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Bi-level stochastic programming for optimal modular construction yard deployment based on Benders decomposition

Huiwen Wang[1] | **Wen Yi**[1] | **Peng Wu**[2] | **Lu Zhen**[3] | **Albert P. C. Chan**[1]

[1]Department of Building and Real Estate, The Hong Kong Polytechnic University, Kowloon, Hong Kong

[2]School of Design and the Built Environment, Curtin University, Perth, Australia

[3]School of Management, Shanghai University, Shanghai, China

Correspondence
Wen Yi, Department of Building and Real Estate, The Hong Kong Polytechnic University, Kowloon, Hong Kong.
Email: wen.yi@polyu.edu.hk

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Abstract

To promote wider adoption of modular construction (MC), many governments in high-density regions are planning to establish module storage yards (MSYs) to support local contractors in achieving just-in-time module supply chain. Given the limited availability of developable land and government budgets, an optimal MSY deployment plan is urgently needed. This paper represents the first attempt at capturing the fundamental government–contractor interactions and formulating a bi-level stochastic program to maximize MSY utilization and minimize MC logistics costs. To address the computational challenges posed by a hierarchical model structure, a solution method based on Benders decomposition is designed to solve the problem to optimality. Benchmarked against particle swarm optimization through extensive numerical experiments, the solution method shows a 15% average improvement in solution quality (in medium- and large-scale instances), highlighting its superior computational performance. A real-world Hong Kong case is conducted as methodology validation and application that provides governments with optimal decisions on MSY deployment including the area of the MSY to be established and module storage service pricing.

1 | INTRODUCTION

Modular construction (MC) is revolutionizing the built environment by delivering a greener and faster alternative to traditional cast-in-situ construction. Over the past two decades, MC has gained renewed attention due to the growing global demand for sustainability. Australia and the United States increasingly adopt MC for healthcare and educational facilities, while Sweden and Singapore institutionalize it for high-rise residential projects. The exploration of MC is particularly encouraged in high-density areas. Typically, such regions face the challenges of limited land availability and high labor cost (Planning Department of Hong Kong, 2016; U.K. Council on Tall Buildings & Urban Habitat, 2018). MC represents an effective solution to address these issues as its adoption is promising to increase construction productivity and reduce labor demands (Y. Jiang et al., 2024; Xiao et al., 2025). Despite these benefits, the real-life implementation of MC is hindered by various factors, with logistics being a major constraint. In high-density areas, MC projects rely heavily on overseas module sourcing (Bertram et al., 2019; Construction Industry Council (CIC) of Hong Kong, 2021a). Various cross-border transit challenges, such as lengthy transportation and customs requirements, can lead to uncertain delivery times of modules at site (CIC of

Hong Kong, 2024). Additionally, construction sites are congested, with limited areas for storage purposes. Early module deliveries can cause traffic congestion as trailers must wait off-site, whereas late deliveries delay projects. Therefore, contractors in densely populated regions have been actively seeking solutions to ensure the on-time delivery of modules of required quality and in the right quantities, as it is essential for successful MC implementation.

To facilitate the just-in-time MC logistics, many governments have established or are planning to establish MC hubs to provide manufacturing or storage capabilities for prefabricated modules. For example, Singapore has spearheaded the establishment of six module manufacturing factories, mitigating MC logistics uncertainties by providing contractors with domestic sourcing options (Building & Construction Authority (BCA) of Singapore, 2020). The case of Singapore highlights several strategic insights that should be mindful for other governments in the planning stage of local module storage yards (MSYs). First, a large workspace is required for the fabrication work of precast modules, which can be problematic in some high-density regions owing to the limited supply of developable land (Nekouvaght Tak et al., 2020). Second, initial investments in developing module manufacturing factories are substantial (Yi et al., 2024), which can lead to significant financial pressure on the government. Third, high land costs and initial investments inevitably raise the prices of locally produced modules, which may prompt contractors to stick to overseas modules for their more favorable pricing. Therefore, for high-density areas with limited developable land and tight financial budgets, establishing a public MSY is a more appropriate solution to mitigate the uncertainties of MC logistics. The Hong Kong government, for example, plans to make land available specifically for the storage of precast modules (Chief Executive of Hong Kong, 2022). Then, the supply chain of MC projects consists of (1) module fabrication in non-local factories, (2) cross-border transportation of modules from factories to MSY, (3) temporary module storage at the local MSY, and (4) domestic transportation of modules from MSY to site for installation. As a local MSY provides module storage buffers near sites, its establishment is expected to enhance the supply chain resilience of MC projects in high-density regions (Housing Bureau of Hong Kong, 2020).

Despite governments' commitments to strengthening local storage capabilities for modules, current MSY planning is still in its infancy, focused solely on selecting suitable land for MSYs (CIC of Hong Kong, 2021b). A detailed MSY deployment plan is urgently needed, which should carefully consider the relationships between the government and contractors to ensure effectiveness (Yi et al., 2023). The government's MSY deployment decisions (e.g., the area of the MSY, the service pricing for module storage at MSY) directly influence contractors' decisions on MC logistics (e.g., module transport schedule and route, module storage plan) with the objective of minimizing the total costs, which will, in turn, relate to government's intention to maximize the use of the MSY established. Motivated by this need, this paper formulates an optimal MSY deployment plan given the limited land availability and government budgets through bi-level programming, which is expected to mitigate cross-border logistics challenges for MC contractors and facilitate MC promotion for governments. The research contributions are twofold: (i) Theoretically, an innovative bi-level framework is proposed to explore the above interactive relationships between the government and contractors in the context of MSY planning. To solve the proposed program to optimality, this paper proposes a Benders decomposition-based method that modifies the standard optimality cut to accommodate the optimization of integer variables. (2) Practically, the establishment of local module storage capabilities effectively mitigates the logistics challenges facing the industry and is promising to increase the uptake of sustainable construction methods.

Subsequently, Section 2 reviews the relevant literature. Section 3 presents a bi-level programming model with the consideration of a regional government and multiple MC contractors. A tailor-made algorithm is developed in Section 4 to solve the model to optimality. Section 5 reports the experiments and results. Section 6 discusses the applicability and novelties of the proposed method. Section 7 summarizes the whole research and provides potential directions for future research.

2 | LITERATURE REVIEW

Logistics challenges have been recognized as a major hindrance to MC adoption (Feldmann et al., 2022; H. Wang, Liao, et al., 2024). The paradigm of "off-site production followed by on-site installation" in MC greatly complicates the intermediate logistics process (Jin et al., 2022). In response, both theoretical and practical efforts have been made to facilitate cost-efficient and timely module delivery.

Explorations have been dedicated to developing a roadmap for the optimal transportation planning of precast modules, as MC logistics is closely related to contractors' profits. Zhai et al. (2019) developed an automated module transportation platform, integrating digital technologies such as Internet of Things, building information modeling, and computer vision, to facilitate effective monitoring of cross-border module transportation. Godbole et al. (2018) simulated the vertical motions of modules transported by truck-trailers on rough roads to enhance the efficiency of module loading and transportation. Despite significant contributions of these endeavors, their solutions are only applicable to projects that can adopt the "manufacturing–transportation–installation" mode. Usually, contractors in high-density regions have to identify additional areas near site due to the limited on-site storage space for precast modules (Hussein et al., 2022). This inspired several studies to incorporate temporary module storage strategies into the MC supply chain management to enhance overall resilience. Almashaqbeh & El-Rayes (2022) proposed a mixed integer programming model to minimize the overall costs of module transportation and storage. Through an in-depth examination of model properties, Yi et al. (2023) provided valuable insights into MC logistics that effectively balance cost efficiency with reduced carbon footprints. However, these studies have a notable research gap, as the models and methods they proposed did not factor in MC supply chain uncertainties. Various uncertainties inherently occur in three phases: off-site production, transportation, and on-site construction (Bertram et al., 2019). As the transitional link between controlled factory and site environments, transportation faces the greatest uncertainties due to its exposure to external disruptions from bad weather to customs delays (Eltoukhy et al., 2025; Legislative Council of Hong Kong, 2022). Only Hsu et al. (2018, 2019) and H. Wang, Lim, et al. (2024) approached the MC transportation planning problem using stochastic programming, but the focus is on the uncertainty of module demands at construction sites. As on-site uncertainties partially stem from transportation uncertainties, the MC supply chain cannot be fully optimized without managing transportation uncertainties (Wuni et al., 2020). There is thus a pressing need for further exploration into the design of optimal module transportation and storage plans that consider uncertainties in cross-border transport to minimize logistics costs while ensuring timely on-site installation.

Apart from theoretical efforts focused on contractors' perspective, governments of high-density regions are also actively engaged in addressing MC logistics challenges. For example, CIC of Hong Kong (2021a, 2021b, 2024) released a series of transportation handbooks for precast modules, sharing insights and practical experiences from real-world projects to assist contractors. Similarly, BCA of Singapore (2024) specified legal regulations for module transport within Singapore and summarized key logistics-related factors that must be considered by contractors. Although these regions have varying social backgrounds and contexts for MC implementation, resulting in slight differences in their respective optimal logistics solutions, existing reference materials published by governments fail to incorporate rigorous optimization framework—yet optimization is key to identify mathematically sound and policy-optimal decisions (Adeli & Karim, 1997; Adeli & Park, 1996). Serving as a starting point, these materials universally focus on a single-level perspective, that is, guiding individual contractors to transport precast modules at minimum logistics costs. However, studies on MC promotion have highlighted the significance of the hierarchical decisive interactions between the government and construction stakeholders. Zhu et al. (2024) analyzed the relationships between a regional authority and contractors and proposed a bi-level model to maximize the economic and environmental benefits for both entities. Du et al. (2022) identified the optimal government subsidy rate and the optimal project assembly rate using game theory. These studies acknowledged the limitations of a single-level program and revealed that governments play a pivotal role in helping contractors overcome barriers to the adoption of MC. However, they focused on applying a bi-level program to mitigate cost-related barriers (e.g., the lack of financial incentives for MC adoption), yet the bi-level relationships remain underexplored within the context of MSY deployment and module logistics planning. As attempts have been made by governments on developing MC hubs to help contractors address logistics-related barriers (BCA of Singapore, 2024; Chief Executive of Hong Kong, 2022), it is imperative to employ bi-level programming to develop optimal MSY deployment and MC logistics plans.

Stakeholders in real-world settings have asymmetric or even conflicting objectives. Bi-level programming is a powerful modeling framework designed to capture the hierarchical decision-making processes involving two interdependent entities. Its efficacy is well recognized in supply chain management and related domains. For example, Amirtaheri et al. (2017) developed a bi-level model for production–distribution network optimization, where manufacturer production planning and distributor logistics coordination are simultaneously considered. Similarly, Saranwong and Likasiri (2017) implemented a bi-level framework for sugarcane distribution center location problems, where government objectives interact with farmer cooperative logistics decisions. Additionally, the necessity of bi-level programming is also highlighted by researchers in the field of policy analysis (Béland et al., 2022; Durazzi, 2022; Zhou et al., 2025). These studies reveal that an upper-level decision failing to anticipate the responses from the lower level can result in poor policy outcomes. Regarding the MSY deployment problem, governments (as policy-makers) should anticipate the potential feedback from contractors (as policy-takers) to ensure effective mitigation of MC logistics challenges. A bi-level programming framework is well-suited to model and analyze this problem. Having that said, solving bi-level problems is very challenging due to their non-convexity and non-deterministic polynomial-time (NP)-hard nature (Ben-Ayed, 1993). Exact methods are computationally intractable for most bi-level problems, making heuristics or metaheuristics the predominant approaches. For example, Kieffer et al. (2019) developed a genetic programming hyper-heuristic method and showed its superiority in handling large-scale bi-level programs. Rokbani et al. (2021) proposed an ant colony optimization algorithm for bi-level traveling salesman problems that demonstrated notable improvements in both quality and efficiency. The above developments suggest ground for further research into tailor-made solution methods for bi-level programming problems.

Despite the growing body of literature on designing effective MC logistics solutions, two noticeable research gaps persist. Specifically, the uncertainties inherent in MC logistics, especially those pertaining to cross-border module transportation in import-reliant, high-density areas, require further investigation. Additionally, the interactions between government and contractors in the context of MSY deployment remain unexplored. Neglecting this essential bi-level mechanism adversely impacts the promotion of MC (Yi et al., 2023). To bridge these gaps, this paper formulates an innovative bi-level stochastic program, coupled with a tailor-made algorithm, to generate optimal solutions that can maximize the benefits of both the government and contractors.

3 | PROBLEM STATEMENT

3.1 | Description of the MSY deployment problem

Assume that I (indexed by i) MC projects are to be constructed in a region over a planning period of T days (indexed by t). Precast modules used in these projects are procured from offshore manufacturers and then transported to sites for efficient assembly. A wide range of uncertainties inherent in the cross-border transportation process, for example, traffic congestion and variable customs clearance times (CIC of Hong Kong, 2021b; U.S. Department of Transportation, 2023), can lead to uncertain time of module transportation, necessitating the use of stochastic programming in this paper. Let Ω denote the number of possible scenarios (indexed by ω), with each scenario having an equal probability of occurrence. The time required to transport the modules of project i required at the beginning of day t from the factory to the checkpoint and complete customs clearance in scenario ω is defined as a random parameter $u^1_{i,t}(\omega)$, with a minimum value $U^{\min}_{i,t} = \min_{\omega=1,\ldots,\Omega} u^1_{i,t}(\omega)$ and a maximum value $U^{\max}_{i,t} = \max_{\omega=1,\ldots,\Omega} u^1_{i,t}(\omega)$ for modules of project i required at the beginning of day t. Note that our method is also compatible with scenarios with different probabilities. For example, consider historical transportation data indicating three possible values of $u^1_{i,t}(\omega)$: 1 day (30%), 3 days (50%), and 5 days (20%). In this case, Ω can be set to 10 (each with 10% probability), where $u^1_{i,t}(\omega)$ takes the value of 1 day in three scenarios, 3 days in five scenarios, and 5 days in two scenarios. After customs clearance, it takes another u^2_i days to transport the modules completed with customs to the site of project i and the unit transportation cost is o^2_i (\$/ton). The logistics timeline and flow of modules are illustrated as case (i) of Figure 1. In the problem setting, the installation schedule of precast modules of each project i is predetermined. Parameter $d_{i,t}$ indicates the number of modules planned to be assembled on the site of project i at the beginning of day t. Therefore, to ensure that module installation can be arranged as scheduled, $d_{i,t}$ tons of modules must be cleared through customs at the beginning of day $t - u^2_i$. This further implies that the transport of modules from the factory must start at the beginning of day $t - u^2_i - U^{\max}_{i,t}$. If the cross-border transportation takes $U^{\max}_{i,t}$ days (including the time for customs clearance), the modules will arrive at site exactly on day t without incurring additional storage costs; otherwise, they have to be temporarily stored for a maximum of $U^{\max}_{i,t} - U^{\min}_{i,t}$ days. The cost of on-site module storage for the contractor of project i is p_i (\$/ton).

Considering that construction sites are congested with limited areas for module storage, the regional government has spared an available land of a maximum area of a (m^2), planning to establish a public MSY. Specifically, the government needs to make a one-time decision on the area of the MSY to be established, denoted by variable x. The conversion from m^2 to ton is quantified by a coefficient e, indicating that 1 m^2 MSY can store e tons of MC modules. The unit cost of establishing the MSY (the sum of the unit land cost, construction cost, and operating cost) is denoted by c \$/m^2. Then, starting from the first day (i.e., $t = 1$), the government decides the service price for module storage at the MSY, with such a decision made every L_1 days. Here, L_1 refers to the government's decision cycle. The total number of the government's decision cycles throughout the planning period is denoted by N_1 and indexed by n_1, satisfying that $N_1 = \frac{T}{L_1}$ and $N_1 \in Z_+$. Variable y_{n_1} (\$/ton) indicates the daily price of storing modules at the MSY determined by the government in its n_1th decision cycle, $n_1 = 1, \ldots, N_1$. The government budget for MSY deployment is B (\$). The aim is to maximize the contractors' use of the established MSY.

Upon the establishment of the MSY, contractors then make MSY rental plans to minimize their total logistics costs. Their decisions on reserving MSY capacity for module storage are made every L_2 days (e.g., 30 days). The

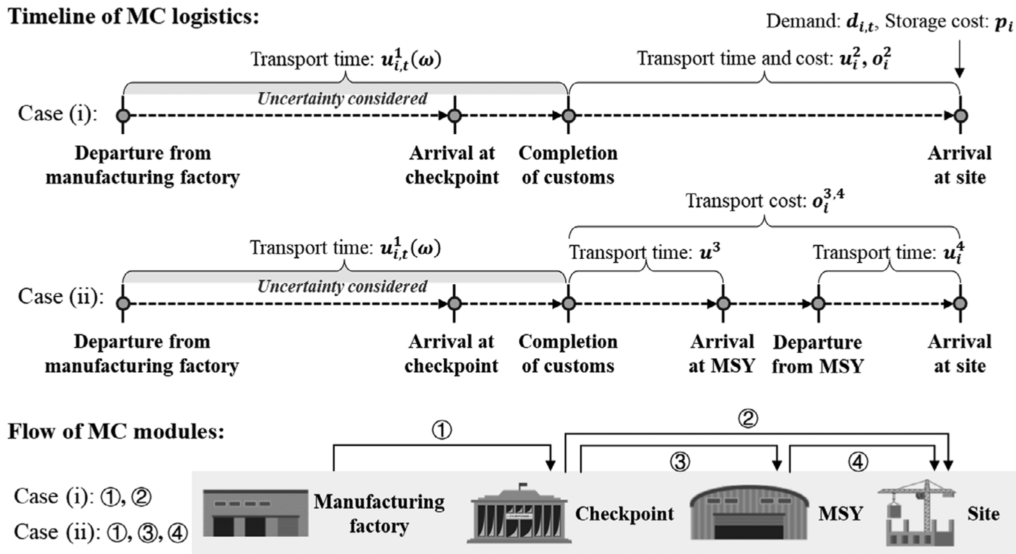

FIGURE 1 Two modular construction (MC) logistics cases: (i) direct transport from factory to site, (ii) transport from factory to module storage yard (MSY) for storage and from MSY to site.

number of contractors' decision cycles is N_2 and indexed by n_2, satisfying that $N_2 = \frac{T}{L_2}$, $N_2 \in Z_+$, and $\frac{L_1}{L_2} \in Z_+$. Define variable α_{i,n_2} (ton) as the MSY rental capacity for module storage determined by the contractor of project i in its n_2th decision cycle, $n_2 = 1, \ldots, N_2$. For example, when $L_1 = 180$ and $L_2 = 30$, the government first decides the value of y_1 at the beginning of Day 1 with this module storage price being valid for 180 days from $t = 1$ to $t = 180$. Then, after observing the price set by the government, the contractor of project i decides the values of $\alpha_{i,1}, \ldots, \alpha_{i,6}$ at the beginning of Days 1, 31, 61, 91, 121, 151, respectively, by paying the total module storage costs of $\sum_{n_2=1}^{6} 30 y_1 \alpha_{i,n_2}$ for the 180 days. Denote $\beta_{i,t}(\omega)$ (ton) as the number of modules of project i required on site at the beginning of day t that are sent to MSY for storage in scenario ω. Denote $\gamma_{i,t}(\omega)$ (ton) as the total number of modules of project i being stored at the MSY at the beginning of day t in scenario ω. Additionally, if the number of modules to be stored exceeds the MSY rental capacity, the excessive modules will have to be stored on site at a (typically) higher cost of p_i. In addition to the differing storage costs, the duration for modules stored at the MSY may also vary from that for on-site storage. Although the contractors do not know which specific scenario will occur when organizing transportation (i.e., the actual time required for cross-border transportation and customs clearance), the number of days that the modules need to be stored (either on site or at the MSY) is known to the contractors for each specific scenario. As mentioned above, the transportation of modules from the factory of project i must start at the beginning of day $t - u^2_i - U^{\max}_{i,t}$ in order to align with module installation schedule on day t. If the modules of project i required on site at the beginning of day t are stored on site, the storage duration is $U^{\max}_{i,t} - u^1_{i,t}(\omega)$ days in scenario $\omega = 1, \ldots, \Omega$. If they are sent to the MSY for storage, the storage duration is $U^{\max}_{i,t} - u^1_{i,t}(\omega) + u^2_i - (u^3 + u^4_i)$ days in scenario $\omega = 1, \ldots, \Omega$, where u^3 and u^4_i indicate the transportation time from the checkpoint to the MSY and from the MSY to the site of project i, respectively. The relevant transportation cost is $o^{3,4}_i$ (\$/ton) for project i. The logistics timeline and flow of modules are illustrated in case (ii) of Figure 1. For simplicity, let $\tilde{T}_{i,t}(\omega)$ be the set of demand days for modules of project i that are being stored at the MSY at the beginning of day t in scenario ω. For example, Project 1 requires 20 tons of modules on site at the beginning of Day 20 (i.e., $d_{1,20} = 20$). The time of cross-border transportation is of three scenarios, where $u^1_{1,20}$ (1) = 5, $u^1_{1,20}$ (2) = 3, $u^1_{1,20}$ (3) = 1, $U^{\min}_{1,20} = 1$, and $U^{\max}_{1,20} = 5$. The transportation from the checkpoint to the site, from the checkpoint to the MSY, and from the MSY to the site takes 1 day (i.e., $u^2_1 = u^3 = u^4_1 = 1$). To eliminate any delays in on-site installation, the transport of the 20 tons of modules from the factory must start at the beginning of Day 14. Depending on scenarios, the modules will arrive at the checkpoint after completing customs procedures at the beginning of Day 19 (in Scenario 1) or Day 17 (in Scenario 2) or Day 15 (in Scenario 3). In Scenario 1, given that $u^4_1 = 1$, the modules can be transported directly from the checkpoint to the site without the need for temporary storage. However, in Scenarios 2 and 3, temporary storage becomes necessary. If the modules are sent to the MSY for storage, the storage period in Scenario 2 begins from Day 18 (as $u^3 = u^4_1 = 1$), with the modules stored for a single day. This implies that Day 20 is an element in the set $\tilde{T}_{1,18}(2)$. Similarly, in Scenario 3, the storage period spans 3 days,

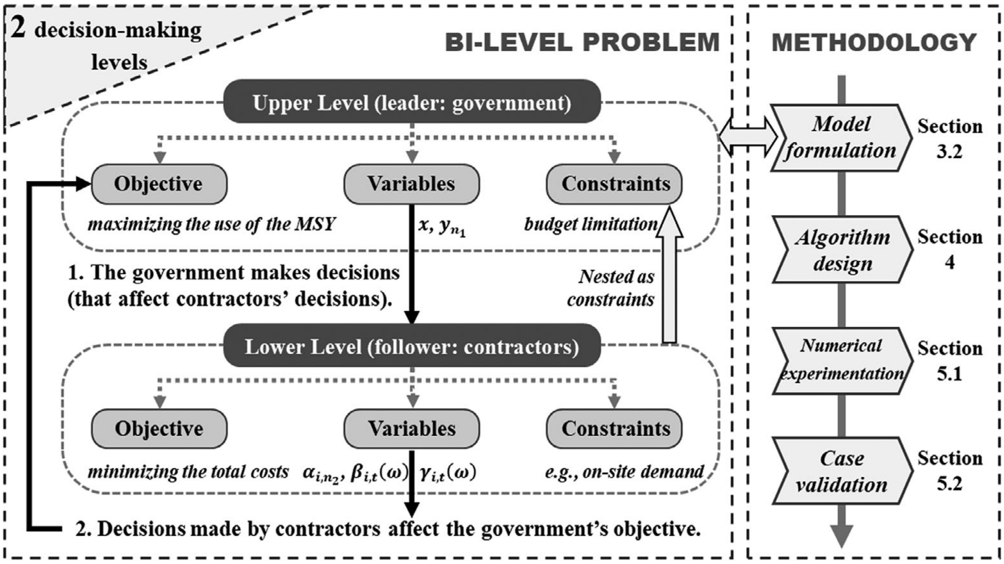

FIGURE 2 The bi-level MSY deployment problem.

beginning from Day 16. Thus, Day 20 is included in the sets $\tilde{T}_{1,16}(3)$, $\tilde{T}_{1,17}(3)$, and $\tilde{T}_{1,18}(3)$.

The interactive relationships between the government's and contractors' decisions are illustrated in Figure 2. At the upper level, the government, acting as the leader, first decides the area of the MSY to be established (variable x) and the service pricing for module storage at MSY (variable y_{n_1}). These two decisions are directly related to the maximum number of modules that contractors can store at the MSY and the relevant storage costs, thus greatly influencing the contractors' MC logistics decisions. At the lower level, contractors, as followers, observe the decisions made by the government and decide the optimal module transportation and storage plan to minimize the costs. Their decisions then affect the government's objective of maximizing the use of the MSY, creating an interdependent relationship between the two levels of decision-making. The bi-level programming model is presented in Section 3.2. Note that all the notation used is listed in "Notation" section at the end of this paper.

3.2 | Model formulation

3.2.1 | Upper-level model

$$[\mathrm{M}^{\mathrm{G}}]\max \sum_{i=1}^{I}\sum_{n_2=1}^{N_2}\alpha_{i,n_2} \tag{1}$$

$$\text{s.t.}\quad cx - L_2\sum_{i=1}^{I}\sum_{n_1=1}^{N_1}\sum_{n_2=1+(n_1-1)L_1/L_2}^{n_1L_1/L_2}\alpha_{i,n_2}y_{n_1} \le B \tag{2}$$

$$0 \le x \le A, x \in Z_+ \tag{3}$$

$$1 \le y_{n_1} \le \max_{i=1,\cdots,I} p_i, \forall\, n_1 = 1,2,\cdots,N_1, y_{n_1} \in Z^+. \tag{4}$$

Objective function (1) indicates that the government aims to maximize contractors' use of the established MSY. Constraint (2) requires that MSY investment does not exceed the upper limit B. As $L_1/L_2 \in Z_+$, any government's decision cycle $n_1 = 1,\dots,N_1$ includes contractors' decision cycles $n_2 = 1+(n_1-1)L_1/L_2,\dots,n_1L_1/L_2$. The government's incomes from providing module storage services to contractor of project i in its n_1th decision cycle is thus $L_2\sum_{n_2=1+(n_1-1)L_1/L_2}^{n_1L_1/L_2}\alpha_{i,n_2}y_{n_1}$. Constraints (3) and (4) define the variable domains.

3.2.2 | Lower-level model

$$[\mathrm{M}^{\mathrm{C}}]\min \sum_{i=1}^{I}\sum_{n_1=1}^{N_1}\sum_{n_2=1+(n_1-1)L_1/L_2}^{n_1L_1/L_2} L_2 y_{n_1}\alpha_{i,n_2}$$

$$+\frac{1}{\Omega}\sum_{\omega=1}^{\Omega}\sum_{i=1}^{I}\sum_{t=1}^{T} o_i^{3,4}\beta_{i,t}(\omega)$$

$$+\frac{1}{\Omega}\sum_{\omega=1}^{\Omega}\sum_{i=1}^{I}\sum_{t=1}^{T} A_{i,t}(\omega)\left(d_{i,t}-\beta_{i,t}(\omega)\right) \tag{5}$$

$$\text{s.t. } \gamma_{i,t}(\omega) \le \alpha_{i,n_2}, \forall i = 1,\dots,I, n_2 = 1,\dots,N_2,$$

$$t = 1+(n_2-1)L_2,\dots,n_2L_2, \omega = 1,\dots,\Omega \tag{6}$$

$$\sum_{i=1}^{I}\gamma_{i,t}(\omega) \le ex, \forall t = 1,\dots,T, \omega = 1,\dots,\Omega \tag{7}$$

$$\sum_{t\in\tilde{T}_{i,t'}(\omega)}\beta_{i,t}(\omega) = \gamma_{i,t'}(\omega), \forall i = 1,\dots,I,$$

$$t' = 1, \dots, T, \omega = 1, \dots, \Omega \tag{8}$$

$$0 \le \alpha_{i,n_2} \le ex, \forall i = 1, \dots, I, n_2 = 1, \dots, N_2 \tag{9}$$

$$0 \le \beta_{i,t}(\omega) \le d_{i,t}, \forall i = 1, \dots, I, t = 1, \dots, T,$$

$$\omega = 1, \dots, \Omega \tag{10}$$

$$\beta_{i,t}(\omega) = 0, \forall i = 1, \dots, I, \omega = 1, \dots, \Omega,$$

$$t = 1, \dots, T, t \notin \bigcup_{t'=1}^{t} \tilde{T}_{i,t'}(\omega) \tag{11}$$

$$\gamma_{i,t}(\omega) \ge 0, \forall i = 1, \dots, I, t = 1, \dots, T, \omega = 1, \dots, \Omega. \tag{12}$$

Objective function (5) calculates the logistics costs of I construction projects in two stages, where $A_{i,t}(\omega)$ is used to denote $o_i^2 + p_i(U_{i,t}^{\max} - u_{i,t}^1(\omega))$ for simplicity. Constraint (6) ensures that the number of precast modules of project i stored at the MSY on any day $t = 1 + (n_2 - 1)L_2, \dots, n_2 L_2$ cannot exceed the rental capacity determined by its contractor in the n_2th decision cycle. Further, Constraint (7) requires that the number of precast modules at the MSY by all projects does not exceed the maximum capacity of the MSY established. Constraint (8) calculates the total number of modules of project i that are being stored at the MSY at the beginning of day t' in scenario ω. Specifically, if $t \in \tilde{T}_{i,t'}(\omega)$, meaning that t is one of the demand days for modules of project i that are being stored at the MSY at the beginning of day t in scenario ω, then $\beta_{i,t}(\omega)$ tons of modules should be counted into the storage amount. Constraints (9)–(12) define the variable domains.

4 | SOLUTION METHOD

Bi-level programming problems can be approached using either exact solution methods or heuristic algorithms. Typically, exact methods applied to bi-level models are developed based on the enumeration of upper-level variables coupled with a commercial solver to address the lower-level model (Forghani et al., 2020). While exact methods ensure the optimality of solutions, they can be computationally intensive and time-consuming as the problem scale increases. Delving into the bi-level problem where $T = 360$, $I = 15$, and $N_2 = 12$, the number of logistics plans is 2(whether to rent MSY or not) $\times 12 = 24$ for a single contractor, indicating that the possible number of logistics plans for all contractors is 24^{15}. This implies that the bi-level stochastic program proposed in Section 3 is difficult to solve using enumeration-based exact methods, as their computational inefficiency becomes particularly pronounced when dealing with problems of such scale and intricacy. In contrast, heuristic algorithms, such as particle swarm optimization (PSO), can efficiently calculate a high-quality solution (Imran Hossain et al., 2019) and have been widely employed to bi-level problems (Kuo & Han, 2011). These algorithms achieve high efficiency by leveraging effective strategies or rules to narrow the search scope (Tan et al., 2025; J. Wang et al., 2018), but they may not yield global optimal solutions (X. Chen et al., 2024; Liu et al., 2025). Although the optimality gap may seem very negligible (e.g., the objective value of the solution obtained by a heuristic algorithm is only 1% away from that of the optimal solution), the additional costs (associated with the 1% gap) could be substantial when considering the massive volume of MC module transportation in a region. Given the limitations of existing solution methods, there is a clear need for an advanced technique to compute optimal solutions while being more efficient than exhaustive enumeration.

Motivated by the above considerations, this paper develops a tailor-made method based on Benders decomposition. A series of cuts is introduced to direct the iteration process, thereby enhancing efficiency. Equally important, it ensures that the pruned regions do not contain global optimal solutions, thereby preserving optimality. Figure 3 presents an overview of the proposed method. First, the dual model of model [M^C] is developed as model [DM^C]. According to the strong duality property, the bi-level model presented in Section 3 can be reformulated as a single-level model [SM^GC]. Model [SM^GC] is decomposed into a master problem [MP] and a subproblem [SP] based on Benders decomposition. Optimality cuts and feasibility cuts will be iteratively added to [MP], making its objective (i.e., the upper bound of model [SM^GC]) progressively converge toward that of [SP] (i.e., the lower bound of model [SM^GC]). The algorithm terminates when the upper bound is less than or equal to the lower bound. Sections 4.1 and 4.2 detail the key procedures of the solution method proposed.

4.1 | Reformulation as a single-level stochastic program

The hierarchical structure of bi-level programming problems poses great challenges to model solving, as the lower-level problem must be solved optimally for every feasible decision made by the upper-level problem (Chang & Mackett, 2006), leading to a potentially enormous computational burden. Fortunately, in this case, the lower-level model [M^C] is linear. By leveraging the strong duality property—the optimal value of [M^C] is equal to that of its dual problem (denoted by [DM^C])—we can

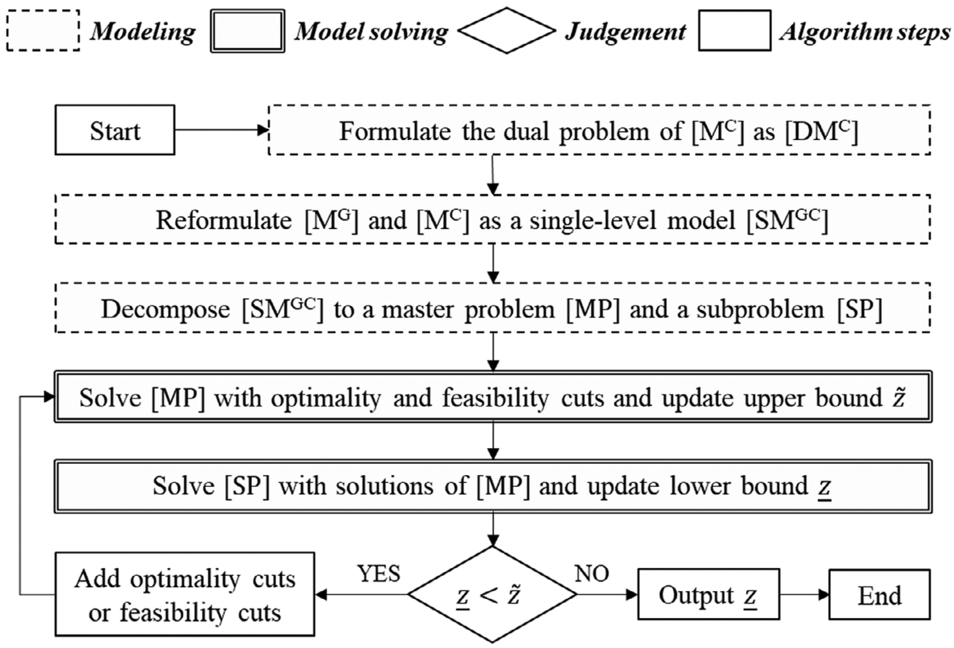

FIGURE 3 Framework of the proposed solution method based on Benders decomposition.

reformulate the original bi-level stochastic program into a more tractable single-level stochastic program. Model $[\mathrm{DM^C}]$ is presented below, where $\pi^6_{i,n_2,t}(\omega)$, $\pi^7_t(\omega)$, $\pi^8_{i,t}(\omega)$, π^9_{i,n_2}, $\pi^{10}_{i,t}(\omega)$, and $\pi^{11}_{i,t}(\omega)$ are dual variables corresponding to Constraints (6)–(11), respectively.

$$[\mathrm{DM^C}]\ \max \sum_{i=1}^{I}\sum_{n_2=1}^{N_2}\pi^9_{i,n_2}ex + \sum_{t=1}^{T}\sum_{\omega=1}^{\Omega}\pi^7_t(\omega)\,ex + \sum_{i=1}^{I}\sum_{\omega=1}^{\Omega}\sum_{t=1}^{T}\left(\frac{1}{\Omega}A_{i,t}(\omega) + \pi^{10}_{i,t}(\omega)\right)d_{i,t} \tag{13}$$

$$\text{s.t. } L_2 y_{n_2/(L_1/L_2)} + \sum_{t=1+(n_2-1)L_2}^{n_2L_2}\sum_{\omega=1}^{\Omega}\pi^6_{i,n_2,t}(\omega) - \pi^9_{i,n_2} \ge 0, \quad \forall i=1,\dots,I, n_2=1,\dots,N_2 \tag{14}$$

$$\frac{1}{\Omega}\left(o^{3,4}_i - A_{i,t}(\omega)\right) - \pi^{10}_{i,t}(\omega) - \pi^{11}_{i,t}(\omega) + \sum_{t'=1|t\in\tilde{T}_{i,t'}(\omega)}^{T}\left(\pi^8_{i,t'}(\omega)\right) \ge 0,$$

$$\forall i=1,\dots,I, t=1,\dots,T, \omega=1,\dots,\Omega, t\notin\bigcup_{t'=1}^{t}\tilde{T}_{i,t'}(\omega)$$

$$\frac{1}{\Omega}\left(o^{3,4}_i - A_{i,t}(\omega)\right) - \pi^{10}_{i,t}(\omega) + \sum_{t'=1|t\in\tilde{T}_{i,t'}(\omega)}^{T}\left(\pi^8_{i,t'}(\omega)\right) \ge 0 \tag{15}$$

$$\forall i=1,\dots,I, t=1,\dots,T, \omega=1,\dots,\Omega, t\in\bigcup_{t'=1}^{t}\tilde{T}_{i,t'}(\omega)$$

$$-\pi^8_{i,t}(\omega) - \pi^6_{i,t/L_2,t}(\omega) - \pi^7_t(\omega) \ge 0 \tag{16}$$

$$\forall i=1,\dots,I, t=1,\dots,T, \omega=1,\dots,\Omega$$

$$\pi^6_{i,n_2,t}(\omega) \le 0, \forall i=1,\dots,I, n_2=1,\dots,N_2 \tag{17}$$

$$t=1,\dots,T, \omega=1,\dots,\Omega \tag{18}$$

$$\pi^7_t(\omega) \le 0, \forall t=1,\dots,T, \omega=1,\dots,\Omega \tag{19}$$

$$\pi^8_{i,t}(\omega)\ free, \forall i=1,\dots,I, t=1,\dots,T, \omega=1,\dots,\Omega \tag{20}$$

$$\pi^9_{i,n_2} \le 0, \forall i=1,\dots,I, n_2=1,\dots,N_2 \tag{21}$$

$$\pi^{10}_{i,t}(\omega) \le 0, \forall i=1,\dots,I, t=1,\dots,T, \omega=1,\dots,\Omega \tag{22}$$

$$\pi^{11}_{i,t}(\omega) \le 0, \forall i=1,\dots,I, t=1,\dots,T, \omega=1,\dots,\Omega. \tag{23}$$

The objective function of model $[\mathrm{M^C}]$ can be expressed by $Z_1(\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma})$, where vectors $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ are newly defined as follows: $\boldsymbol{\alpha}:=(\alpha_{i,n_2}, i=1,\dots,I, n_2=1,\dots,N_2)$, $\boldsymbol{\beta}:=(\beta_{i,t}(\omega), i=1,\dots,I, t=1,\dots,T, \omega=1,\dots,\Omega)$, and $\boldsymbol{\gamma}:=(\gamma_{i,t}(\omega), i=1,\dots,I, t=1,\dots,T, \omega=1,\dots,\Omega)$. Likewise, the objective function of model $[\mathrm{DM^C}]$ can be expressed by $Z_2(\boldsymbol{\pi}^6,\boldsymbol{\pi}^7,\boldsymbol{\pi}^8,\boldsymbol{\pi}^9,\boldsymbol{\pi}^{10},\boldsymbol{\pi}^{11})$, where vectors $\boldsymbol{\pi}^6:=(\pi^6_{i,n_2,t}(\omega), i=1,\dots,I, n_2=1,\dots,N_2, t=1+(n_2-1)L_2,\dots,n_2L_2, \omega=1,\dots,\Omega)$, $\boldsymbol{\pi}^7:=(\pi^7_t(\omega), t=1,\dots,T, \omega=1,\dots,\Omega)$,

$\boldsymbol{\pi}^8 := (\pi^8_{i,t}(\omega), i = 1, \ldots, I, t = 1, \ldots, T, \omega = 1, \ldots, \Omega)$, $\boldsymbol{\pi}^9 := (\pi^9_{i,n_2}, i = 1, \ldots, I, n_2 = 1, \ldots, N_2)$, $\boldsymbol{\pi}^{10} := (\pi^{10}_{i,t}(\omega), i = 1, \ldots, I, t = 1, \ldots, T, \omega = 1, \ldots, \Omega)$, and $\boldsymbol{\pi}^{11} := (\pi^{11}_{i,t}(\omega), i = 1, \ldots, I, t = 1, \ldots, T, \omega = 1, \ldots, \Omega)$. According to the property of strong duality, a feasible primary and dual pair, that is, $(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma})$ of model [M$^{\mathrm{C}}$] and $(\boldsymbol{\pi}^6, \boldsymbol{\pi}^7, \boldsymbol{\pi}^8, \boldsymbol{\pi}^9, \boldsymbol{\pi}^{10}, \boldsymbol{\pi}^{11})$ of model [DM$^{\mathrm{C}}$], represents a pair of optimal solutions to the primary and dual problems if it satisfies that $Z_1(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}) \le Z_2(\boldsymbol{\pi}^6, \boldsymbol{\pi}^7, \boldsymbol{\pi}^8, \boldsymbol{\pi}^9, \boldsymbol{\pi}^{10}, \boldsymbol{\pi}^{11})$. Define vector $\boldsymbol{y} := (y_{n_1}, n_1 = 1, \ldots, N_1)$. The bi-level model proposed in Section 3 can be reformulated as the following single-level model [SM$^{\mathrm{GC}}$]:

$$\text{SM}^{\text{GC}}] \quad \max_{x, \boldsymbol{y}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\pi}^6, \boldsymbol{\pi}^7, \boldsymbol{\pi}^8, \boldsymbol{\pi}^9, \boldsymbol{\pi}^{10}, \boldsymbol{\pi}^{11}} \sum_{i=1}^{I} \sum_{n_2=1}^{N_2} \alpha_{i,n_2} \tag{24}$$

s.t. Constraints (2)–(4), (6)–(12), and (14)–(23)

$$Z_1(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}) \le Z_2\left(\boldsymbol{\pi}^6, \boldsymbol{\pi}^7, \boldsymbol{\pi}^8, \boldsymbol{\pi}^9, \boldsymbol{\pi}^{10}, \boldsymbol{\pi}^{11}\right). \tag{25}$$

4.2 | Benders decomposition-based method

In the previous subsection, the hierarchical structure inherent in the original bi-level program is eliminated by transforming the model into a single-level program using the strong duality property. However, given extensive constraints with nonlinear components, model [SM$^{\mathrm{GC}}$] is still challenging to solve. In Section 4.2, Benders decomposition is applied to decompose it into a master problem [MP] and a subproblem [SP] for efficient model-solving, which are formulated as follows.

$$[\text{MP}] \quad \max \xi \tag{26}$$

s.t. Constraints (3) and (4).
[SP] Objective function (24)
s.t. Constraints (2), (6)–(12), (14)–(21), and (25).

Upon solving [MP], the optimal values of x and $\boldsymbol{y}$ can be obtained. These values are subsequently used as parameters to solve [SP]. If [SP] is feasible, an optimality cut, as expressed by the following Equation (27), is generated and added as an additional constraint to [MP]:

$$\begin{aligned} \xi \le\ & \bar{\pi}^2 (B - cx) + \sum_{t=1}^{T} \sum_{\omega=1}^{\Omega} \bar{\pi}^7_t(\omega)\, ex + \sum_{i=1}^{I} \sum_{n_2=1}^{N_2} \bar{\pi}^9_{i,n_2} ex \\ & + \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{\omega=1}^{\Omega} \bar{\pi}^{10}_{i,t}(\omega)\, d_{i,t} + \sum_{n_2=1}^{N_2} \sum_{i=1}^{I} \bar{\pi}^{14}_{i,n_2} L_2 y_{n_2/(L_1/L_2)} \\ & + \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{\omega=1}^{\Omega} \frac{1}{\Omega} \bar{\pi}^{15}_{i,t}(\omega) \left(o^{3,4}_i - A_{i,t}(\omega) \right) \\ & + \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{\omega=1}^{\Omega} \frac{1}{\Omega} \bar{\pi}^{16}_{i,t}(\omega) \left(o^{3,4}_i - A_{i,t}(\omega) \right) \\ & + M \left(|x - \check{x}| + \sum_{n_1=1}^{N_1} \left| y_{n_1} - \check{y}_{n_1} \right| \right), \end{aligned} \tag{27}$$

where $\check{x}$ and $\check{y}_{n_1}$, $n_1 = 1, \ldots, N_1$, refer to a feasible solution to [MP] such that the corresponding [SP] is feasible. In Equation (27), M is a sufficiently large constant, and $\bar{\pi}^2$, $\bar{\pi}^7_t(\omega)$, $\bar{\pi}^9_{i,n_2}$, $\bar{\pi}^{10}_{i,t}(\omega)$, $\bar{\pi}^{14}_{i,n_2}$, $\bar{\pi}^{15}_{i,t}(\omega)$, and $\bar{\pi}^{16}_{i,t}(\omega)$ are the dual variables corresponding to Constraints (2), (7), (9), (10), (14)–(16), respectively, in model [SM$^{\mathrm{GC}}$]. Otherwise, if [SP] is infeasible, a feasibility cut, as expressed by the following Equation (28), is generated and added as an additional constraint to [MP]:

$$1 \le |x - \check{x}| + \sum_{n_1=1}^{N_1} \left| y_{n_1} - \check{y}_{n_1} \right|, \tag{28}$$

where $\check{x}$ and $\check{y}_{n_1}$, $n_1 = 1, \ldots, N_1$, refer to a feasible solution to [MP] such that the corresponding [SP] is infeasible. The iterative process of solving [MP] and [SP] continues until convergence (i.e., the lower bound of the problem is no less than the upper bound). The pseudocode is detailed as follows.

ALGORITHM 1 (Benders decomposition-based method)

Set lower bound $\underline{z} = 0$ and upper bound $\tilde{z} = \sum_{i=1}^{I} \sum_{t=1}^{T} d_{i,t}$. Initialize the set of optimality cuts $\Theta^{\mathrm{V}} = \emptyset$, set of feasibility cuts $\Theta^{\mathrm{F}} = \emptyset$, and set of solutions that are feasible to [MP] but infeasible to [SP] $\Theta^{\mathrm{S}} = \emptyset$.
While $\underline{z} < \tilde{z}$ **do**
  Solve [MP] and get optimal solution x and $\boldsymbol{y}$.
  Denote the objective as obj^{MP} and update $\tilde{z}$ with obj^{MP}.
  Solve [SP] and check feasibility.
  If [SP] is feasible **then**
    Get optimal solution $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$. Add Benders' optimality cut (Equation 27) to Θ^{V}.
  Else
    Add solution x and $\boldsymbol{y}$ to Θ^{S}. Add Benders' feasibility cut (Equation 28) to Θ^{F}.
  End if
  Denote the objective as obj^{SP} and update $\underline{z} \leftarrow \max\{\underline{z}, obj^{\mathrm{SP}}\}$.
End while
Output x, $\boldsymbol{y}$, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ as an optimal solution. Output $\underline{z}$ as the optimal objective value.

TABLE 1 Solution quality: Comparison with particle swarm optimization (PSO).

Instance group (ISG) and ISG setting		CaseID	Objective obtained by PSO (obj_1)	Objective obtained by the proposed method (obj_2)	Gap
1	$T = 16$	1	60	60	0.0%
	$I = 2$	2	50	50	0.0%
	$\Omega = 2$	3	59	59	0.0%
		4	53	53	0.0%
		5	56	56	0.0%
2	$T = 160$	1	1041	1114	6.6%
	$I = 15$	2	1026	1118	8.2%
	$\Omega = 3$	3	1010	1118	9.7%
		4	986	1109	11.1%
		5	973	1105	11.9%
3	$T = 360$	1	3881	4478	13.3%
	$I = 20$	2	3626	4500	19.4%
	$\Omega = 5$	3	3551	4496	21.0%
		4	3490	4480	22.1%
		5	3329	4481	25.7%

Note: The "Gap" column quantifies the improvement in solution quality achieved by the proposed method compared to PSO, which is calculated by $(obj_2 - obj_1)/obj_2$. The PSO algorithm is implemented with a swarm of 50 particles, cognitive and social coefficients of 0.6, and an inertia weight within the range [0.6, 1.0] that progressively increases during iterations. PSO terminates when the number of iterations reaches 100 or no solution improvement is observed for three consecutive iterations. Five seed-varied cases were conducted per ISG. To ensure run-to-run consistency of PSO, parameters used in each individual case are generated by fixed random seeds.

5 | EXPERIMENTS AND VALIDATION

Extensive computational experiments are designed and carried out on a workstation (2.40 GHz, Intel Core i9, 64GB) using Visual Studio 2019 C#, CPLEX 12.7.1 in Section 5.1. Section 5.2 applies the method to a real-world case of Hong Kong.

5.1 | Performance evaluation by numerical experiments

In the experimental setting, three instance groups (ISGs) of different problem scales are designed by varying the values of key parameters (i.e., those directly influencing the number of decision variables and constraints in the corresponding mathematical model), including planning period T, project amount I, and scenario amount Ω. Five different cases are generated in each ISG by randomly setting the values of the remaining parameters, yielding 15 test cases in total.

For comparison, PSO—a well-established heuristic method for solving bi-level models—is also developed. The results of the two methods are detailed in Table 1. The numerical results presented in Table 1 reveal several important insights. Previous studies recognize that PSO has satisfactory solution quality across various complicated bi-level programming problems (Han et al., 2016; J.-J. Jiang et al., 2021). This aligns with our observations from small-scale experiments. In all the five test cases of ISG 1, PSO can generate optimal objective values as the proposed solution method. Figure 4 shows an illustrative case (Case 1 of ISG 1), with both methods obtaining the optimal solutions. However, as the problem scale increases (ISG 2 and ISG 3), PSO is prone to be trapped in local optima. In contrast, the proposed method always delivers optimal solutions. This superior computational performance is quantitatively evidenced by average optimality gaps of 9.5% (ISG 2) and 20.3% (ISG 3) between the solutions obtained by the two methods. These observations validate the remarkable solution quality of our proposed method. In terms of computational efficiency, PSO outperforms the proposed method, as expected for a heuristic algorithm. Specifically, for ISG 1, both methods can generate solutions within 1 min. For ISG 3, PSO is far more efficient to yield a solution. Despite this, it should be noted that MSY deployment belongs to a strategic decision-making problem where solutions are implemented over long-term horizons. In such contexts, obtaining guaranteed high-quality solutions is far more valuable than efficient calculation of suboptimal results. Our method's ability to deliver high-quality solutions within a practically acceptable time-frame (hours for one-time strategic decisions) fulfills the critical need, justifying its contribution over heuristic alternatives.

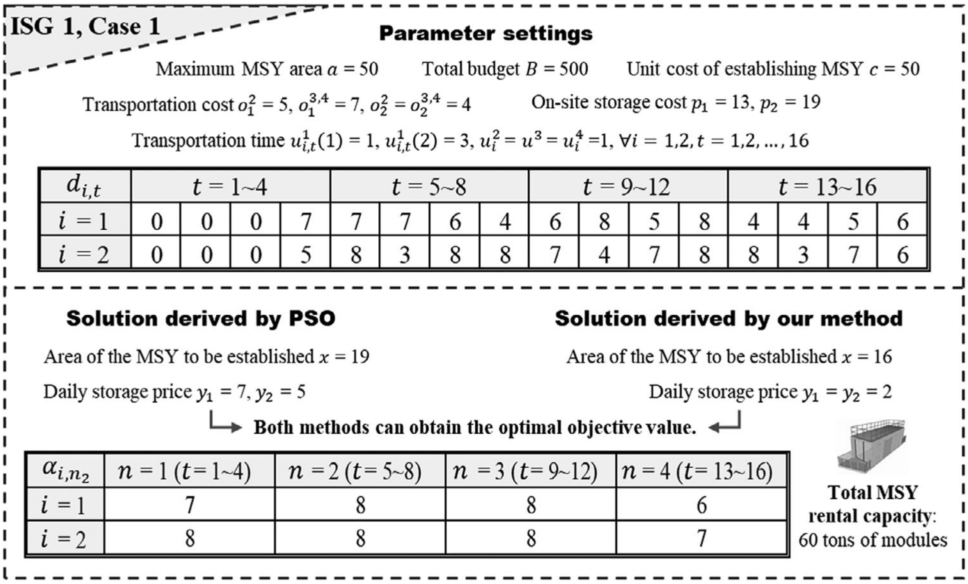

FIGURE 4 Parameter settings and solutions to an illustrative case (Case 1 of ISG 1). ISG, instance group; PSO, particle swarm optimization.

5.2 | Validation and application in a real case

In this subsection, a Hong Kong case study is conducted to validate the methodology for addressing real-world decision problems and to derive practical insights for governments aiming to deploy MSYs. Data used in the case study were detailed as follows.

Regarding MC contractors and project volumes in Hong Kong, the data on housing developments across 18 districts in 2024 were collected from the Housing Bureau (2024) and the Buildings Department of Hong Kong (2024), setting $T = 360$ and $I = 18$. Values for $\tilde{T}_{i,t}(\omega)$ and $d_{i,t}$ were set based on the housing development information presented in Table 2. Assume that the government updates module storage prices at the MSY every 180 days, and contractors make their decisions on MSY capacity reservation every 30 days. Thus, $L_1 = 180$, $L_2 = 30$, $N_1 = 2$, and $N_2 = 12$. Additionally, the Hong Kong government is attempting to allocate an industrial area of 10,300 m^2 in the Northern Metropolis for developing storage facilities for MC modules imported from the greater bay area (GBA) (Chief Executive of Hong Kong, 2022; CIC of Hong Kong, 2021b; Planning Department of Hong Kong, 2021). Thus, $a = 10,300$. According to the budget plan of the government, HK$2.2 billion (about $283 million) will be allocated to the Construction Innovation and Technology Fund (CITF) to promote the industry's use of advanced technologies (Financial Secretary of Hong Kong, 2024). The CITF funding is allocated across five strategic areas, with MC identified as a key priority (CITF of Hong Kong, 2025). Thus, B is set to HK$440 million. The storage area for an MC module typically requires twice its base area to accommodate necessary clearance for its movement and loading/unloading operations in the MSY. Given the typical dimension of a 21-ton MC module, that is, 4.450 m in length and 2.385 m in width (CIC of Hong Kong, 2022), the coefficient e is set to 1.

Regarding the cost of deploying an MSY, while no official data were released by the government of Hong Kong, this cost can be estimated by accounting for the land cost, construction cost, and operation cost. Specifically, the rental rate for non-residential land in New Territories, where the proposed MSY would be located, is HK$1198/m^2 per month (Census & Statistics Department of Hong Kong, 2024), approximately HK$14,500/m^2 per year. The annualized MSY construction and operation costs are approximately HK$2000/m^2 and HK$36,000/m^2 (CIC of Hong Kong, 2018; H. Wang, Ling, et al., 2024), respectively. Thus, c is set to HK$52,500/m^2.

Regarding module transportation, MC projects in Hong Kong are primarily supplied by module manufacturing factories in Foshan, Shenzhen, Huizhou, Dongguan, and Jiangmen (CIC of Hong Kong, 2024). The geographical proximity enables efficient transportation, with imported MC modules arriving at the Lok Ma Chau checkpoint in Hong Kong within 1 day. However, the time required for customs clearance is subject to significant variability, ranging from several minutes to multiple hours, especially during peak periods such as public holidays, tourist seasons, and emergencies (D. Chen et al., 2022; CIC of Hong Kong, 2023). In the case study, two different scenarios are considered and thus $\Omega = 2$. One scenario represents expedited customs clearance, where the

TABLE 2 Housing developments across Hong Kong's 18 districts in 2024.

Districts	Public housing (no. of flats)	Private housing (m^2)	Total modular construction (MC) volumes (ton)
Central and West District	0	59,314	31,651
Eastern District	0	79,387	42,362
Southern District	600	23,537	27,598
Wan Chai District	0	95,912	51,180
Yau Tsim Mong District	0	213,271	113,804
Kowloon City District	4300	237,082	234,280
Kwun Tong District	2000	379,069	252,401
Sham Shui Po District	900	22,238	34,423
Wong Tai Sin District	0	6088	3249
North District	800	118,734	83,408
Kwai Tsing District	0	33,594	17,926
Tsuen Wan District	0	31,683	16,906
Tuen Mun District	5000	263,569	265,958
Yuen Long District	700	181,327	114,302
Tai Po District	0	7804	4164
Sha Tin District	0	62,823	33,523
Sai Kung District	6400	12,293	166,963
Islands District	9800	393,243	455,455
Sum	29,800	2,220,968	1,949,552

Note: Data in the second and third columns are sourced directly from reports published by the Housing Bureau (2024) and the Buildings Department of Hong Kong (2024), which were converted to the unit of "ton" (see the Appendix) and aggregated to derive the total MC volumes in the last column.

transportation of modules from GBA to Hong Kong, including customs processing, can be completed within one day. The other scenario represents prolonged customs clearance, where the relevant cross-border time is 2 days. The values of parameters u_i^2, u^3, and u_i^4 are all set to 1. Additionally, the costs of module transportation are calculated by multiplying the travel distances provided by the public route planning interface of Amap by a unit cost of HK\$1.2/(ton $\cdot$ km). Table 3 records the values of o_i^2 and $o_i^{3,4}$.

Finally, the values of p_i are determined based on the land rental rates for the respective district where the site of project i is located. The daily rentals for land in the three main regions of Hong Kong are HK\$40/m^2 in New Territories, HK\$38/m^2 in Kowloon, and HK\$41/m^2 in Hong Kong (Census & Statistics Department of Hong Kong, 2024). As on-site storage costs typically exceed the basic rentals, p_i is assigned random values ranging from one to two times the basic land rentals.

Following data preparation, this paper then calculates the MSY deployment solutions using both the PSO heuristic method and the proposed solution method. The latter delivers an MSY deployment solution with an objective value of 157,930 tons, while the PSO only yields a suboptimal solution with an objective value of 115,833 tons. The 26.7% optimality gap suggests that, at equivalent budget levels, the solution obtained by the proposed method enables higher MSY service uptake among contractors, compared to the PSO-generated solution. Optimal values of upper-level decisions derived by the proposed method are reported in Table 4. Specifically, the case study suggests that the Hong Kong government should establish an MSY with an area of 9662 m^2 and impose a storage fee of HK\$16 per ton on contractors, which is expected to attract an annual module storage volume of 157,930 tons. The derived results further imply that (1) the 10,300 m^2 of industrial land available in Yuen Long District, Northern Metropolis, is sufficient to establish an MSY in Hong Kong at the current budget level; (2) the identical optimal module storage price y_{n_1} across decision cycles $n_1 = 1, \ldots, N_1$ implies minimal need for governmental price revisions under stable cost conditions.

To assess the robustness of the optimal solution derived, particularly the strategic-level decision variable x (i.e., the construction area of the MSY), this study further performs a sensitivity analysis on parameter c (the unit cost for MSY establishment), which is an aggregate measure encompassing MSY's unit land acquisition, construction, and operational costs. As such, the variability in c may significantly impact the MSY strategic planning decision. Our experiments take the original value of c (HK\$52,500/m^2) as the benchmark and evaluate cases where c is increased by 1% (HK\$53,025/m^2), 2%

TABLE 3 Transportation costs of MC modules.

Districts	Transportation costs (Lok Ma Chau–site)	Transportation costs (Lok Ma Chau–MSY–site)
Central and West District	44.59	63.90
Eastern District	51.28	71.52
Southern District	52.80	72.11
Wan Chai District	49.12	68.45
Yau Tsim Mong District	40.01	59.42
Kowloon City District	43.06	62.48
Kwun Tong District	43.02	67.97
Sham Shui Po District	37.88	56.74
Wong Tai Sin District	39.38	63.48
North District	10.39	46.03
Kwai Tsing District	32.38	51.52
Tsuen Wan District	29.26	48.65
Tuen Mun District	26.16	27.78
Yuen Long District	14.56	26.82
Tai Po District	18.30	47.23
Sha Tin District	32.80	59.62
Sai Kung District	51.62	75.50
Islands District	48.01	49.24

Note: Transportation costs are calculated by a unit cost of HK\$1.2/(ton•km; H. Wang, Ling, et al., 2024) and the travel distances sourced from Amap (https://lbs.amap.com/api).

(HK\$53,550/m^2), and 3% (HK\$54,075/m^2), denoted as Case 1 through Case 3, respectively. Results show that the optimal MSY construction area (9662 m^2) remains effective in all three cases. This implies that, even if the government's decision on x is made based on an underestimated cost c (e.g., assuming the baseline HK\$52,500/m^2 when the actual cost ranges up to HK\$54,075/m^2), the constraints on investment budget can still be satisfied through minor adjustments to the operational-level decision y_{n_1} (i.e., module storage price at the MSY). The objective values are 155,491 tons (98.5% of the benchmark objective value), 152,267 tons (96.4%), and 142,612 tons (90.3%) for Cases 1–3, respectively. The above results demonstrate the practical resilience of the optimal solution provided to MSY strategic planning.

6 | DISCUSSIONS

Grounded in the topic of MC logistics management, this paper designs optimal plans for MSY deployment to enhance the resilience of MC supply chains. Despite many governments' commitment to MSY deployment, relevant studies are limited. Among the few existing works (CIC of Hong Kong, 2021b), the focus has solely been

TABLE 4 Optimal solution to MSY deployment in the Hong Kong case.

Area of the MSY to be established, x	Daily storage price at the MSY, y_{n_1}	Number of MC modules stored at the MSY, Objective function (1)
9662 m^2	HK\$16/ton	157,930 ton

on identifying suitable MSY locations, failing to design a detailed deployment plan (e.g., the area of the MSY, module storage pricing of the MSY). This paper captures government–contractor interactions and MC transportation uncertainties to design a bi-level stochastic program, offering practical guidance for MSY deployment in high-density urban regions.

While the incorporation of bi-level decision-making makes the problem closer to real-life scenarios, the resulting model is of high complexity. In the existing literature, bi-level problems are primarily solved by heuristic algorithms. To address computational challenges, this paper designs a tailor-made solution method, which can yield optimal solutions outperforming those derived by the PSO heuristic algorithm by an average gap of 15% (as shown by medium- and large-scale instances). Although the proposed method significantly outperforms PSO in terms of solution quality, its efficiency is lower, compared to heuristic algorithms. This is relevant for the bi-level problem studied in this paper, which incorporates stochastic scenarios. When the number of scenarios grows, the solving speed will inevitably decrease. Fortunately, the current literature offers established techniques for generating scenarios that maximize accuracy with minimal number of scenarios (K. Wang & Jacquillat, 2020; Zhang et al., 2023).

The models and solution method proposed in this paper were validated by a case study of Hong Kong, demonstrating their practical effectiveness. Notably, the methodology is also adapted to other regions for MSY deployment. Beyond this real case, extensive numerical experiments were performed, illustrating how governments can adjust model parameters based on regional specifics to derive optimal solutions.

The practical value and methodological contributions of this study are summarized as follows. This paper represents the first attempt to capture the hierarchical decision-making structure of the two entities for MSY planning purposes. The development of local module storage facilities can effectively mitigate the logistics challenges facing MC contractors and thus promote the uptake of sustainable construction methods. In addition to practical relevance, this study also offers methodological novelties. The standard Benders optimality cut is modified to accommodate optimization problems with integer variables. The positive performance of the proposed method motivates its future applications to similar stochastic programming problems with a bi-level structure.

Despite the above merits, this work still has limitations, which can be extended in the following ways. First, the problem setting of this paper is based on an intended location for establishing MSYs (e.g., a site in Yuen Long determined by the government in the Hong Kong case). Follow-up work could extend to site selection decisions prior to MSY deployment using combinatorial optimization. Second, developing advanced techniques for scenario generation and reduction is a valuable research direction. Since the focus of this research is on designing a bi-level MSY planning framework, this paper does not delve into this issue. Future studies could focus on generating minimal, yet sufficiently accurate, scenarios based on the real-world transportation data collected by MC contractors. Third, the efficiency of the proposed Benders decomposition method, though acceptable for strategic MSY planning, remains inferior to heuristic methods (Siddique & Adeli, 2014a, 2014b). Future research could develop effective acceleration strategies to enhance its computational efficiency. Exploring alternative reformulations or metaheuristics to approximate the global optimal solutions to the bi-level optimization is also a valuable option (Siddique & Adeli, 2015, 2016). Finally, due to data availability constraints, our analysis focuses on a single Hong Kong case study involving relatively short-distance cross-border transportation of precast modules. An important opportunity for future studies lies in incorporating richer datasets to model more complex transportation scenarios and conduct comparative analyses across multiple regions. Such efforts could provide policymakers and stakeholders with broader insights into MSY deployment.

7 | CONCLUSION

Motivated by the pressing need for developing government-led storage yards for precast modules, this paper formulates a bi-level stochastic programming framework for optimal MSY deployment planning in high-density regions. The aim of this study is to mitigate MC supply chain challenges and promote the uptake of MC technologies.

The problem under investigation is formulated as a bi-level stochastic program that factors in the government–contractor interactions and transportation uncertainties. To reduce the computational complexity, the model is reformulated into a single-level structure using the property of strong duality. A solution method based on Benders decomposition is designed for model calculation. Specifically, optimality and feasibility cuts are generated and added to the master problem obtained after decomposition as constraints, which accelerates iterative convergence while ensuring solution optimality.

Extensive numerical experiments find that the proposed method outperforms the PSO heuristic algorithm, achieving superior computational performance with an average 15% improvement in solution quality. Furthermore, a real-case analysis based on Hong Kong data reveals that a bi-level programming framework is essential for effective MSY deployment planning, enabling governments to account for potential feedback from MC contractors. This framework is specifically designed to maximize the use of the established MSY and minimize MC transportation and storage costs.

Overall, this study advances MSY planning by integrating a bi-level decision-making model with a tailor-made solution method. The numerical results provide governments in high-density regions with useful insights on MSY deployment.

NOTATION

Notation used in models $[\mathrm{M}^{\mathrm{G}}]$ and $[\mathrm{M}^{\mathrm{C}}]$

$A_{it}(\omega)$ $o_i^2 + p_i(U_{i,t}^{\max} - u_{i,t}^1(\omega))$;

a the maximum area for MSY establishment;

B the maximum investment for MSY establishment;

c the unit cost of establishing MSY;

$d_{i,t}$ the number of modules of project i planned to be assembled on site at the beginning of day t;

e the conversion coefficient from m^2 to ton;

I the number of construction projects;

i index of construction project;

L_1 the decision cycle of the government's pricing decision for module storage;

L_2 the decision cycle of the contractors' rental decision for MSY capacity;

M a sufficiently large constant;

N_1 the number of the government's decision cycles;

n_1 index of government's decision cycle, $n_1 = 1, \dots, N_1$;

N_2 the number of the contractors' decision cycles;

n_2 index of contractors' decision cycle, $n_2 = 1, \dots, N_2$;

o_i^2 the transportation cost from the checkpoint to the site of project i;

$o_i^{3,4}$ the transportation cost from the checkpoint to the MSY and then from the MSY to the site of project i;

p_i the on-site storage cost for contractor of project i;

T the number of days in the planning horizon;

$\tilde{T}_{i,t}(\omega)$ the set of demand days for modules of project i that are being stored at the MSY at the beginning of day t in scenario ω;

$u_{i,t}^1(\omega)$ the time required to transport modules of project i from the factory at the beginning of day t to the checkpoint and complete customs clearance in scenario ω;

t index of day, $t = 1, \dots, T$;

u_i^2 the transportation time from the checkpoint to the site of project i;

u^3 the transportation time from the checkpoint to the MSY;

u_i^4 the transportation time from the MSY to the site of project i;

$U_{i,t}^{\min}$ $\min\limits_{\omega=1,..,\Omega} u_{i,t}^1(\omega)$;

$U_{i,t}^{\max}$ $\max\limits_{\omega=1,..,\Omega} u_{i,t}^1(\omega)$;

Ω the number of scenarios;

ω index of scenario;

x the area of the MSY to be established;

y_{n_1} the daily price of storing modules at the MSY determined by the government in its n_1th decision cycle;

$\boldsymbol{y}$ a vector defined as $(y_{n_1}, n_1 = 1, \dots, N_1)$;

$Z_1(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma})$ the objective function of model [M$^{\mathrm{C}}$];

α_{i,n_2} the MSY rental capacity for module storage determined by the contractor of project i in its n_2th decision cycle;

$\boldsymbol{\alpha}$ a vector defined as $(\alpha_{i,n_2}, i = 1, \dots, I, n_2 = 1, \dots, N_2)$;

$\beta_{i,t}(\omega)$ the number of modules of project i required on site at the beginning of day t that are sent to MSY for storage in scenario ω;

$\boldsymbol{\beta}$ a vector defined as $(\beta_{i,t}(\omega), i = 1, \dots, I, t = 1, \dots, T, \omega = 1, \dots, \Omega)$;

$\gamma_{i,t}(\omega)$ the total number of modules of project i that are being stored at the MSY at the beginning of day t in scenario ω;

$\boldsymbol{\gamma}$ a vector defined as $(\gamma_{i,t}(\omega), i = 1, \dots, I, t = 1, \dots, T, \omega = 1, \dots, \Omega)$;

Notation used in models [DM$^{\mathrm{C}}$], [SM$^{\mathrm{GC}}$], [MP], and [SP]

$\check{x}$ a feasible solution of x to [MP];

$\check{y}_{n_1}$ a feasible solution of y_{n_1} to [MP];

$Z_2(\boldsymbol{\pi}^6, \boldsymbol{\pi}^7, \boldsymbol{\pi}^8, \boldsymbol{\pi}^9, \boldsymbol{\pi}^{10}, \boldsymbol{\pi}^{11})$ the objective function of model [DM$^{\mathrm{C}}$];

$\tilde{z}$ the upper bound of model [SM$^{\mathrm{GC}}$];

$\underline{z}$ the lower bound of model [SM$^{\mathrm{GC}}$];

obj^{MP} the objective value of model [MP];

obj^{SP} the objective value of model [SP];

Θ^{V} the set of optimality cuts;

Θ^{F} the set of feasibility cuts;

Θ^{S} the set of solutions that are feasible to [MP] but infeasible to [SP];

ξ an auxiliary variable in model [MP];

$\bar{\pi}^2$ the dual variable corresponding to Constraint (2) in model [SM$^{\mathrm{GC}}$];

$\pi_{i,n_2,t}^6(\omega)$ the dual variable corresponding to Constraint (6) in model [M$^{\mathrm{C}}$];

$\boldsymbol{\pi}^6$ a vector defined as $(\pi_{i,n_2,t}^6(\omega), i = 1, \dots, I, n_2 = 1, \dots, N_2, t = 1 + (n_2 - 1)L_2, \dots, n_2 L_2, \omega = 1, \dots, \Omega)$;

$\bar{\pi}_t^7(\omega)$ the dual variable corresponding to Constraint (7) in model [SM$^{\mathrm{GC}}$];

$\pi_t^7(\omega)$ the dual variable corresponding to Constraint (7) in model [M$^{\mathrm{C}}$];

$\boldsymbol{\pi}^7$ a vector defined as $(\pi_t^7(\omega), t = 1, \dots, T, \omega = 1, \dots, \Omega)$;

$\pi_{i,t}^8(\omega)$ the dual variable corresponding to Constraint (8) in model [M$^{\mathrm{C}}$];

$\boldsymbol{\pi}^8$ a vector defined as $(\pi_{i,t}^8(\omega), i = 1, \dots, I, t = 1, \dots, T, \omega = 1, \dots, \Omega)$;

$\bar{\pi}_{i,n_2}^9$ the dual variable corresponding to Constraint (9) in model [SM$^{\mathrm{GC}}$];

π_{i,n_2}^9 the dual variable corresponding to Constraint (9) in model [M$^{\mathrm{C}}$];

$\boldsymbol{\pi}^9$ a vector defined as $(\pi_{i,n_2}^9, i = 1, \dots, I, n_2 = 1, \dots, N_2)$;

$\bar{\pi}_{i,t}^{10}(\omega)$ the dual variable corresponding to Constraint (10) in model [SM$^{\mathrm{GC}}$];

$\pi_{i,t}^{10}(\omega)$ the dual variable corresponding to Constraint (10) in model [M$^{\mathrm{C}}$];

$\boldsymbol{\pi}^{10}$ a vector defined as $(\pi_{i,t}^{10}(\omega), i = 1, \dots, I, t = 1, \dots, T, \omega = 1, \dots, \Omega)$;

$\pi_{i,t}^{11}(\omega)$ the dual variable corresponding to Constraint (11) in model [M$^{\mathrm{C}}$];

$\boldsymbol{\pi}^{11}$ a vector defined as $(\pi_{i,t}^{11}(\omega), i = 1, \dots, I, t = 1, \dots, T, \omega = 1, \dots, \Omega)$;

$\bar{\pi}^{14}_{i,n_2}$ the dual variable corresponding to Constraint (14) in model [SM^{GC}];

$\bar{\pi}^{15}_{i,t}(\omega)$ the dual variable corresponding to Constraint (15) in model [SM^{GC}];

$\bar{\pi}^{16}_{i,t}(\omega)$ the dual variable corresponding to Constraint (16) in model [SM^{GC}]

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APPENDIX: UNIT CONVERSION METHOD (HOUSING DATA TO TONS)

The data of public housing in Hong Kong (flats/year) shown in Table 2 were converted to MC volumes (ton/year) using Equation (A1):

$$\text{MC volumes} = 100\% \times 25.063 \times \text{No. of flats} \tag{A1}$$

where the coefficient 25.063 is the average MC volume per public housing flat (CIC of Hong Kong, 2018). Additionally, the data of private housing in Hong Kong (m^2/month) were converted to MC volumes (ton/year) using Equation (A2):

$$\text{MC volumes} = 12 \times 0.55\% \times 8.085 \times \text{Floor area} \tag{A2}$$

where 0.55% is the MC adoption rate in Hong Kong's private housing, and 8.085 is the conversion factor from square meters to metric tons (CIC of Hong Kong, 2018; H. Wang et al., 2025; Yi et al., 2024).