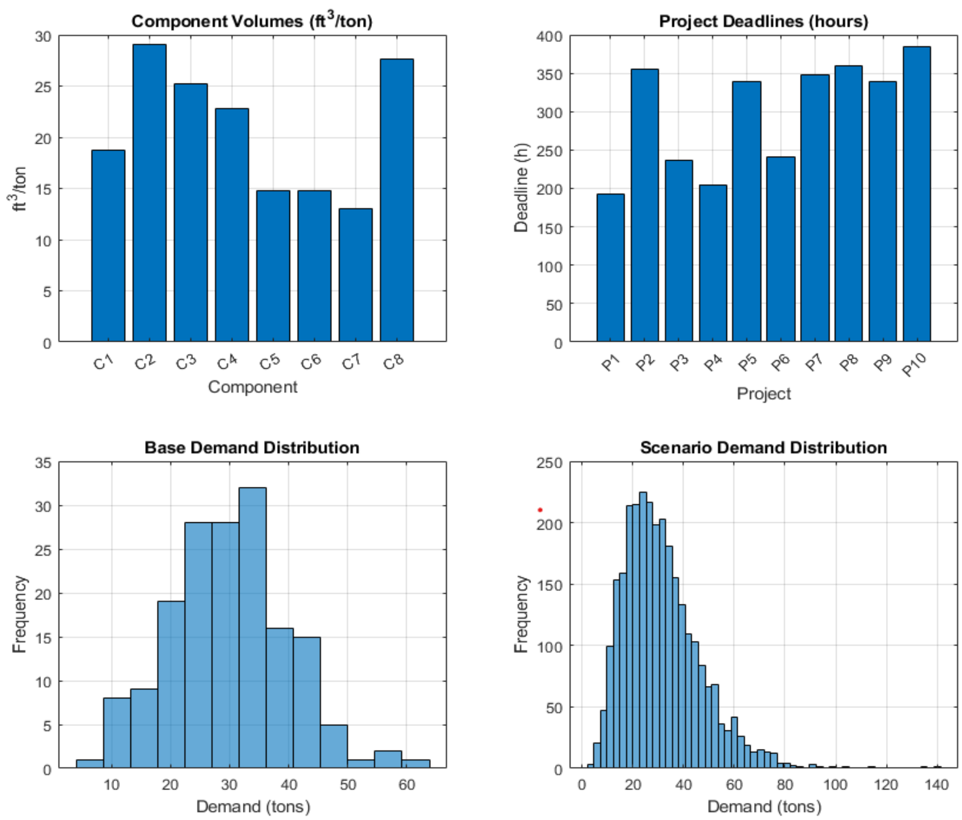


Figure 5.7. PC components requirements in multiple projects

This large dataset was applied in our PCD model for optimizing allocation of different transportation modes under multiple uncertain demand and travel time scenarios. Total 10 projects data from multiple highways and bridges construction were considered for initial analysis where different demand and travel time scenarios were assumed to represent uncertainty.

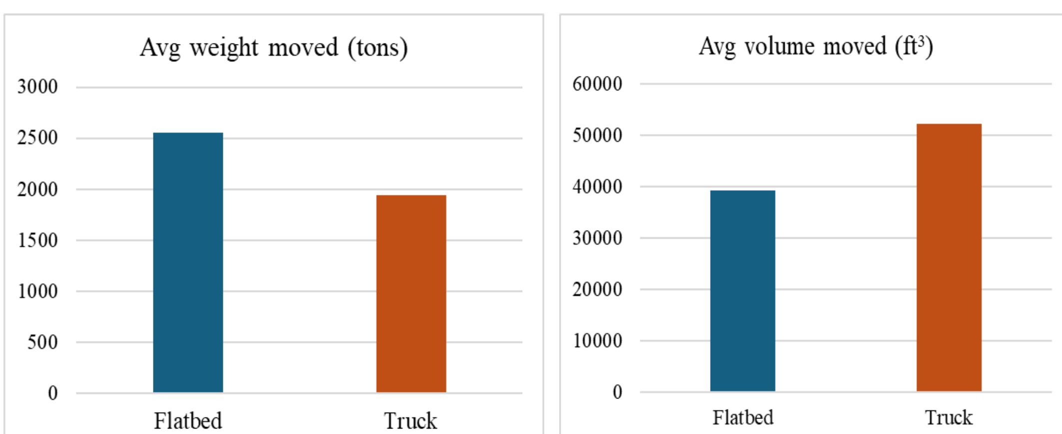


Figure 5.8. Average usage of two transporters

Again, construction project of a certain bridge does not require PC components all the time since there are requirements of several in-site concrete products for such construction projects. Therefore, there are several scenarios where for any specific construction project, there is no demand for any PC components in any lot. Figure 5.8 shows precast components moving from the PC manufacturer to the construction site using two transport modes. A flatbed makes 8 trips at about 88% of its capacity, while a standard truck makes 5 trips at about 97% (nearly full loads). Together, these multi-modal shipments carry the required pieces from the plant to the site efficiently.

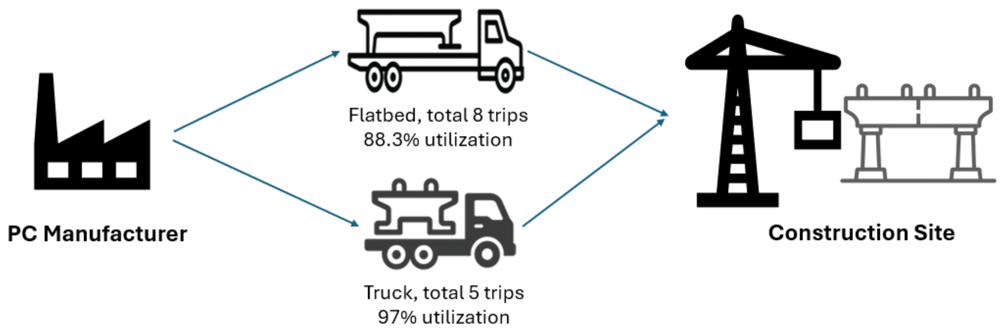


Figure 5.9. Optimal allocation of the two transportation modes

Figure 5.9 shows how the genetic algorithm's (GA) best cost improves over generations (computational efficiency). It starts high (about 1.32×10^5) and drops quickly in the first 8–12 generations, meaning the algorithm finds much better solutions early on. After that, the curve flattens near 1.15×10^5 around generation 15, with only tiny gains afterward and a small dip again near generation 39. In plain terms: big improvements happen early, then progress slows a lot, so the search has essentially converged by about 15–20 generations.

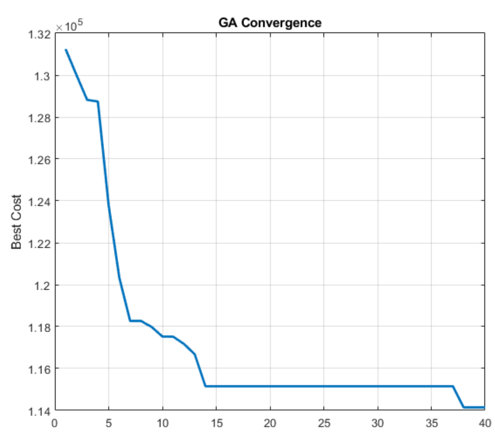


Figure 5.10. Cost convergence to minimized value over generations.

5.4 Results from RG 4:

The proposed structure for a physics informed neural network (PINN) is designed to predict concrete strength while respecting known physical behavior. The model is built using dense layers whose widths are chosen from a range of sixty-four to two hundred fifty-six units. The activation functions can be selected from ReLU, SELU, or ELU. Each dense layer is followed by batch normalization and a dropout layer with a rate between zero and zero point four to reduce overfitting and improve generalization. A key part of this model is the physics informed component, which ensures that the predictions obey known material behavior. The network enforces monotonic relationships between input features and predicted strength. Strength should increase as the curing age increases and decreases as water content increases, which is consistent with the traditional law relating water content and strength. The strength should also increase as the proportions of cement, slag, and ash increase. These monotonic conditions are implemented by computing partial derivatives of the network output with respect to the inputs and constraining their signs. This penalty is included in a physics loss term. The model is trained by minimizing a total loss that combines the ordinary cross entropy loss with the physics loss multiplied by a tuning parameter. This tuning parameter, along with learning rate, batch size, dropout, batch normalization, and the overall architecture, is selected through a random search process. The model that performs best on the validation set is then retrained using the combined training and validation data.

The performance of the proposed PINN classifier is evaluated through an extensive hyperparameter search followed by final training and testing. The best performing model configuration emerges after exploring a wide range of variations in layer depth, hidden unit sizes, activation functions, dropout rates, optimizers, and physics loss weights. The optimal architecture consists of 2 hidden layers with 160 units in the 1st layer and 256 units in the 2nd layer, using a ReLU activation function. A dropout rate of zero point four provides effective regularization, while batch normalization does not contribute to improved performance and therefore is not selected. The Adam optimizer with a learning rate of 0.003 offers stable and efficient convergence. This configuration achieves the best validation accuracy of about 97.1% percent during the hyperparameter search stage.

The learning curves (5.11) for the final model show consistent behavior between the training and validation accuracy across two hundred epochs. Both curves increase rapidly during the early stages of learning and gradually stabilize around ninety-six to ninety-seven percent. This pattern indicates reliable learning without any signs of instability. The close alignment between the training and validation curves confirms that the model does not overfit. The validation accuracy (Figure 5.11) remains consistently close to the training accuracy throughout training, which reflects strong generalization to unseen samples. The loss component plot further supports this conclusion. The training and validation total losses decreased steadily before reaching stable low values. The cross-entropy loss follows a smooth decline trend, while the physics loss remains small. This behavior demonstrates that the physics-based constraints integrate smoothly into the training process and do not create optimization difficulties.

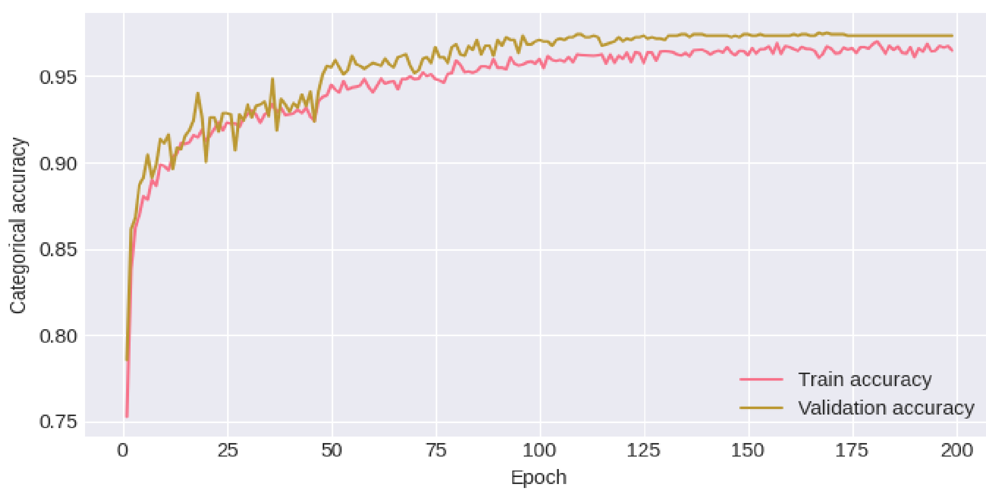


Figure 5.11. Training vs Validation Accuracy of PINN

The results from the hyperparameter trials (5.12) display a wide variation in validation accuracy, which shows that the search process is essential for identifying a stable configuration. Despite this variability, the best trial reaches a validation accuracy of zero point nine seven one. This value is consistent with the accuracy obtained during the final training phase, which supports the robustness of the chosen model. The comparison between validation and test accuracy illustrates that the model performs almost identically on both datasets. The validation accuracy from the search is zero point nine seven one, while the final test accuracy reaches zero point nine seven three. The very small difference between these two values indicates strong generalization and confirms that the model does not overfit to the validation set during the tuning stage.

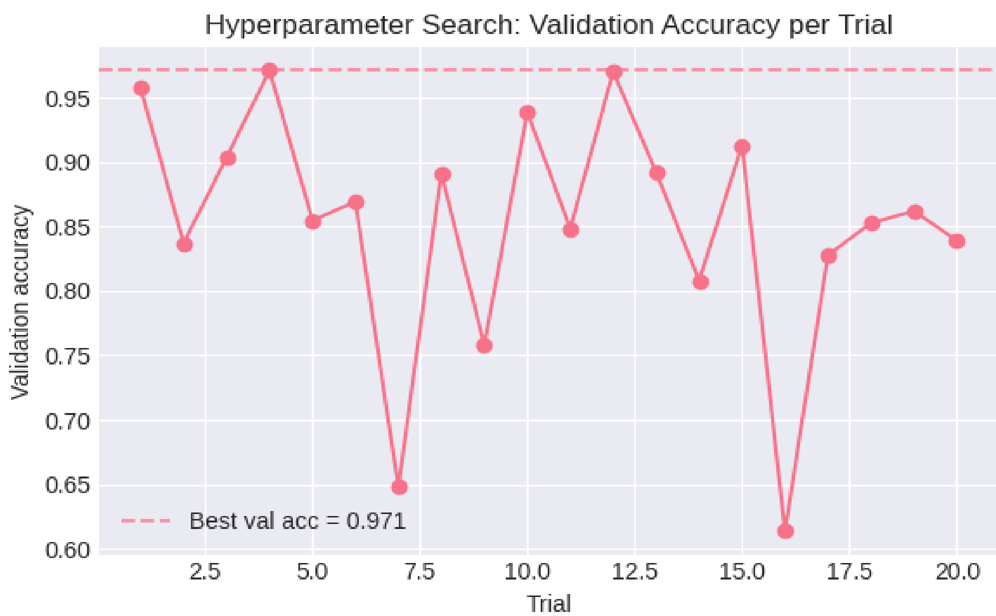


Figure 5.12. Hyperparameter Search for Validation Accuracy per trial

Overall, the results demonstrate that the physics informed classifier consistently predicts concrete strength classes with high accuracy across training, validation, and testing. The integrated physics-based constraints guide the network to follow realistic material behavior while maintaining strong predictive power. The stability of learning curves (5.11), the close correspondence between validation and test accuracy, and the low magnitude of physics loss all confirm that the model exhibits both reliable performance and physical consistency. This establishes the proposed framework as a robust and effective approach for concrete strength classification.

Table 5.3. Accuracy results of PINN

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Class 1	0.98	0.96	0.97	352
Class 2	0.98	0.98	0.98	681
Class 3	0.94	0.99	0.96	171
Overall Accuracy	**0.97**	**—**	**—**	**1204**

The results (Table 5.3) summarize the performance of the proposed physics informed neural network classifier on the test dataset. The classification report shows that the model achieves strong predictive accuracy across all three concrete strength classes. Class 1 and Class 2 both reach a precision value of zero point nine eight, indicating that almost all predictions made for these two classes are correct. Their recall values of zero point nine six and zero point nine eight respectively show that the model identifies most true samples for these groups. Class 3 has a slightly lower precision of zero point nine four, but it compensates with an extremely high recall of zero point nine-nine, meaning that nearly all true high strength samples are detected correctly. The F1 scores remain consistently high for all classes, ranging from zero point nine six to zero point nine eight, and the overall accuracy across the one thousand two hundred four test samples is zero point nine seven. This confirms that the classifier performs reliably across the entire dataset.

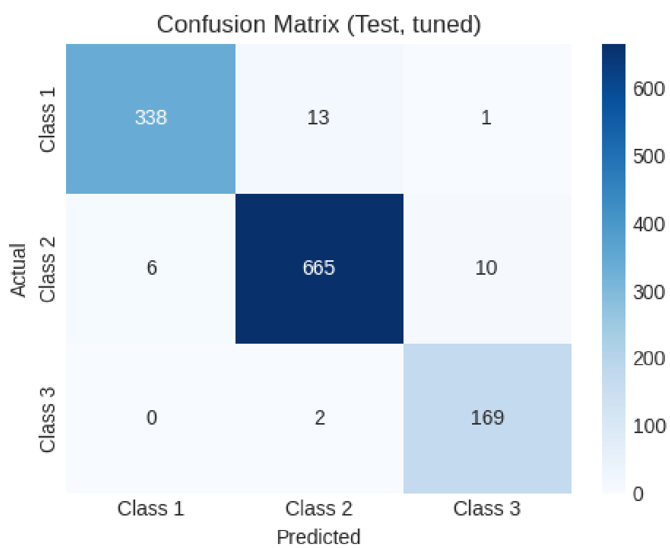


Figure 5.13. Confusion matrix of proposed PINN

The confusion matrix (5.13) further supports these findings by providing a detailed view of prediction outcomes. For Class 1, the model correctly predicts three hundred thirty-eight samples, with only a small number misclassified as Class 2 or Class 3. Class 2 shows the strongest performance, with six hundred sixty-five correct predictions and minimal errors. This demonstrates the model's ability to handle the largest class without suffering from imbalance-related bias. Class 3 also displays strong detection performance, with one hundred sixty-nine correct predictions and only two samples misclassified as Class 2. The matrix reveals that misclassifications tend to occur between adjacent classes, which is expected in a continuous strength domain where boundaries are often smooth rather than sharply defined.

Taking together, these results show that the model provides stable, accurate, and trustworthy predictions across all categories, with misclassifications limited to expected boundary transitions. The strong consistency between metrics and the structure of the confusion matrix confirms that the physics informed approach enhances generalization and improves reliability for practical applications.

6. Conclusion and Recommendations

This research project presents a unified framework that connects procurement, production, curing, yard operations, and outbound delivery within a single decision-support system for precast concrete supply chains. The findings demonstrate that treating these stages jointly rather than as isolated problems produces significant reductions in cost, delays, material waste, and reliability failures.

From Research Goal 1, the cooperative inventory policy for perishable raw materials successfully minimized total annual cost by optimizing ordering quantity, reorder point, and shipment frequency. The model effectively handled uncertain demand and variable lead times while respecting the shelf-life constraints of cementitious materials. Numerical experiments showed that two shipments per cycle provided the lowest cost, reducing both holding cost and perishability risk. The results highlight that synchronized vendor–manufacturer coordination prevents shortages and ensures that raw materials used in precast production maintain acceptable quality.

From Research Goal 2, the curing cost minimization model demonstrated substantial savings in pallet cycles and curing costs by generating optimized pallet layouts. The iterative column-generation approach produced patterns that tightly pack multiple components on a single pallet. This reduced total pallet cycles, kiln usage, and energy consumption while maintaining mold, spacing, and weight rules. The same framework was shown to be valuable not only for curing operations but also for outdoor yard storage management, where companies like WASKEY and Premier Concrete struggle with limited space, irregular component sizes, and inefficient stacking. The algorithm’s ability to generate compact non-overlapping arrangements offers a scalable solution for both curing and yard storage environments.

From Research Goal 3, the two-stage stochastic delivery model provided an effective way to allocate transportation modes under uncertain demand and travel times. The genetic algorithm with SAA and greedy recourse policy reduced total transportation and penalty costs by selecting the appropriate number of vehicles per mode and optimally assigning batches across scenarios. The model achieved high utilization of existing transport capacity, reduced unmet demand, and improved the on-time service rate. Cost convergence patterns showed that the algorithm stabilizes quickly, offering a computationally feasible tool for large-scale precast logistics planning.

From Research Goal 4, the Physics-Informed Neural Network (PINN) accurately predicted compressive strength categories while enforcing material-science monotonicity rules. The final model achieved test accuracy above 97%, demonstrated no overfitting, and produced physically consistent predictions across cement content, water ratio, SCM proportions, and curing age. PINN provided a reliable bridge between upstream procurement decisions and downstream strength outcomes, enabling manufacturers to evaluate how changes in material quality or curing conditions affect concrete performance.

Overall, the combined outcomes show that an integrated approach offers major gains in cost-effectiveness, reliability, sustainability, and operational stability for precast concrete supply systems.

6.1 Conclusions

This project confirms that precast concrete supply chains function as an interconnected system where one decision influences multiple downstream operations. Models that treat procurement, curing, yard layout, and delivery separately overlook the cumulative impact of delays, perishability, poor storage conditions, and suboptimal routing. By developing optimization and machine-learning tools across all major stages of the supply chain, this study provides a holistic solution that addresses real problems faced by precast facilities such as Premier Concrete, Gainey's, and WASKEY. The results show measurable improvements:

- lower procurement and holding costs under uncertain demand,
- fewer pallet cycles and reduced kiln running time,
- improved yard space utilization and reduced internal truck movement,
- reduced early/late penalties and transportation costs,
- accurate prediction linked to mix design and curing conditions.

The integrated framework therefore enhances cost efficiency, production reliability, and sustainability across the entire precast lifecycle.

6.2 Recommendations for Future Research

1. Expand Multi-Material and Multi-Vendor Coordination

Future studies should incorporate multiple vendors supplying different perishable raw materials simultaneously. Each material has a unique shelf-life, demand pattern, and cost structure, creating complex substitution and coordination dynamics. Integrating multiple vendors would more closely reflect real manufacturing challenges.

2. Extend Yard Layout Optimization Beyond Curing

Although the curing-layout algorithm works for yard storage, future research should incorporate yard-specific constraints such as:

- crane operating zones,
- forklift turning radii,
- ground-bearing limits,
- priority stacks for outbound shipments,
- dynamic rearrangement costs.

Yard operations tend to change daily based on order urgency, crane availability, and trailer arrival times areas requiring dynamic and real-time extensions of the model.

3. Integrate Delivery Routing With Real-Time GPS and Traffic Information

The current delivery model uses probabilistic travel times. Future work should incorporate live GPS data, congestion patterns, and weather delays using machine-learning prediction models or reinforcement learning. This would support real-time rescheduling and adaptive routes.

4. Develop a Digital Twin for Precast Supply Chains

Combining all models: procurement, curing, yard layout, delivery, and strength prediction, into a unified digital twin would allow manufacturers to simulate system-wide impacts of decisions in real time. A digital twin would also support predictive maintenance, automated scheduling, and long-term capacity planning.

5. Expand the PINN to Predict Durability and Long-Term Performance

Future PINN models should incorporate temperature history, humidity, admixture chemistry, shrinkage behavior, and field curing conditions to predict durability metrics such as:

- chloride penetration,
- freeze-thaw resistance,
- carbonation depth,

- long-term modulus of elasticity.

This would integrate materials science with logistics and production decisions.

6.3 Challenges and Potential Barriers for Future Research

1. **Data Availability and Quality:** Real-world data on demand, curing temperatures, yard movements, crane logs, and strength outcomes are often incomplete, inconsistent, or proprietary. Many companies are reluctant to share internal operational data.
2. **High Computational Burden**: Models involving stochastic optimization, dynamic yard layout, and multi-agent routing require significant computing power. Scaling them to large facilities may require specialized hardware and parallelization.
3. **Industry Resistance to Operational Changes**: Precast facilities often rely on long-standing manual processes. Implementing advanced optimization or PINN-based decision tools may face adoption barriers due to training needs or cultural resistance.
4. **Integration With Legacy Systems**: Existing ERP, production, and inventory systems at many facilities are outdated and may be incompatible with modern optimization engines.
5. **Physical Constraints Not Captured in Models**: Yard operations involve worker behavior, weather disruptions, crane breakdowns, and unexpected changes in project demand factors that are hard to encode mathematically.
6. **Regulatory and Safety Considerations**: Any automated yard or curing optimization must consider OSHA rules, equipment safety, and load-bearing constraints, which can introduce additional constraints not modeled here.

7. Practical applications

This research provides a comprehensive framework that strengthens the durability and service life of transportation infrastructure by improving the planning, production, curing, storage, and delivery of precast concrete components. Roads, bridges, and highway structures depend heavily on the consistent quality and timely availability of precast elements.

7.1 Application of the Research Segments:

The results from this research have direct practical value for transportation infrastructure by improving the efficiency and consistency of precast component production. Optimized mold and pallet usage ensures components are cast with proper curing, stable scheduling, and minimal variability, which strengthens product quality before installation. This leads to precast girders, panels, and barriers with higher reliability and fewer defects, resulting in longer-lasting and more durable highways and bridges. By stabilizing the upstream manufacturing process, the overall resilience and service life of transportation infrastructure are significantly improved.

7.1.1 Application of Research Goal 1: Perishability Aware Procurement Planning:

The U.S. precast concrete industry currently generates approximately USD 21–22 billion annually and is projected to exceed USD 36 billion by 2033, growing at a compound annual rate of about 6 % (Khaustovich, 2025). Figure 7.1 illustrates the rising revenue trend of the U.S. precast concrete industry from 2019 to 2022, measured in million USD. The industry's revenue grew steadily from around $17,100 million in 2019 to $19,600 million in 2022, marking a strong upward trajectory. The curve steepens sharply between 2021 and 2022, indicating a period of accelerated market expansion driven by renewed infrastructure spending, increased urban development, and the growing shift toward off-site precast solutions. This consistent and rapid revenue growth demonstrates a booming demand for precast concrete components across U.S. transportation and building projects. The steep rise reflects how precast construction is becoming a preferred solution for efficiency, quality, and sustainability. Such expansion amplifies the need for an efficient supply chain that can keep up with rising demand while minimizing costs and delays. As production scales, inefficiencies in material procurement, shipment scheduling, or inventory control could cause costly bottlenecks or material wastage. Therefore, developing a cooperative, optimized vendor–manufacturer supply network as proposed in your research, is essential to sustain profitability, ensure timely deliveries, and maintain quality in this rapidly growing U.S. precast concrete market.

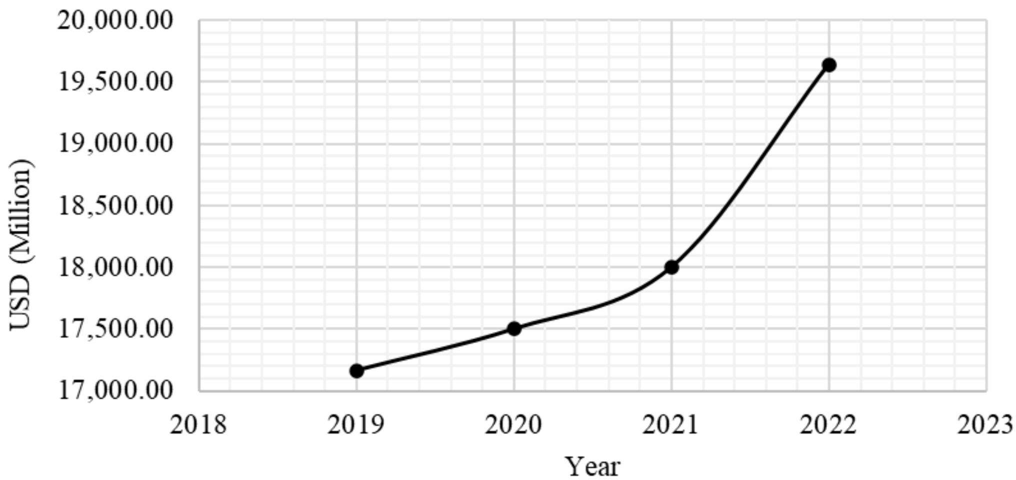


Figure 7.1. Revenue in precast market in year 2019-2022. Data source: Khaustovich, 2025

Therefore, this research goal is applied to the real purchasing process of a precast manufacturer that orders raw materials for manufacturing different precast components. The model considers travelling time of these raw materials and demands vary with respect to time following specific probabilistic distribution with real shelflife restrictions. The cooperative model directly determines ordering quantity, reorder point, and shipment frequency. This has immediate application for manufacturers such as Premier Concrete Products and WASKEY that handle perishable raw materials including cement, admixtures, grouts, and epoxy based products.

7.1.2 Application of Research Goal 2: Curing and Yard Layout Optimization:

The curing layout model is applied directly to real curing chamber operations by generating pallet arrangements that respect true pallet dimensions, mold restrictions, spacing rules, and weight limits used inside precast facilities and also satisfies the demands and deadlines for different precast concrete components. Real component dimensions from multiple projects are used to produce feasible layouts that can be placed on pallets without overlapping. The same method applies naturally to outdoor yard storage where precast companies face congestion, long crane movement, and inefficient stacking. Evidence from WASKEY and Premier Concrete shows that the generated layout patterns can be used to organize large products in the yard, reduce stress, and prepare components for shipment.

Table 7.1. Optimization performance of Column Generation (CG) algorithm over iterations

CG Round	LP Objective Value	Number of Patterns	Slack Types	Total Slack
1	14,961,087.417	25	23	989.00
2	11,192,634.117	34	19	725.50
3	8,391,900.587	41	16	535.22
4	5,521,425.739	47	12	346.01
5	3,140,942.012	56	9	210.59
6	1,899,664.115	61	5	115.39
7	14,929.395	68	0	0.00

These results translate into several practical advantages for precast production systems by improving how molds and pallets are used, reducing waste, and increasing operational stability. As column generation identifies more efficient placement patterns for components, the plant is able to use mold and pallet space more effectively, lowering mold changeover frequency and increasing casting throughput. The reduction and eventual elimination of slack means the model satisfies all type-specific placement requirements without overproduction or shortages, removing the need for emergency molds, extra curing beds, or unplanned adjustments. Achieving a zero-slack solution also provides a fully feasible and stable production plan, which supports predictable casting schedules, consistent curing cycles, and smoother coordination with delivery operations. The substantial decrease in the LP objective confirms that the facility can achieve the same production output with fewer mold uses, fewer pallet movements, and reduced labor and resource requirements, creating a leaner and more cost-efficient operation. The generated patterns also help plants handle diverse component sizes such as girders, barriers, panels, piles, and caps by systematically identifying feasible combinations that fit within mold constraints. Finally, obtaining a complete and feasible set of pallet and mold patterns forms the basis for an integrated supply chain, since these patterns directly support downstream scheduling, curing resource allocation, yard operations, and transportation planning, which aligns with the broader optimization framework involving procurement, production, and delivery.

7.1.3 Application of Research Goal 3: Two Stage Delivery Optimization for Multi Project Distribution:

This research goal uses real multi project data collected from highway and bridge construction projects. Actual batch quantities, delivery deadlines, and transport modes such as flatbeds and trucks are used to run the model. The two stage delivery formulation evaluates delivery schedules under uncertain demand and variable travel times that precast suppliers experience during routine shipments. The results include mode allocation, vehicle utilization, batch assignment, and timing related outcomes that match the decisions made daily by dispatch planners. These applications show that the model can be used immediately for planning shipments, adjusting mode usage, and supporting decision making in distribution operations.

7.1.4 Application of Research Goal 4: Physics Informed Neural Network for Strength Classification:

The physics informed neural network is applied to a well-known experimental dataset that represents real mix design variables used in precast plants. The model reads cement content, slag, ash, water, superplasticizer, aggregate proportions, and curing age which match the actual production records of precast concrete. It classifies concrete into strength groups similar to the categories used in transportation projects for structural acceptance. The physics based conditions built into the network reflect known material behavior observed in precast manufacturing. This allows direct use of the model as a supporting tool for quality assessment, mix evaluation, and curing related decision making in precast facilities.

Table 7.2. Optimized parameter of PINN predictive model

Parameter	**Best Value**
Number of layers	2
Units	[160, 256]
Activation function	ReLU
Dropout	0.4
Batch normalization	False
Optimizer	Adam
Learning rate (LR)	0.003
Batch size	32
$\lambda_{physics}$	2.0
Best Validation Accuracy	**0.9709**

Table 7.2 lists the best hyperparameters found for the physics informed neural network classifier. The optimal model uses two hidden layers with 160 and 256 units and the ReLU activation function. A dropout rate of 0.4 is applied, while batch

normalization is not used. The Adam optimizer with a learning rate of 0.003 and a batch size of 32 provides the best performance. The physics regularization weight $\lambda_{\text{phys}} = 2.0$ ensures strong enforcement of the included physical constraints. With this setup the model reaches a high validation accuracy of 0.9709. This tuned model provides fast and reliable strength classification for different concrete mixes, helping precast plants screen mix designs more efficiently and reducing unnecessary laboratory testing. The strong physics regularization ensures predictions follow expected trends such as strength increasing with age and decreasing with excess water, which supports safe decisions about demolding, lifting, and shipping times. Its stable performance also allows integration into production planning and material procurement tools, improving scheduling, resource use, and overall operational consistency in precast concrete manufacturing.

7.2 Impact of Research:

This framework directly addresses the operational weaknesses that often reduce concrete quality, accelerate deterioration, and cause repeated delays in real world projects. The outcomes of this research provide clear pathways for precast manufacturers and transportation agencies to improve long term infrastructure performance through better supply chain coordination and stronger material control.

7.2.1 Impact on Procurement and its Connection to Infrastructure Durability:

Durability begins with the quality and freshness of raw materials used in concrete production. Many precast plants experience problems when cement or admixtures exceed their shelf life, which weakens hydration, reduces early strength, and increases long term cracking risk in highway structures.

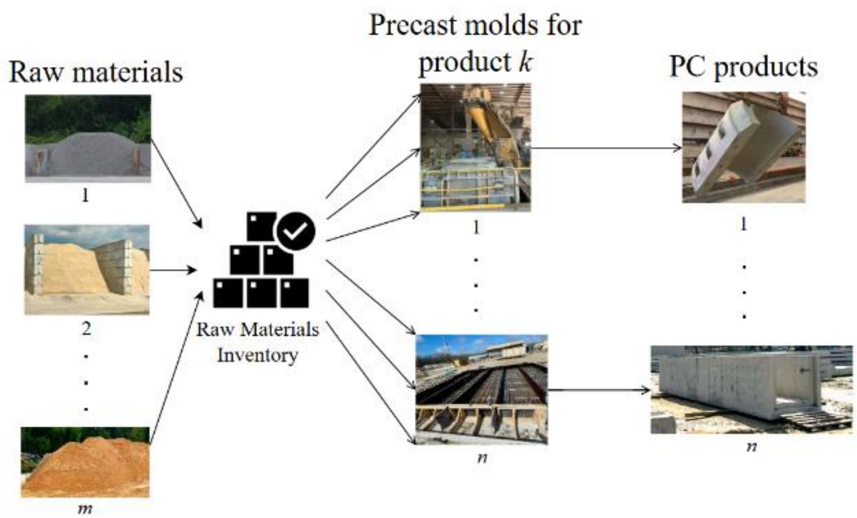


Figure 7.2. Efficient material handling in precast manufacturing

The cooperative procurement model and efficient raw-materials handling (Figure 7.1) ensure that raw materials arrive before quality degradation begins. By optimizing ordering quantity, reorder points, and delivery cycles under uncertain demand and lead time, manufacturers avoid using aged or unstable materials. This stabilizes the early-strength development of precast elements, reduces permeability, and enhances resistance to freeze thaw cycles, chloride intrusion, and fatigue loading in transportation structures. Better control of material freshness translates directly to longer lasting bridge girders, slabs, deck panels, and highway barriers.

7.2.2 Impact of Curing Optimization on Structural Strength and Durability:

Curing is one of the most influential factors on long term performance of precast concrete. Poor curing leads to insufficient hydration, surface scaling, shrinkage cracking, and reduced load carrying capacity of precast components used in roads and bridges.

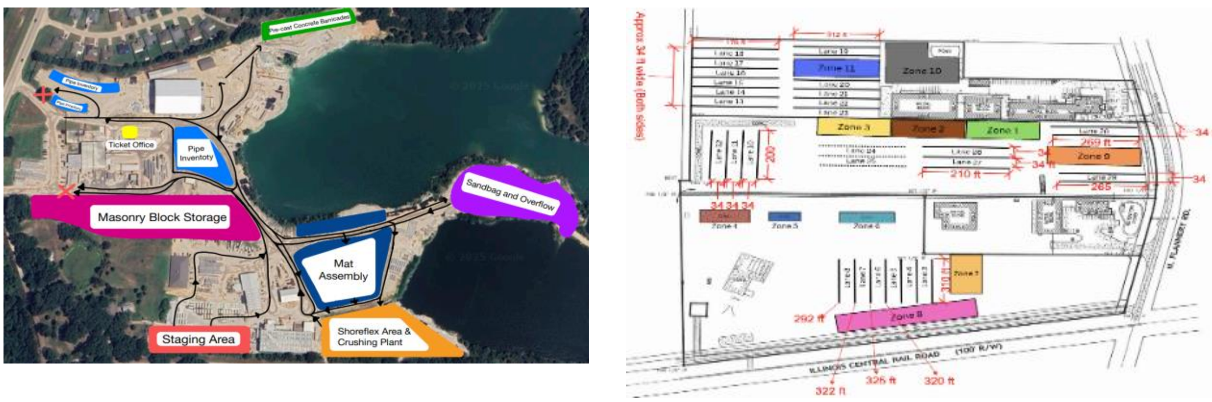
The curing cost minimization model increases durability by arranging components on pallets in a way that allows more efficient and uniform curing. When more components fit within the curing chamber without violating spacing or weight rules, manufacturers achieve:

- more consistent temperature and moisture distribution
- fewer interruptions in kiln cycles
- reduced thermal gradients and curing delays.
- lower risk of differential curing defects

By preventing under cured or over cured zones in the concrete, the model supports stronger and more reliable precast elements that maintain structural performance over decades of service. This has direct implications for bridge spans, precast pile caps, manholes, and box culverts that must withstand long term traffic and environmental loads.

7.2.3 Impact of Yard Layout Optimization on Component Integrity:

Improper storage and yard congestion often lead to cracking, chipping, warping, or improper stacking of precast units. Many facilities like Premier Concrete Products (PCP) and WASKEY report that poor yard layout increases handling stresses and delays loading for shipment, which exposes elements to unnecessary weathering.



(a) (b)

Figure 7.3. Optimized yard layout for PCP

For instance, efficient yard layout and crane operations are vital to prevent damage to precast components during curing and handling. At Premier Concrete (PCP), time-motion studies and truck flow analysis led to one-way routing, storage zones, and FIFO inventory (Figure 7.2a), reducing congestion and improving access. At Waskey, GPS crane data and BlueBeam simulations guided linear pathways, sector assignments, and staging zones (Figure 7.2b), cutting crane idle time and handling risks. These optimizations improved efficiency, durability, and reliability of precast operations. By addressing site-specific issues at PCP and Waskey, we achieved measurable improvements: truck path deviation time at PCP was reduced by 18%, while Waskey saw a 15% decrease in crane travel time, 10% less stoppage, and up to 30% better material handling efficiency. These changes enhanced workflow, reduced risks, and protected the structural integrity of precast components.

Therefore, the study regarding pallet and yard layout model provides optimized placement patterns that:

- reduce excessive lifting and repositioning.
- minimize crane travel and internal truck movement.
- prevent stacking arrangements that overstress components.
- reduce accidental impacts during handling.

Reducing mechanical and environmental stresses before installation increases the long-term durability of precast elements by preserving their as-designed strength and surface quality. This benefits all transportation projects where early damage can propagate into long term structural defects.

7.2.4 Impact of Delivery Optimization on Project Reliability:

Transportation infrastructure frequently suffers when precast components arrive late, out of sequence, or damaged due to inefficient routing or oversized delays. Poor delivery planning leads to extended on site storage, unprotected weather exposure, and forced design adjustments. The two-stage delivery optimization model reduces these issues by:

- selecting the right number and type of vehicles
- allocating batches based on capacity and cost.
- accounting for variable travel times and demand uncertainty
- minimizing late arrivals and early idle delivery

This ensures components reach construction sites in the proper condition at the correct time. Reducing unnecessary exposure and on site waiting protects component durability and allows contractors to install units at the optimal maturity and strength level. This supports long term structural reliability, especially for precast bridge decks, beams, pavement slabs, and drainage structures.

7.2.5 Impact of the Physics Informed Neural Network on Durability and Quality Assurance:

The physics informed neural network predicts compressive strength based on mix proportions, curing conditions, and other material variables while enforcing material science rules. For precast manufacturers and transportation agencies, this tool creates a powerful way to identify potential weakness in components before they reach the project site. The PINN improves durability by enabling:

- early detection of mixtures that may underperform.
- prediction of strength development trends before destructive testing

- validation of curing consistency across different batches
- quality based adjustments in material selection or curing conditions.

This strengthens quality assurance and reduces the risk of installing components that do not meet required structural performance. Better prediction of compressive strength improves safety and longevity for transportation structures, reducing maintenance needs and extending the life cycle of precast systems.

7.3 Feasibility and Implementation Plans

Implementation is highly feasible due to the following reasons:

- The required data already exists in most precast facilities.
- No physical redesign of manufacturing plants is needed.
- The models are modular and can be adopted step by step.
- Computational requirements are manageable with standard computers.
- Integration with existing ERP or scheduling tools is straightforward.

Implementation Plan

Phase 1: Data and system preparation: Collect procurement, curing, yard, and delivery data from plant records and defining operational constraints.

Phase 2: Pilot testing: Test procurement and curing models on selected materials and curing chambers and comparing cost savings and quality improvements.

Phase 3: Yard and delivery integration: Apply optimized layouts and delivery planning tools to reduce handling damage and improve arrival timing.

Phase 4: PINN integration: Use strength prediction to support quality checks and adjust curing or mix proportions early in the process.

Phase 5: Full scale deployment: Combine all components into a unified decision platform and continuously update parameters based on plant performance.

7.4 Impact on Durability of Transportation Infrastructure:

By improving material freshness, curing uniformity, storage safety, delivery reliability, and strength prediction accuracy, this research directly enhances the long-term durability of precast components used across roads, bridges, and other transportation systems. The models ensure that precast elements are produced under optimal conditions, handled carefully, and delivered at the correct maturity. This leads to fewer defects, higher strength retention, lower maintenance needs, and longer service life for critical transportation infrastructure.

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