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RESEARCH ARTICLE

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An estimated Time of Arrival (ETA) model for achieving Just-in-Time (JIT) modular construction delivery in high-density cities

Abstract Modular construction (MC) is a sound strategy to alleviate global issues such as housing crisis, labor shortage, and stagnant productivity. Project managers are aspired to achieve a Just-in-Time (JIT) delivery of their MC logistics. However, the efforts often fall short without the presence of a dedicated Estimated Time of Arrival (ETA) model. This study aims to bridge this gap by developing a MC-oriented ETA model. It does so by first identifying critical factors influencing ETA accuracy in general logistics and then developing an ETA model prototype, which is then calibrated using simulations and data collected from the Internet of Things (IoTs) applied in real-life MC projects in Hong Kong, China. Validated through a cross-border MC project in China's Greater Bay Area, the MC-oriented ETA model achieved 90.6% prediction accuracy (±10 min), reduced transportation delays by 37.5%, and slashed daily planning time from 46.75 to 18.75 min. It is expected that the ETA model can be used in predictive planning of MC logistics delivery in the future. Ultimately, it can lead to the development of smart logistics planning and control systems to expedite MC housing delivery and alleviate urban congestion in high-density cities, offering valuable insights for policymakers, construction stakeholders, and supply chain managers.

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Keywords modular construction, estimated time of arrival model, high-density cities, just-in-time delivery, logistics planning

1 Introduction

Modular Construction (MC) has emerged as a vital solution for productive and quality housing supply, particularly in high-density urban areas like Singapore and Japan (Lu et al., 2022). This novel construction method starts with building standardized three-dimensional modules in offsite before moving them to the installation location (Construction Industry Council [CIC], 2018). MC promises several benefits compared to conventional cast in situ method, such as faster completion times, potential cost reductions, decreased labor needs (Wuni & Shen, 2020), better safety for construction workers (Lu et al., 2021) and stronger environmental sustainability measures (Wuni & Shen, 2020). These advantages have established MC as a modern method of construction to solve urban housing deficits while promoting sustainability objectives (Rehman et al., 2023).

Efficient logistics and supply chain management (LSCM) is essential for successfully implementing MC projects, especially when involving global procurement processes (Wu et al., 2022a). Its importance stems from the need to coordinate multiple stakeholders in different time zones while maintaining tight delivery schedules (Wu et al., 2022a). It is a common strategy for high-wage economies (e.g., Singapore or Japan) to procure their MC logistics from their reachable, adjacent markets (e.g., China's Greater Bay Area, Malaysia, or others) to take advantage of reduced costs and space constraints in these offsite places (Lu et al., 2022). According to the Observatory on Economic Complexity (OEC, 2021), the global prefabricated construction market reached $9.1 billion in

2019, reflecting the increasing adoption of offsite construction methods worldwide. The combination of global MC procurement and the high-density urban environments characteristic of cities significantly amplifies LSCM complexity.

A Just-In-Time (JIT) delivery has been proposed to facilitate off-site production, transportation, and onsite installation in MC-LSC (Wu et al., 2022b; Wang et al., 2024). JIT refers to the strategy of scheduling the delivery of materials and components to the construction site precisely when they are needed for installation or assembly (Wang et al., 2024). The goal is to minimize onsite inventory, reduce traffic congestion risks, and improve efficiency by ensuring that materials arrive precisely when needed (Wang et al., 2024). This approach is particularly crucial in dense urban environments, where space constraints make storing bulky MC modules on-site impractical or even impossible (Wu et al., 2024).

In practice, LSC managers mainly rely on estimated time of arrival (ETA) predictions for logistics planning to better achieve JIT. Here, ETA refers to the prediction of when a particular vehicle, shipment, or individual is expected to arrive at a specific destination (Bodunov et al., 2018). It is commonly used in logistics, transportation, and travel to provide accurate and timely information about arrival times, allowing for better planning and coordination (Chondrodima et al., 2022). Unfortunately, there is no such MC-oriented ETA model in presence. Managers often borrow the models from the buses, private cars, or even taxi service sectors.

This study aims to develop an ETA model for achieving JIT logistics for MC, particularly in high-density cities where delivery has experienced enormous challenges. The research has three key objectives: (1) to identify and analyze the critical factors influencing ETA accuracy in MC logistics; (2) to develop the MC-oriented ETA model for JIT logistics implementation; (3) to validate the proposed ETA model through a real-world case study in high-density urban Hong Kong, China. The paper is structured as follows: Section 2 reviews existing literature on MC logistics and current ETA solutions while identifying research gaps; Section 3 outlines the research methodology; Section 4 presents the critical factors influencing ETA accuracy in MC logistics and the proposed model; Section 5 demonstrates the developed system and evaluates its performance; and Sections 6 and 7 provide discussion and conclusions, respectively, on the findings and implications of this work.

2 Background

2.1 MC logistics and supply chain

MC-LSC proceeds through the three distinct stages of preparation, execution, and completion (Rehman et al., 2023). The process begins when factory managers complete transport document signatures based on module specifications (e.g., ID, weight, and type) and finishes when drivers deliver quality-certified modules with signed confirmations (Wu et al., 2022a). Transporting goods happens through land routes or sea routes or through multimodal combinations (Yang, 2020) and increasing international shipments in metropolitan zones necessitate customs inspection (Wu et al., 2024). High-density environments present distinct challenges to this global supply chain network.

Several persistent concerns about MC logistics in the context of high-density cities have been reported in the literature. First, in the transport preparation stage, MC logistics companies must allocate substantial financial and human resources to conduct physical measurements to estimate rough arrival times (Hsu et al., 2018). Secondly, additional costs may be associated with the early or late delivery of modules in high-density cities. The causes may be late or early departures, extreme weather conditions, and severe traffic congestion (Construction Industry Council [CIC], 2020). It may also be caused by imprecise coordination between multiple stakeholders, including manufacturers, transporters, and on-site installation teams (Yang, 2020). Thirdly, limited parking spaces at high-density urban construction sites also pose significant logistical challenges (Wang et al., 2024). For example, multiple MC trucks may arrive simultaneously, causing traffic congestion in local communities. Fourthly, buffers for MC logistics are difficult to find in high-density cities, which is a long-standing problem (Yang et al., 2021). These operational challenges underscore the critical need for digital solutions that can provide accurate ETA to achieve JIT logistics for MC in congested urban settings.

2.2 Current ETA models for logistics and supply chain

During the planning stage, LSC managers often utilize ETA to guarantee timely deliveries and smooth operations (Chondrodima et al., 2022). ETA is a fundamental logistics indicator that determines when shipments and vehicles will reach their destinations. It enhances supply chain efficiency through improved scheduling capabilities and resource distribution while strengthening customer communication (Bodunov et al., 2018). Existing ETA models in LSCM are mainly derived from transportation industries such as freight, maritime, and ride-hailing services (Bodunov et al., 2018). Traditional methods use historical traffic information and real-time GPS monitoring to estimate arrival times (Chondrodima et al., 2022). The application of machine learning techniques including regression models, neural networks and ensemble methods is growing to enhance ETA accuracy by evaluating dynamic factors like traffic congestion and weather conditions (Balster et al., 2020; Basturk & Cetek, 2021).

These models which cater to standard cargo or passenger vehicles fail to address MC logistics' specific requirements including unique speed pattern and various regulatory limitations such as customs clearance as well as urban last-mile delivery obstacles (Wu et al., 2024).

The latest advancements in predictive analytics now allow ETA systems to become more responsive to changes in JIT supply chains (Al-Naim & Lytkin, 2021). Recent studies indicate that prediction errors in freight logistics can be minimized by integrating real-time traffic data and vehicle telemetry within data-driven models (An et al., 2022). MC logistics continues to receive inadequate service because most ETA models fail to incorporate the necessary multi-stage coordination among offsite factories, transport operators and construction sites (Lu et al., 2022). High-density urban environments present more complex challenges like restricted unloading areas and traffic delays and these factors remain unaddressed by standard ETA models (Balster et al., 2020). The absence of current solutions reveals a demand for a dedicated ETA framework focused on MC to handle its special logistical challenges in congested urban settings. Recent studies propose advanced ETA frameworks for urban environments (e.g., Zhang et al., 2018a; Rogel et al., 2021) and digital twins for MC logistics (Lee & Lee, 2021; Belfadel et al., 2023). However, these focus on generic vehicles or passenger transport and lack MC-specific adaptations. Our study advances this field by:

1. *Targets MC-Specific Challenges*: While existing ETA models address urban congestion (Zhang et al., 2018a; Rogel et al., 2021), none account for MC's unique constraints—oversized load regulations, hydraulic trailer dynamics, and site-access limitations—integrated into real-time predictions.

2. *Combines High-Fidelity Simulation with Operational Data*: Unlike prior digital twin frameworks (e.g., Lee & Lee, 2021; Belfadel et al., 2023) that simulate generic traffic flows, our model fuses high-fidelity traffic microsimulation (SUMO) with Building Information Modeling (BIM) simulations with *actual* MC telematics (e.g., load-specific kinematics, permit status) for granular accuracy.

3. *Validates in High-Density Urban Contexts*: Prior works rely on laboratory or small-scale tests (e.g., Lee & Lee, 2021; Belfadel et al., 2023), we demonstrate real-world feasibility via 127 MC deliveries in Hong Kong's dense urban corridors.

This tailored approach bridges a critical gap by addressing how MC logistics demand urban-aware ETAs that simultaneously comply with structural and regulatory constraints not considered in standard models.

3 Research methods

The research used a mixed-methods approach which involved both qualitative and quantitative techniques to create and test an MC-focused ETA model for JIT logistics within high-density urban settings. Three sequential phases formed the structure of the research to address each key objective of the study, as shown in Fig. 1.

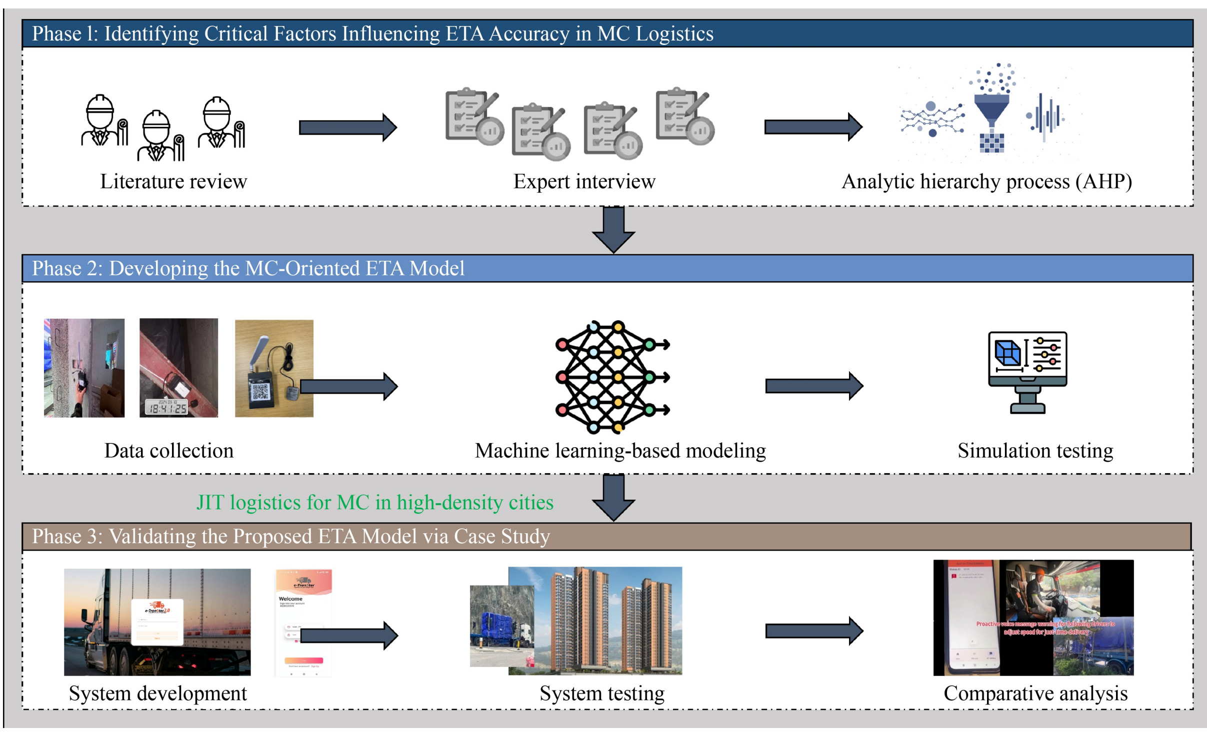


Fig. 1 Research methods of this study.

3.1 Literature review, expert interview and analytic hierarchy process

The first phase focused on identifying and analyzing the critical factors influencing ETA accuracy in MC-LSC. During the initial phase, researchers worked to identify and examine key factors that affect ETA accuracy in the MC-LSC. The research team conducted an extensive literature review to explore existing ETA models in logistics and evaluate their relevance to MC. The literature review process followed a structured search protocol across multiple academic databases which included Scopus, Web of Science, and Google Scholars. The primary search terms used included combinations of (“estimated time of arrival” OR “ETA prediction”) AND (“logistics” OR “supply chain”) AND (“modular construction” OR “modular integrated construction” OR “prefabricated construction”) AND (“urban” OR “high-density”). Between 2000 and 2025, researchers identified 217 peer-reviewed articles through their search which they reduced to 43 relevant studies after conducting both title/abstract screening and full-text review.

Through purposive sampling, we conducted semi-structured interviews with 12 industry experts representing key stakeholders across the MC-LSCM (Table 1), which summarizes the background information of each interviewee.

Each semi-structured interview (60–90 min duration) followed a standardized protocol for interview design organized around three key investigative domains:

1) Current practices: Exploration of ETA forecasting methods currently employed in MC logistics operations.

2) Operational challenges: Identification of key obstacles to achieving on-time deliveries in high-density urban environments.

3) Critical factors: Discussion of variables most significantly impacting ETA accuracy (e.g., route constraints, weather conditions, load characteristics).

The research team implemented rigorous data organization procedures:

• All interviews were audio-recorded with participant consent and professionally transcribed.

• Field notes were taken during each session to capture contextual observations.

• Interview materials were securely stored and anonymized for analysis.

Regarding data analysis, thematic analysis was conducted using NVivo 12 software through a rigorous three-phase process:

1) Open coding: Initial review identified 67 discrete factors affecting ETA accuracy.

2) Axial coding: Factors were grouped into 8 thematic categories (e.g., Route & Distance, Regulatory Constraints).

3) Selective coding: Final refinement of themes through iterative peer review among research team members.

To ensure validity, we implemented two verification measures:

1) Member checking: Preliminary findings were shared with four participants for feedback and validation.

2) Inter-coder reliability: A subset of transcripts (25%) was independently coded by two researchers, achieving 88% agreement.

MC logistics ETA accuracy influencing factors received systematic priority ordering through the Analytic Hierarchy Process (AHP). As shown below, a balanced team of eight domain experts, including four industry practitioners (selected from the original 12 interviewees) and four academics, performed pairwise comparisons of all identified factors. The evaluation structure guaranteed complete examination of inter-factor links while Expert Choice software processed the results to establish weighted priorities. The monitoring process

Table 1 Background of interviewees

No.	Interviewee role	Organization type	Years of experience	Specialization area
1	MC Logistics manager	Modular manufacturer A	9	Offsite production and transport planning
2	MC Logistics manager	Modular manufacturer B	7	Supply chain optimization, Urban module deliveries
3	MC Logistics manager	Modular manufacturer C	10	Offsite production and transport planning
4	MC Logistics manager	Logistics Provider Y	7	Oversize load permits
5	Project manager	Project client	5	High-rise MC projects, Route optimization, Urban freight corridors
6	Project manager	Project client	8	High-rise MC projects,
7	Transport planner	Traffic consultancy	6	Oversized load movements
8	Site manager	Contractor A	12	High-rise MC projects
9	Site engineering	Contractor B	9	High-rise MC projects
10	Site engineering	Contractor C	10	High-rise MC projects
11	Government regulator	Housing authority	14	High-rise MC projects, JIT implementation
12	Government regulator	Housing authority	5	High-rise MC projects

rigorously tracked consistency ratios to ensure validation thresholds were maintained during the entire procedure.

• Expert panel: 4 industry practitioners (from the initial 12 interviewees), 4 academics (all with ⩾ 5 years of MC logistics experience)

• Hierarchy design 3-level structure: Goal → 8 main categories → 29 sub-factors

• Comparison scope: Pairwise comparisons (complete matrix)

• Judgment scale: Saaty's 1–9 ratio scale (anchored with verbal descriptors)

• Consistency check: Automated CR calculation (acceptance threshold: CR < 0.1)

• Software tool: Expert Choice v11.5 (with sensitivity analysis features)

3.2 Data collection, machine learning-based modeling, and simulation testing

Phase II focused on developing an ETA model for MC, which leveraged the key factors identified in Phase I. Three MC projects in Hong Kong provided the research team with complete logistics data, including results from two completed projects and one ongoing project, with 3099 modules delivered. Custom-developed IoT sensors units (Fig. 2a) were deployed to gather complete logistics data during shipments from the factories in China' Mainland to Hong Kong construction sites, each containing:

1. a u-blox NEO-M9N GNSS module (GPS) with 2.5m positional accuracy for real-time location tracking;
2. a Bosch BMI160 IMU (3-axis accelerometer) sampling at 100Hz to capture detailed motion dynamics;
3. an nRF52832 Bluetooth 5.0 Low Energy module for short-range data transmission and geofenced event detection; and
4. BLE beacons for temporal markers
5. BME280 environmental sensors for temperature (−40°C to 85°C), humidity (0–100%), and pressure monitoring; and

These devices captured synchronized data streams at 0.3 s intervals, enabling precise analysis of:

Speed Patterns:

• Continuous speed profiles (0–120 km/h range) with ± 0.1 km/h resolution

• Acceleration/deceleration rates (± 16 g range) for load dynamics analysis

• Vibration spectra (5–500 Hz) to monitor road-induced shocks

Route Execution:

• Complete path tracing with 3σ positional accuracy

• Road-type compliance verification through map-matching algorithms

• Dwell time calculations at toll booths and customs checkpoints

Temporal Markers:

• μs-precise timestamps for duration calculations

• Event-based triggers (loading/unloading transitions)

• Synchronized UTC references across all sensor nodes

Environmental Factors:

• Ambient temperature fluctuations during transit

• Humidity impacts on material integrity

• Shock events (> 5 g threshold) indicating potential handling issues

The research team held two focused training sessions to educate five MC factory employees about sensor installation procedures and troubleshooting techniques (Fig. 2(b)) for proper system implementation. The research team supplemented the IoT sensor data by integrating the critical data sets detailed in Table 2. These include historical traffic patterns from clients' intelligent transportation systems, weather data from meteorological agencies, module specifications, and regulatory and permit records from government transport authorities. The latter ensures compliance with legal constraints (e.g., oversized load permits, off-peak travel mandates, and customs clearance times), preventing delays due to regulatory violations. Together, these data sets provide essential contextual parameters for modeling urban delivery constraints, environmental effects, and administrative dependencies in MC-based ETA predictions.

Next, the research team developed the MC-oriented ETA model by implementing ensemble machine learning

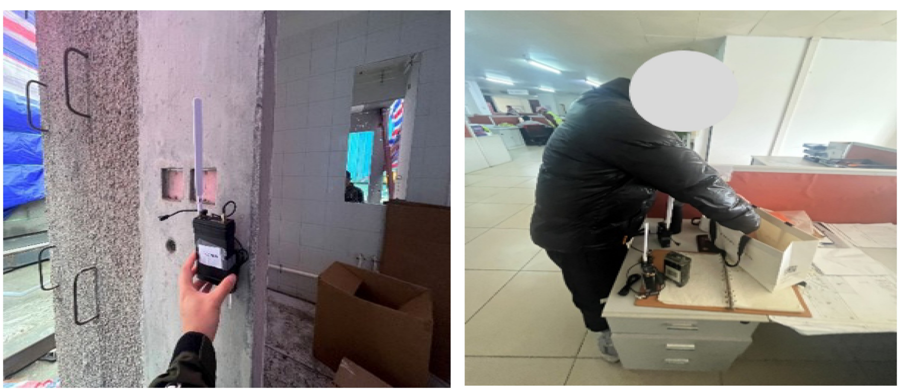


Fig. 2 Data collection processes for (a) IoT sensor attachment and (b) A typical training session of IoT sensor installation.

Table 2 Data collection sources

Data category	Source	Key parameters collected
MC vehicle IoT tracking	Transport vehicle telematics	- Real-time position - Speed - Route execution (permitted routes, road type compliance) - Acceleration/deceleration patterns - Fuel consumption (heavy load impact)
Historical MC traffic data	Project clients' intelligent transportation systems	- Hourly average speeds (accounting for road curvature/inclines) - Congestion patterns (peak/off-peak for oversized loads) - Road closure/accident history
Weather & environmental data	Hong Kong Observatory Mainland China meteorological stations	- Wind speed (risk thresholds for tall modules) - Rainfall/snowfall (site access mud/delays) - Temperature (material checks) - Visibility/road surface conditions
Module specifications	Project documentation Manufacturer datasheets	- Dimensions (L × W × H; permit requirements) - Gross weight (axle load limits) - Shipping configuration (hydraulic trailer adjustments) - Special handling notes (e.g., stacking restrictions)
Regulatory & permit data	Government transport authorities Logistics partners	- Oversize/overweight permit status - Travel time restrictions (off-peak mandates) - Customs clearance times (import/export)

methods such as Random Forest (RF) and eXtreme Gradient Boosting (XGBoost) due to their ability to process high-dimensional heterogeneous data sets and quantify feature importance. The modeling pipeline used collected data as input features and conducted feature engineering to create time-dependent variables such as peak-hour congestion indices and route-specific speed profiles. Using bootstrap aggregation with 100 decision trees prevented overfitting in the RF algorithm while XGBoost achieved better prediction results through gradient boosting after grid search hyper-parameter tuning set learning rate to 0.01 and max_depth to 6. The model training process used 10-fold cross-validation to guarantee generalizability. A weighted average of RF and XGBoost outputs formed the final ensemble approach that balanced bias-variance tradeoffs. The MC-oriented ETA model is established through a three-phase framework:

1) Input Layer:

• Static Inputs: Road network data, module dimensions, and legal constraints from Table 6.

• Dynamic Inputs: Real-time traffic, weather, and site availability, updated every 15 min via IoT sensors.

2) Processing Layer:

• Computes base travel time (Eq. (1)) and 8 penalty terms (Eqs. (2)–9) using the deterministic framework in Section 4.2.

• Machine learning refines parameters (e.g., α, β) and predicts disruptions.

3) Output Layer:

• Primary Output: Predicted ETA (Eq. (10)).

• Secondary Outputs: Risk flags (e.g., wind delays, route violations) for logistics planners.

Before deployment in the real world, the MC-oriented ETA model underwent extensive simulation-based testing to mimic urban logistics conditions in Hong Kong, China. The simulation platform integrates high-fidelity traffic microsimulation SUMO-BIM to create dynamic test scenarios encompassing peak and off-peak traffic patterns, dynamic weather changes, unexpected infrastructure disruptions, and mixed fleet vehicle interactions. We used Monte Carlo simulations with 1,000 iterations to statistically evaluate the model's performance under stochastic urban scenarios while tracking 95th percentile prediction accuracy and analyzing edge case failures like severe congestion during typhoons. The Hardware-in-the-Loop (HIL) system connected the ETA model with active traffic control Application Programming Interface (APIs) for real-time decision latency testing, maintaining a sub-500ms response time. A multi-layered validation strategy confirms operational robustness before launching in the field.

3.3 A case study of cross-border MC logistics in the Greater Bay Area, China

A case study involves a thorough examination of a specific unit, enabling detailed analysis of particular instances within a broader phenomenon (Lu et al., 2022). This research investigates a real-world MC project for public housing at the Anderson Road Quarry Site in Hong Kong, China. The project entailed manufacturing and transporting over 2,000 prefabricated modules from Zhuhai, China, to the high-rise residential construction site in Hong Kong via the Hong Kong-Zhuhai-Macao Bridge (see Fig. 3). It was selected due to its representative challenges, including cross-border logistics complexities, urban density constraints, jurisdictional requirements, and stringent JIT delivery demands. The GBA implementation demonstrates strong potential for scalability, as the region's logistics challenges (e.g., customs complexity, urban density, and JIT demands) mirror those of other

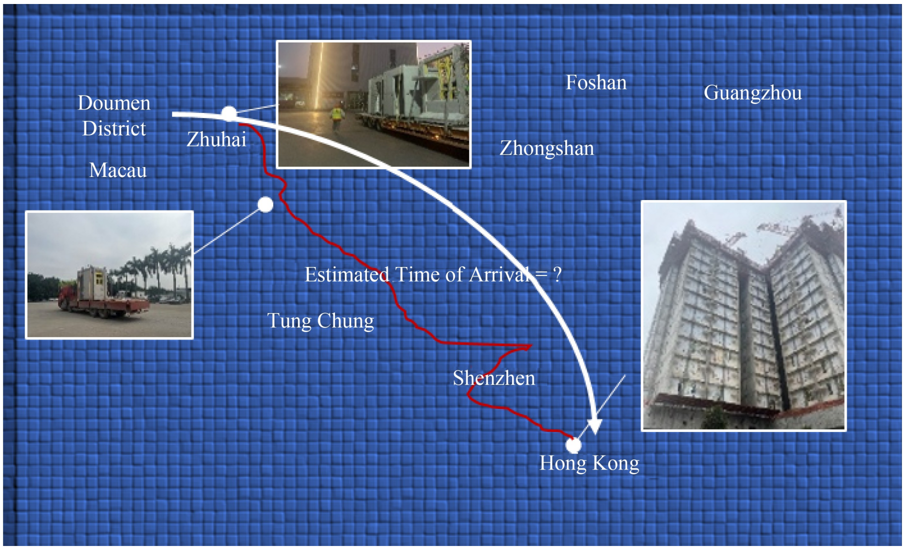


Fig. 3 Delivery route in the case project.

global megacities. While the case study results confirm the model's efficacy in this context, further testing in diverse high-density urban environments is recommended to fully validate its adaptability.

The feasibility of the developed system is demonstrated in the case project, involving the delivery of 127 MC modules using our proposed MC-oriented ETA planning system. A controlled comparative evaluation method assessed identical module deliveries of 127 units on the Zhuhai-to-Hong Kong route. Our proposed system managed 127 deliveries while traditional delivery protocols guided the control group's operations over the same time period. The experimental framework permitted direct performance evaluations between systems under identical geographical, temporal, and logistical conditions. The assessment examined multiple key performance indicators (KPIs) for the MC-oriented ETA planning model while systematically presenting quantitative results in Table 3.

The metrics in Table 3 combine industry-standard KPIs with MC-specific modifications: (1) Accuracy vs. Actual Arrival adapts the Mean Absolute Percentage Error (MAPE) metric (Nguyen et al., 2021); (2) Accuracy vs. Map Services extends navigation comparison frameworks (Wang et al., 2019) with MC route validation; (3) Delay Reduction follows Lin et al. (2013) on-time standards but uses MC-specific thresholds (± 10 min); and (4) Planning Efficiency modifies supply chain cycle time metrics (Nguyen et al., 2021) for MC scheduling.

4 Results and findings

4.1 Critical factors influencing ETA accuracy in MC logistics

MC logistics maintains dependable JIT delivery through precise ETA predictions. We performed a systematic evaluation of critical factors impacting ETA precision in MC supply chains by integrating literature review results with interview data. The analysis identifies key operational barriers and provides methods to enhance the delivery precision. The literature identifies several vital factors that affect ETA accuracy in logistics, including route and distance, traffic conditions, speed and movement patterns, weather conditions, vehicle and load characteristics, time and date elements, road infrastructure quality, and external and legal constraints. While these factors together affect delivery schedules, they fail to consider the distinct characteristics of MC delivery trucks.

The critical factors affecting ETA precision for MC logistics are presented in Table 4, which merges interview

Table 3 Definitions of metrics used for the evaluation

MC-oriented ETA planning model	Definition	Basis
Accuracy of MC-oriented ETA prediction model vs Actual arrival time in the case project)	This metric measures how closely the predicted ETA aligns with the actual arrival time.	Adapted from MAPE standard (Wang et al., 2019)
Accuracy of MC-oriented ETA prediction model vs Map Services (Google Map and Baidu Map)	This metric measures how closely the predicted ETA aligns with different existing map services	Enhanced from Wang et al. (2019) framework with MC route validation
Reduction in transportation delays	This metric evaluates the decrease in delays experienced during transportation compared to a baseline or previous performance.	Adapted from Lin et al. (2013) with MC-specific thresholds
Improvement in logistics planning efficiency	This metric assesses how effectively the system optimizes logistics planning, such as scheduling	Modified from Nguyen et al. (2021) cycle time metric

Table 4 Critical factors influencing ETA accuracy in MC logistics

No.	Category	Factors	Sources: literature & interview
1	Route & distance	• Total distance to construction site • Road type (highway, urban, rural) • Permitted routes (avoid low bridges, narrow roads, weight-restricted paths) • Toll booths • Oversized load regulations (restricted travel times)	Ballis & Dimitriou (2010) Barros et al. (2011) Wiegmans et al. (2018) Chondrodima et al. (2022) Abdi & Amrit (2024) Wang et al. (2024) Dalmau et al. (2025)
2	Traffic conditions	• Real-time traffic congestion • Historical traffic patterns • Accidents & road closures • Road curvature and steep inclines (affects speed for heavy MC loads)	Chung & Shalaby (2007) Kaparias et al. (2008) Kwak et al. (2016) Bodunov et al. (2018) Sheikholeslami, A., & Ilati (2018) Zhang et al. (2018b) Khamis et al. (2021) Lin et al. (2023)
3	Speed & movement	• Current MC truck speed • Speed limits on different roads • Acceleration/deceleration delays (heavy loads take longer to brake) • Driving behavior (aggressive/defensive)	Sun et al. (2020) Nguyen et al. (2021) Chen et al. (2022) Zou et al. (2023) Wang et al. (2024)
4	Weather & environment	• Wind restrictions (high winds risk toppling tall modules) • Rain/snow impact (muddy construction site access) • Temperature effects (material expansion/contraction checks) • Visibility & road surface conditions	Lindell & Prater (2007) Kim & Kim (2017) Al-Naim & Lytkin (2021) Du et al. (2022)
5	Vehicle & load factors	• Module weight and dimensions (requires special permits) • Hydraulic trailer adjustments (time for loading/unloading) • Fuel efficiency drop (heavy loads consume more fuel)	Balster et al. (2020) Li et al. (2024)
6	Time & scheduling constraints	• Off-peak travel mandates (some regions ban oversized loads during rush hour) • Delivery window restrictions (site may only accept deliveries at certain times)	An et al. (2022) Pang et al. (2024)
7	Road & infrastructure	• Construction & maintenance zones • Lane closures and reduced speed areas • Rough terrain near site (may require off-road capability)	Wang et al. (2018) Basturk & Cetek, (2021) Halili et al. (2022)
8	External & legal factors	• GPS/navigation system accuracy • Oversize/overweight permits (processing time if last-minute) • Safety inspections (random checks en route) • Customs clearance time (export and import)	Di Martino & Rossi (2016) Weiss (2021) Ye et al. (2022) Seo et al. (2023) Arbabkhah et al. (2024) Yan et al. (2024)

findings with literature review to tackle MC-specific challenges. MC truck operations differ from standard logistics because they necessitate modifications for oversized loads, limited routes, weather conditions like wind risks, and regulatory requirements including permits and travel time restrictions. By considering MC-specific complexities including module dimensions and hydraulic trailer operations along with site-access limitations these factors produce more accurate ETAs.

The ETA model systematically incorporates all critical factors through specific computational implementations. Route and Distance are represented as hard constraints on the path-finding algorithm, with the set of feasible paths excluding roads that do not allow oversized loads. Traffic Conditions utilize real-time congestion data and historical patterns to adjust speed predictions dynamically. Speed and Movement factors account for vehicle-specific kinematics, including longer acceleration and deceleration times for heavy modules. Weather and Environment triggers activate when wind speeds exceed safety thresholds, or precipitation reduces visibility. Vehicle and Load characteristics directly influence routing through permit requirements and hydraulic system setup times. Time and Scheduling constraints enforce delivery windows and off-peak travel restrictions through temporal boundaries. Road and Infrastructure factors model construction zones and rugged terrain through additive delay functions. External and Legal factors incorporate permit processing times and customs clearance durations as probabilistic variables. This comprehensive integration enables the model to generate ETAs that accurately reflect the unique challenges of MC logistics operations.

The computational implementation systematically translates Table 4's critical factors into algorithmic logic through Table 6's variables, with implementation intensity scaled to Table 5's AHP weights. The model prioritizes high-impact factors through dedicated mechanisms: Route & Distance (0.24) governs path-finding via hard-coded exclusions (d_i, $d_{\text{detour},\ l}$), while Vehicle & Load (0.21) controls operational timing through parameters like t_{unload} and λ_i. Mid-tier factors (Weather: 0.13) trigger conditional interrupts (w), and lower-weighted elements

Table 5 AHP-derived category weights (sum = 1.00) and the top sub-factor within each category

Category	Weight	Top sub-factor	Global weight
Route & distance	0.24	Permitted routes	0.12
Vehicle & load factors	0.21	Module weight and dimensions	0.10
Traffic conditions	0.16	Road curvature and steep inclines	0.08
Speed & movement	0.11	Current MC truck speed	0.018
Weather & environment	0.13	Wind restrictions	0.06
Time & scheduling	0.09	Off-peak travel mandates	0.04
Road infrastructure	0.08	Rough terrain near site	0.03
External & legal factors	0.06	Oversize/overweight permits	0.03

Note: Category weights (Column 2) sum to 1.00. Global weights (Column 4) reflect only the top sub-factor's absolute priority.

(Legal: 0.06) introduce controlled stochasticity ($t_{\text{permit},\ k}$). This weighted implementation strategy ensures optimal resource allocation while maintaining comprehensive coverage of all identified MC logistics challenges.

The AHP results were calculated by applying Saaty's 1-9 ratio scale system to conduct 76 pairwise comparisons across an 8-category structure with 29 sub-factors (Table 5) which analysts processed using Expert Choice v11.5 software. The process met rigorous validation requirements and attained a consistency ratio of 0.07 which remains well below the acceptable standard of 0.1. The analysis identified Route & Distance (0.24) and Vehicle & Load Factors (0.21) as top categories but showed Speed & Movement (0.11) as a major operational factor that surpassed traditional logistics metrics, demonstrating MC transportation's distinct operational dynamics. The full priority list for all eight categories appears below in Table 5. In summary, the key factors affecting the accuracy of ETA in MC logistics lay the foundation for building an MC-oriented ETA model.

The AHP-derived weights in Table 5 serve as the blueprint for structuring the MC-oriented ETA model's variables (Table 6). This prioritization ensures computational focus aligns with empirical importance: Route & Distance parameters (d_i, $d_{\text{detour},\ l}$) implement the highest-weighted category (0.24), while Vehicle & Load variables (t_{unload}, accel_i) reflect the second-most critical factor (0.21). The tiered implementation strategy converts global weights into modeling approaches—permitted routes (0.12) became deterministic path constraints, whereas lower-priority elements like External & Legal Factors (0.06) were modeled as probabilistic delays ($t_{\text{permit},\ k}$). This architecture maintains methodological rigor while optimizing computational efficiency by allocating resources according to each factor's demonstrated impact.

4.2 A MC-oriented ETA model

The MC-oriented ETA operationalizes the model established in Tables 4 and 5 through the variables enumerated in Table 6. The development process progressed through three validated stages: (1) comprehensive factor identification via literature review and expert interviews (Table 4), (2) quantitative prioritization using AHP methodology (Table 5; 29 sub-factors, CR = 0.07), and (3) computational implementation. Core parameters including route variables (d_i, $d_{\text{detour},\ l}$) and speed profiles (v_i) directly reflect the top-weighted categories, while secondary influences like weather delays (w) employ conditional functions. All implementations were empirically validated using GBA case data, with constants (α = 1.2) and thresholds calibrated to real-world operational conditions.

The step-by-step formulation of the model is illustrated in this section. First, the base travel time is calculated using the total distance and identified average speed, adjusted for road types and speed limits.

$$T_{\text{base}} = \sum_{i=1}^{n} \frac{D_i}{V_i}. \tag{1}$$

Secondly, each factor from Table 5 is modeled as a time penalty or multiplier. The route and distance category (k_{route}) is then modeled as below.

$$k_{\text{route}} = \sum_{j=1}^{m} t_{toll,j} + \sum_{k=1}^{p} t_{\text{permit},k} + \sum_{l=1}^{q} \left(\frac{d_{\text{detour},l}}{v_{\text{detour},l}} \right). \tag{2}$$

The traffic condition category (k_{traffic}) is then modeled by considering teal-time traffic congestion, historical traffic patterns, accidents and road closures, and toad curvature and steep inclines.

$$k_{\text{traffic}} = \alpha \times T_{\text{base}} \times \left(\frac{C_{\text{current}}}{C_{\text{free flow}}} \right) + \delta \times T_{\text{base}} \times H(t) + \sum_{r=1}^{s} t_{\text{incident},r} + \sum_{i=1}^{n} d_i \times \left(\frac{1}{v_i} - \frac{1}{v_i \times (1 - \eta\theta_i)} \right). \tag{3}$$

Next, the speed and movement (k_{speed}) is molded by considering acceleration and deceleration delays and driving behavior. The current MC truck speed and speed

Table 6 Variables and constants involved in the proposed model

No.	Variable	Explanation
1	d_i	Distance of road segment *i* (e.g., highway, urban, rural)
2	v_i	MC truck average speed for segment *i* (reduced for oversized/heavy loads). [ML-optimized]
3	$t_{\text{toll}, j}$	Delay (hrs) at toll booth *j*
4	$t_{\text{permit}, k}$	Time (hrs) lost due to permit-related stops (e.g., inspection)
5	$d_{\text{detour}, l}$	Extra distance (km) from detour *l* (e.g., avoiding narrow roads)
6	α	α = 1.2: Congestion sensitivity for heavy module loads [ML-optimized]
7	$H(t)$	Historical delay multiplier (1.2 for peak hours), [ML-trained time-series model]
8	$t_{\text{incident},r}$	Delay (hrs) from accident/closure *r*
9	$\eta\theta_i$	Speed reduction due to incline/curvature (θ_i = 0.1, mild, 0.5 severe)
10	a_i	Acceleration/deceleration distance (km) for segment *i*
11	$\text{accel}_i, \text{dccel}_i$	Rates (km/h^2) for MC loads (lower than standard trucks)
12	β	Driving behavior factor (0.1 for defensive driving)
13	w	Downtime (hrs) for wind/rain/temperature checks
14	v_{safe}	Safe operating speeds under weather conditions [ML-derived from incident data]
15	t_{arrival}	$T_{\text{depart}} + T_{\text{base}} + \sum k_j$ (estimated arrival before scheduling constraints)
16	$t_{\text{window\_star}}$	Earliest allowed delivery time at destination (Integrate with site management systems for real-time updates)
17	$t_{\text{offpeak\_start}}$	Next available off-peak travel window start time (Use geo-fenced regulations to determine it dynamically
18	t_{unload}	Time required for unloading modules [MC-specific, ML-calibrated using historical MC operation data]
19	λ_i	Surface roughness multiplier: • 1.0 (paved highway) • 1.2–1.5 (urban roads) • 1.5–2.0 (unpaved/gravel)
20	v_i	Standard speed limit on segment *i* (km/h)
21	$t_{\text{construction}, j}$	Fixed delay at construction zone *j* (hours), typically 0.25–1 h per zone
22	$d_{\text{closure}, k}$	Length of lane closure *k* (km)
23	$V_{\text{reduced}, k}$	Reduced speed in closure (30 km/h)
24	$\text{V}_{\text{normal}, k}$	Normal speed (60 km/h)
25	t_{offroad}	Fixed time for final site access (hours), typically 0.5-2 h depending on terrain.
26	σ	GPS error coefficient (0.01–0.05).
27	p	p = 1 if last-minute, 0 if pre-approved
28	t_{permit}	t_{permit} = 2–24 h (uniformly distributed)
29	N_{inspect}	~Poisson (0.5) (random inspection count)
30	t_{inspect}	t_{inspect} = 1.5 h per MC delivery inspection
31	c	c = 1 for international, 0 for domestic
32	$\text{C}_{\text{current}}$	Real-time traffic density [ML-predicted]
33	$\text{C}_{\text{free flow}}$	Base traffic density under ideal conditions [veh/km] [ML-calibrated per road type: 10 urban, 5 rural, 20 highway]
34	t_{export}, t_{import}	t_{export} = 2 h; t_{import} = 3 h for MC.
35	w_{rain}	Precipitation severity [ML-forecasted]
36	W_{wind}	Wind speed (m/s) [ML-forecasted] with thresholds: • 10 m/s (moderate) • 15 m/s (severe)
37	W_{temp}	Temperature deviation (°C) from material tolerance [ML-predicted] • 5°C (expansion checks) • −5°C (contraction checks)
38	$v_{\text{detour}, l}$	Effective speed (km/h) on detour *l* [ML-optimized using real-time traffic (C_{current}) and historical detour performance]

(*Continued*)

No.	Variable	Explanation
39	$t_{\text{trailer\_setup}}$	Initial time (hrs) to configure hydraulic trailer for module loading, including: • Safety checks • Alignment calibration Typical range: 0.25–0.5 h (site-dependent)
40	$t_{\text{trailer\_adjust}}$	Additional time (hrs) for mid-transport adjustments due to: • Road vibrations • Weather-induced shifts [ML-optimized using historical vibration sensor data]

limits on different roads have been considered in Eq. (1).

$$K_{\text{speed}} = \sum_{i=1}^{n}\left(\frac{a_i}{2\times \text{accel}_i}+\frac{a_i}{2\times \text{dccel}_i}\right)+\beta\times T_{\text{base}}. \tag{4}$$

In addition, the weather and environment category is added to the model as shown below.

$$k_{\text{weather}} = max\left(\frac{w_{\text{wind}}}{v_{\text{safe wind}}},\frac{w_{\text{rain}}}{v_{\text{safe rain}}},\frac{w_{\text{temp}}}{v_{\text{safe temp}}}\right). \tag{5}$$

The vehicle and load category (k_{load}) is also modeled by considering hydraulic trailer adjustments (time for loading/unloading) and fuel efficiency drop.

$$k_{\text{load}} = t_{\text{trailer\_setup}} + t_{\text{trailer\_adjust}} + \sum_{i=1}^{n}\frac{D_i}{V_i}\left(\frac{Fuel_{MC,i}}{Fuel_{\text{standard},i}}-1\right). \tag{6}$$

Equation 7 takes into account time and schedule constraints (k_{time}) and Eq. (8) considers road and infrastructure (k_{road}).

$$k_{\text{time}} = t_{\text{arrival}} + t_{\text{window\_star}} + t_{\text{offpeak\_star}} + t_{\text{unload}}, \tag{7}$$

$$k_{\text{road}} = \sum_{i=1}^{n}\left(\frac{d_i\times\lambda_i}{V_i}\right)+\sum_{j=1}^{m} t_{\text{construction},j} + \sum_{k=1}^{p}\left(\frac{d_{\text{closure},k}}{V_{\text{reduced},k}}-\frac{d_{\text{closure},k}}{V_{\text{normal},k}}\right)+t_{\text{offroad}}. \tag{8}$$

Finally, the external and legal factors related to MC are modeled in Eq. (9).

$$k_{\text{legal}} = \sigma\times T_{\text{base}} + p\times t_{\text{permit}} + N_{\text{inspect}}\times t_{\text{inspect}} + C\times(t_{\text{export}}+t_{\text{import}}). \tag{9}$$

Thus, the final ETA formula is:

$$ETA = T_{\text{base}} + k_{\text{route}} + k_{\text{traffic}} + K_{\text{speed}} + k_{\text{weather}}r + k_{\text{load}} + k_{\text{time}} + k_{\text{road}} + k_{\text{legal}}. \tag{10}$$

The deterministic ETA model (Eqs. (1)–(10)) is augmented with ML in three ways:

1) Variable Calibration: Random forest models optimize parameters (α, β, and η) using 12 months of delivery data.

2) Real-Time Predictions: Long Short-Term Memory networks forecast dynamic variables (c_{current} and w_{weather}) every 15 min.

3) Weight Adaptation: Reinforcement learning adjusts key weights ($k_{\text{traffic,}}$ k_{weathe}) based on recent prediction errors.

4.3 Simulation and robustness validation results

The high-fidelity simulation platform (Fig. 4) validates the MC-oriented ETA model through an integrated system combining SUMO-based microscopic traffic simulation with BIM-derived infrastructure data. The platform comprises four synergistic components: (1) a data layer processing real-time inputs (HKTD vehicle tracking at 10s intervals, GBA route maps, and 1Hz telematics feeds) with weather APIs providing typhoon alerts; (2) a simulation engine generating dynamic urban scenarios using multi-resolution road networks and building geometries, accounting for oversized load constraints; (3) an analysis module employing Monte Carlo methods (1,000 iterations) to evaluate prediction accuracy with actual travel times (92.4% within ± 15-min windows) and route compliance rates; and (4) a visualization interface displaying vehicle trajectories, congestion heat maps, and dynamic ETA adjustments. This architecture enables comprehensive testing of all Table 3 factors while maintaining 95th percentile accuracy in GBA's complex logistics environment. The baseline data sources are:

- HK Transport Dept. (HKTD) vehicle tracking data
- GBA municipal oversize load route maps
- HKTD real-time traffic cameras
- Tencent/AliCloud historical congestion data
- HKTD commercial vehicle speed limits
- GBA telematics (e.g., WeTransport logs)
- HK Observatory typhoon records
- GBA construction site weather logs
- HKTD vehicle specs database
- GBA freight co. fuel reports
- HKTD oversize load travel bans
- GBA site delivery records
- HK Highways Dept. work notices
- GBA GIS road condition maps
- HKTD permit processing logs
- GBA customs clearance times

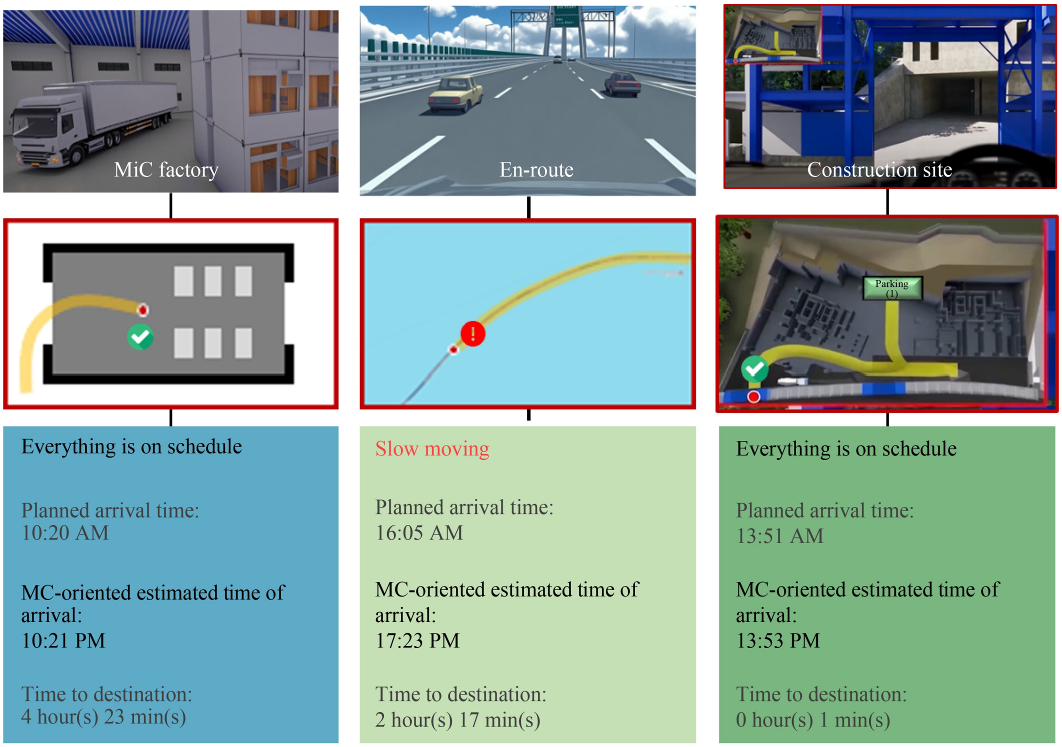


Fig. 4 Simulation of MC-oriented ETA model for achieving JIT-MC delivery in high-density cities.

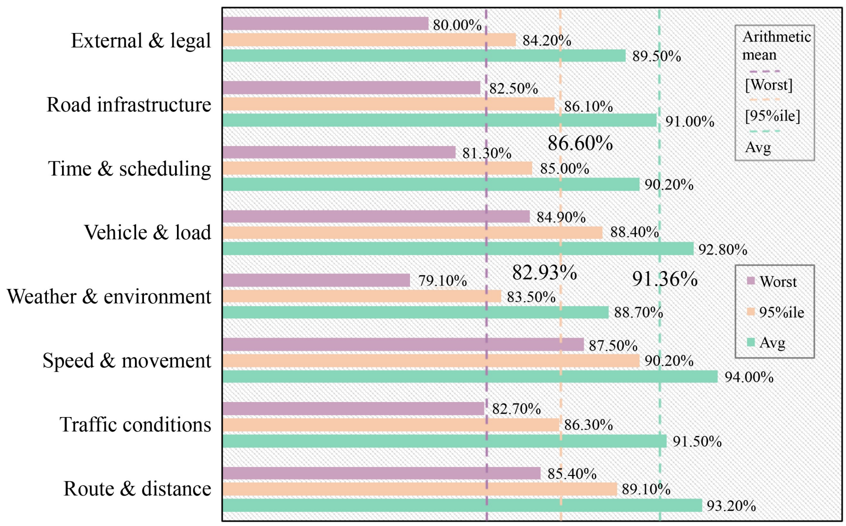


Fig. 5 MC-oriented ETA model accuracy by critical factor category.

As shown in Fig. 5, results demonstrate consistent performance with 91.4% mean accuracy (86.6% at 95th percentile, 82.9% worst-case), revealing critical insights: The highest accuracy levels were achieved by Speed & Movement (94.0%) and Route & Distance (93.2%) while Weather (88.7%) and Legal Factors (89.5%) became the main sources of accuracy limitations. The robust system performance remains evident through the minimal 8.5% difference between mean and worst-case results which highlights traffic congestion and permit processing as main sources of variability to optimize MC-JIT logistics in urban areas.

5 Case study

5.1 System implementation

The system development followed the case project requirements and the proposed model resulting in a system operating on Linux kernel version 5.4.0-58-generic-lpae (Ubuntu 18.04.1 LTS). The system architecture accommodates five key stakeholder organizations: the MC manufacturer, main contractor, third-party transporter, project client, and research team.

We designed a responsive login portal for the frontend interface utilizing both AdminLTE and Flutter frameworks. The interface connects without disruption to the powerful backend system that drives all frontend functional components. The system architecture provides protection to data as it moves through the intuitive user interface and the powerful processing capabilities of the backend system. The implementation of the MC-oriented ETA planning involves the integration of the Formulas 1–10 with the Amap. Figure 6(a) shows the user interface of the MC-oriented ETA planning.

The mobile application utilizes WebSocket protocols to maintain real-time synchronization with the web dashboard. Our system's mobile application operates using Xiaomi 13 phones which run MIUI 14 atop Android 13 to serve as truck drivers' main interface. We chose these devices because of their strong connectivity options such as dual-SIM 5G support and Wi-Fi 6E along with Bluetooth 5.3 capabilities and confirmed future OS update support (shown in Fig. 6(b)). Each driver receives a pre-configured mobile with the MC-oriented ETA application installed, creating a seamless communication channel between the MC-oriented ETA model and the human operators. This setup allows for real-time delivery of voice MC-oriented ETA instructions and route adjustments while maintaining driver focus on road safety.

5.2 System performance evaluation

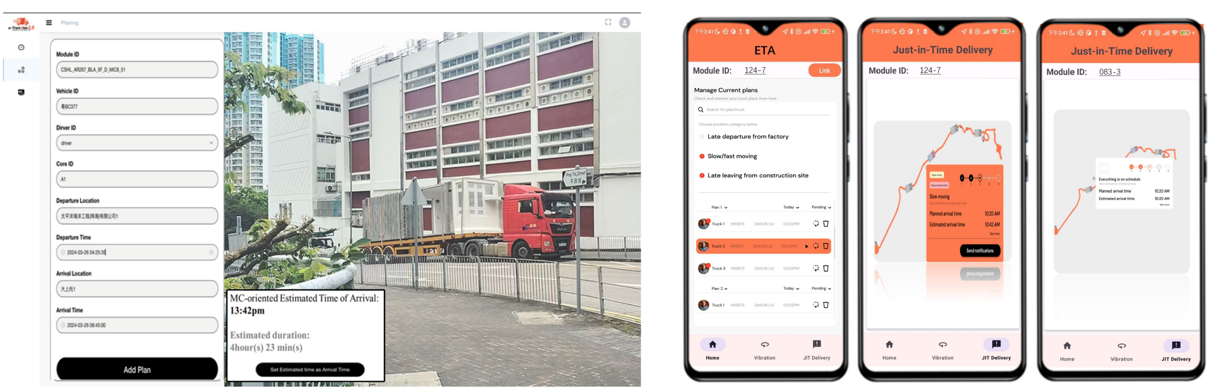
5.2.1 Accuracy of ETA predictions

The IoT sensor network was able to log the precise arrival times for every one of the 127 MC module deliveries as shown in Fig. 7. We measured how accurate MC-oriented ETA predictions and traditional ETA predictions (provided by existing map services) were by setting a tolerance window of ± 10 min around suggested ETAs. The analysis reveals that 89 deliveries (77.3% of accurate predictions) arrived within + 10 min of the projected MC-oriented ETA, while 26 deliveries (22.7%) arrived within −10 min (Fig. 7(a)). Of the 12 inaccurate predictions, 7 cases (58.3%) exceeded the MC-oriented ETA by more than 10 min, with 5 cases (41.7%) arriving more than 10 min early (Fig. 7(a)). These results demonstrate an overall MC-oriented ETA prediction accuracy of 90.6% across all monitored MC deliveries.

In contrast, Google Map and Baidu Map navigation services do not support ETA for MC but support ETA for private cars. As shown in Fig. 7(b), only 43 deliveries were delivered within the suggested ETA, while 94 deliveries were delivered after or before the ETA suggested by Google. Among the inaccurate ETA, 84.3% cases exceeded the ETA by more than 10 min, with 15.7% arriving more than 10 min early (Fig. 7(b)). These results demonstrate an overall google-supported ETA prediction accuracy of 33.9% across all monitored MC deliveries. Similarly, only 38 deliveries were delivered within the suggested ETA, while 89 deliveries were delivered after or before the ETA suggested by Baidu. Among the inaccurate ETA, 89.7% cases exceeded the ETA by more than 10 min, with 10.3% arriving more than 10 min early (Fig. 7(c)). These results demonstrate an overall google-supported ETA prediction accuracy of 29.9% across all monitored MC deliveries.

5.2.2 Reduction in transportation delays

This key performance metric evaluates on-time delivery improvements through comparisons of delay frequencies with standard baseline operational data. MC logistics providers can boost customer satisfaction through reduced transportation delays while also ensuring installation teams follow their schedules and construction sites experience fewer workflow disruptions. The absolute reduction in delayed deliveries during comparable



(a) (b)

Fig. 6 The implementation of the MC-oriented ETA model through: (a) web-dashboards (alpha version); (b) a mobile application.

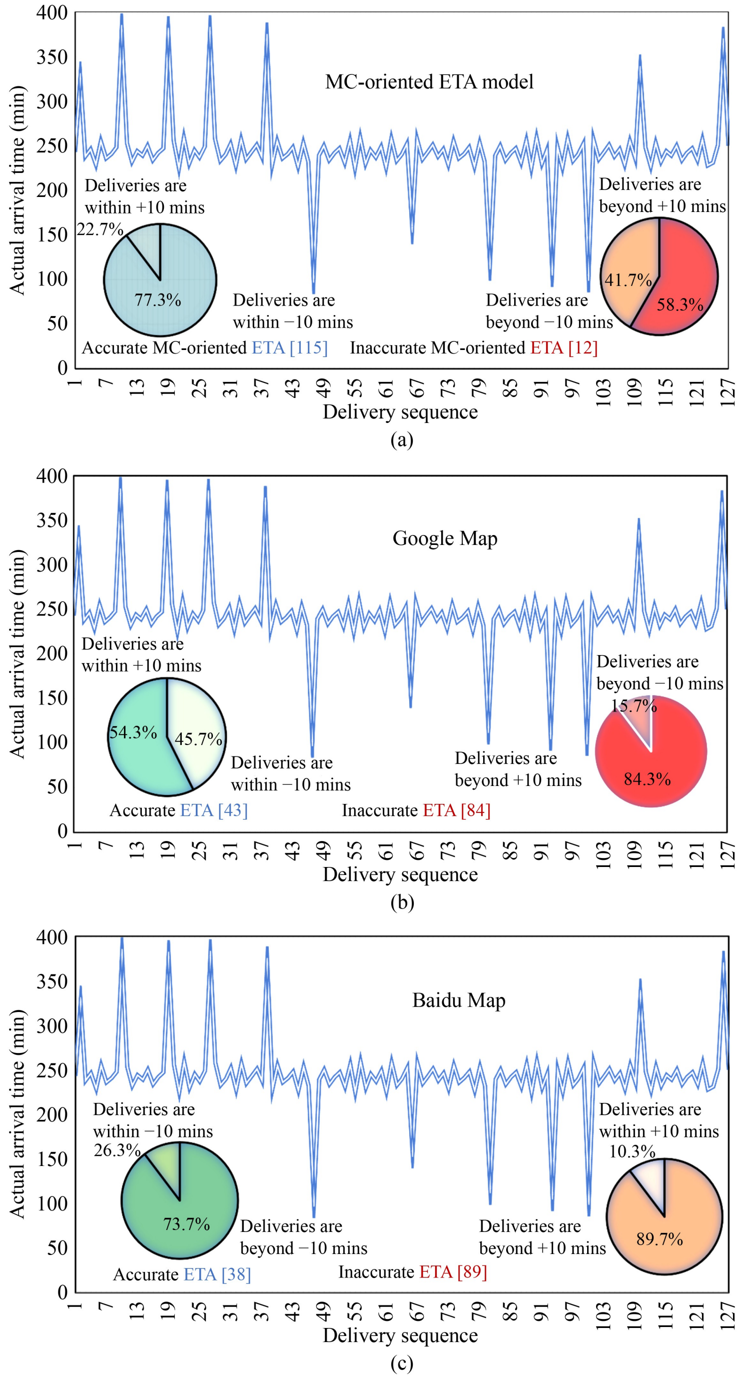


Fig. 7 Accuracy of ETA predictions for (a) MC-oriented ETA model; (b) Google Map; and (c) Baidu Map.

operational periods serves as our measurement of improvement where delayed deliveries are defined as arrivals that exceed planned ETAs by more than 10 min. For example, a hypothetical reduction in monthly delays from 40 to 20 cases would show a 50% improvement in logistics reliability which illustrates the system's potential large-scale impact.

Table 7 exhibits that the system shows steady performance enhancements throughout the majority of evaluation periods. The four evaluation periods (Periods 1–4) correspond to consecutive calendar months of standard operations of the case project, representing the complete construction timeline from initial deliveries to project completion. These periods were selected to provide consistent monthly comparisons of transportation performance under normal operating conditions, with identical system configurations maintained throughout all periods. During the initial implementation phase, the system reduced delays from 12% (3/25 shipments) to 4% (1/25 shipments), representing an 8.0% absolute reduction in

Table 7 Reduction in transportation delays through comparative evaluation

Period	Using the system		Without using the system		Reduction (%)
	Delivery (Delayed)	Delivery (Normal)	Delivery (Delayed)	Delivery (Normal)	
Period 1	1	24	3	22	8.0%
Period 2	1	21	1	21	0.0%
Period 3	2	38	14	26	30.0%
Period 4	3	37	18	22	37.5%
Total	7	120	36	91	—

late arrivals. Subsequent periods brought the most notable improvements by achieving delay reductions of 30.0% and 37.5% during the third and fourth periods. The second evaluation period revealed only minor progress which indicates possible operational irregularities that require additional investigation.

5.2.3 Improvement in logistics planning efficiency

This performance metric provides a quantitative evaluation of how well the system optimizes logistics planning operations. By significantly reducing the time required to generate and update delivery schedules, the solution delivers three key business benefits. First, the system achieves major cost savings through labor efficiency improvements. Secondly, it simultaneously boosts operational speeds. Thirdly, it improves resource management. In this case, planning efficiency gains are measured by analyzing the differences in time needed for schedule development before and after implementing the system. Figures 6 and 8 display how intuitive user interfaces provided by the system simplify the procedures for entering and modifying daily logistics plans. The time savings achieved through system use enable quicker decision-making and improved reaction time to sudden schedule modifications.

In the case project, the system reduced the time required for daily logistics planning in MC from an average of 46.75 min to 18.75 min, and the planning efficiency increased by 60.22%. Table 8 shows the detailed improvement in planning efficiency from the first to the fourth period.

6 Discussion

6.1 Contributions of this study

This paper proposes a MC-oriented ETA planning system model for achieving JIT logistics for MC in high-density

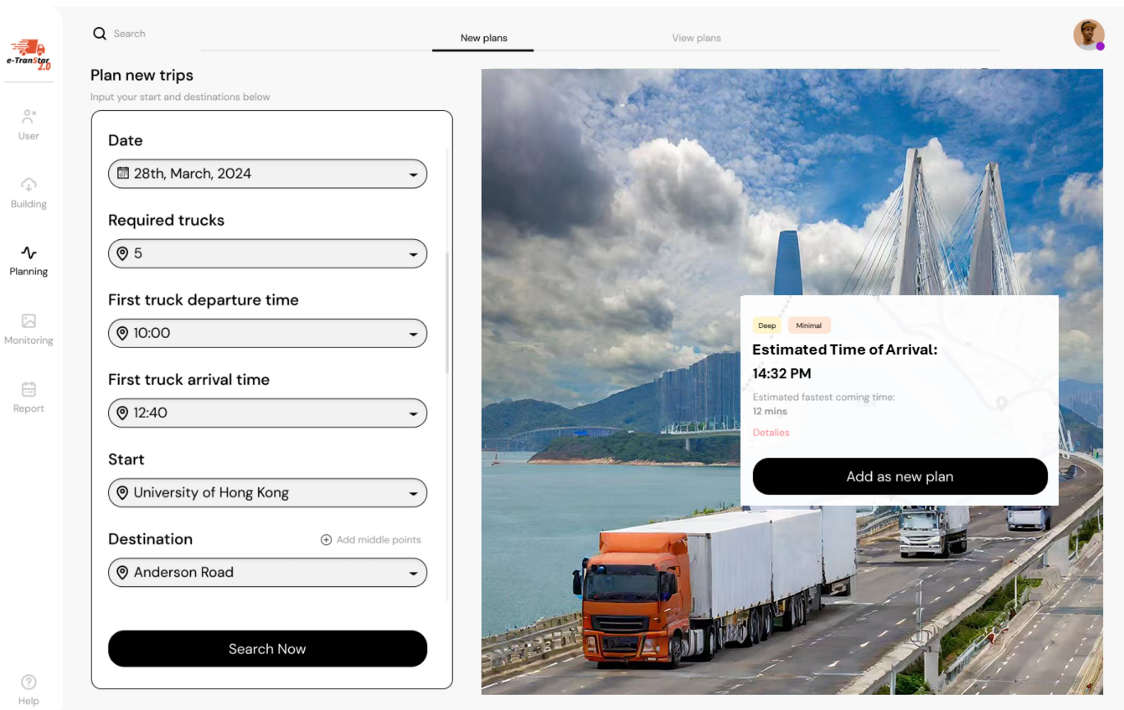


Fig. 8 Improved user interface of the Component 1 for inputting and updating the daily logistics plan (beta version).

Table 8 Improvement in logistics planning efficiency

Period	Time cost (using the system) (min)	Time cost (without using the system) (min)	Improvement (%)
Period 1	15	37	59.46%
Period 2	13	36	63.89%
Period 3	24	57	57.89%
Period 4	23	57	59.65%
Average	18.75	46.75	60.22%

cities. Compared with the previous studies that implemented general ETA in MC logistics, this paper has the following novelties:

• Identifying and analyzing the critical factors influencing ETA accuracy in MC logistics. The research systematically examines key factors that influence ETA accuracy in MC logistics setting it apart from standard transportation models. Traditional ETA models underestimate MC delivery times because of oversized module dimensions, urban traffic constraints, weather sensitivity, and supply chain coordination gaps. The investigation demonstrates that MC logistics require specialized handling procedures and route restrictions for oversized loads along with installation dependencies which necessitate a customized logistical strategy. A customized ETA model designed for MC achieves better prediction accuracy for urban logistical challenges.

• Developing a MC-oriented ETA planning model to predict ETA for MC logistics. This novel model addresses a critical gap in existing map navigation services. While platforms like Baidu and Google Maps provide ETAs for standard vehicles (e.g., cars, buses, and taxis), they do not account for the unique constraints of MC trucking, such as oversized loads and slow speed. By incorporating collected MC logistics time data from real-life projects—the proposed model enhances accuracy in arrival time predictions. The newly developed model has been providing the ability to improve logistical planning in MC projects. The model lays a theoretical foundation for future research in smart logistics for prefabricated construction, bridging the gap between conventional navigation algorithms and the specialized needs of MC logistics in high-density cities.

Possible practical impacts are:

• Reducing the risk of traffic congestions to local communities. The proposed MC-oriented ETA planning model can help reduce traffic congestion risks for local communicates in high density cities. This proactive approach enhances urban mobility of high-density cities while supporting efficient MC logistics, benefiting both construction stakeholders and the general public.

• Minimizing the negative impacts on environments, such as reducing carbon emissions and air pollutions. By achieving JIT logistics for MC in high-density cities, the MC-oriented ETA model helps decrease fuel consumption and greenhouse gas emissions from MC trucks. Such a practical impact aligns with green construction initiatives and urban air quality improvement goals, ensuring that off-site MC production efficiency is not offset by on-road environmental costs. Future integration with electric or low-emission vehicle routing could further enhance these benefits.

• An operable ETA planning system for construction practitioners. This paper goes beyond theoretical models and develops key technologies to support MC project stakeholders through system development. The feasibility of the developed system has been validated through a cross-border MC logistics project and its performance has been systematically evaluated.

6.2 Limitations

The major strength of this study lies in its innovative, proactive approach and the work conducted to instantiate and realize it. Nevertheless, the research has limitations that must be addressed in future studies.

Firstly, only one case study is involved in testing the MC-oriented ETA planning model. The research team has acquired more real-world MC projects in the GBA to calibrate the model under traffic patterns and logistics constraints to improve its robustness, accuracy, and generalizability. Ultimately, this phased validation approach will ensure the model's reliability before broader industry adoption.

Secondly, while MC-oriented ETA planning model demonstrates innovation, its accuracy faces inherent limitations from practical challenges. For instance, insufficient historical MC traffic data reduces prediction precision, particularly for oversized MC truck routes that deviate from standard vehicle patterns. Also, manual inputs (e.g., incorrect destination coordinates) can lead to inaccurate ETA. However, the current version lacks automated validation protocols (e.g., BIM-integrated destination verification). These vulnerabilities highlight critical areas for future upgrades.

Thirdly, while the MC-oriented ETA model demonstrates novelty, its feasibility faces essential limitations from practical challenges. This component has a high dependency on real-time data. Real-time ETA updates rely on accurate, up-to-date information; any delays or errors in data transmission can disrupt scheduling and coordination. In addition, drivers may fail to adhere to the suggested ETA provided by the system, which can lead to delays and inefficiencies. Comprehensive training and incentive mechanisms are expected to be explored in the future.

7 Conclusions

Achieving JIT logistics for modular construction in high-density cities is important for ensuring successful project delivery, minimizing congestions, and optimizing urban development efficiency. This study identified and analyzed the critical factors influencing ETA accuracy in MC logistics. It then developed a MC-oriented ETA planning model for achieving JIT logistics for MC in high-density cities. The MC-oriented ETA planning model focuses on an ETA model for MC logistics companies, enabling MC logistics companies to understand the time required for each MC delivery task from a designated MC factory to the installation site. The proposed model is substantiated by implementing a system and evaluate its performance through simulations and a real-life MC project.

While this study provides valuable insights, its limitations highlight key opportunities for future research. First, the proposed model will be more robust, accurate, and generalizable if implemented in more MC projects. Future research should also develop a comprehensive evaluation framework to assess the performance of the proposed model, considering not only operational metrics (e.g., ETA accuracy) but also environmental metrics such as fuel savings, carbon emissions reduction, and noise pollution mitigation. Second, future investigations could be conducted to improve the accuracy of ETA predictions by addressing data gaps, such as compiling historical MC-specific traffic data sets and integrating automated validation protocols (e.g., BIM-integrated destination validation) to minimize manual input errors. Third, future research should explore training protocols and incentive mechanisms (e.g., financial and reputational reward systems) to ensure consistent adoption of the system. In addition, technologies that can facilitate real-time data infrastructure should be explored for low-latency transmission, such as edge computing, 5G, and cloud blockchain-based data sharing.

Competing Interests The authors declare that they have no competing interests.

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