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# RENOVATION LOGISTICS PARK WITH DIGITAL TWINNING: A SIMULATION-OPTIMIZATION-POWERED TOOLBOX

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## ABSTRACT

Taking into account the crucial node of the logistics network, this paper concentrates on the layout design problem of logistics parks considering numerous uncertain factors during operations. To provide comprehensive support for park planners and managers, a simulation-optimization-powered toolbox is developed for decision-making, with core functions such as park layout design, construction quantity calculations, and performance evaluations. A case study demonstrates the toolbox's effectiveness in assisting users to achieve their desired layout designs, and the result shows that the optimized layout generated by the toolbox can lead to improvements of approximately 13%.

## 1 INTRODUCTION

Serving as a crucial hub within the contemporary logistics network, logistics parks play an indispensable role in supporting everyday life, commerce, and industry by facilitating efficient freight storage and distribution. Typically, freight is first transported to the logistics park, where it is unloaded and directed to the appropriate facilities, such as warehouses; upon receiving new orders, the freight is retrieved and subsequently delivered to the designated destinations (Tang et al. 2013). Given the constraints of limited land availability, it is imperative for logistics park designers to optimize both storage capacity and throughput. Achieving these objectives heavily depends on effective layout planning, particularly in terms of warehouse design and allocation. However, the complexity of traffic and operations within a logistics park, including parking, queuing, and the loading and unloading of heavy vehicles, can pose challenges. Inadequate layout planning may ultimately result in an expensive and underperforming logistics park.

Layout planning of logistics parks can be described as a facility layout problem with unequal areas, and the current process largely relies on expert experience, basic analytical methods, or some algorithmic methods. For example, Bozer and Wang (2012) developed a graph-based heuristic algorithm to determine and manipulate the relative location of the departments in the layout. However, numerous uncertain factors, such as truck arrival patterns, handling times, congestion on vehicle lanes, and queues at park gates and parking lots, make it impossible to develop a precise analytical model for performance evaluation. Moreover, there are thousands of potential warehouse design and allocation combinations, each with significantly different costs and performance. Consequently, creating a simulation model and conducting a cost-benefit analysis for each design is not feasible. As a result, it is crucial to adopt a more scientific approach when determining the layout planning of logistics parks.

With advancements in computer simulation technology, simulation has emerged as a powerful tool to drive the digital transformation of traditional industries. Simulation modeling for factory, warehouse and

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logistics park using commercial simulation software, such as AnyLogic, AutoMod, Arena, and FlexSim, has been well-studied in academia and widely adopted in the industry (Agalianos et al. 2020). Despite the advantages of these simulation software, such as convenient user interface, fascinating animation, and knowledgeable manual, which provide great support for the new users to catch up easily, industries have gradually turned to customized and professional simulation platforms for better support of their projects. For example, based on discrete event simulation, TAAM, AIRTOP, and SIMMOD are developed for airport simulation (Sidiropoulos et al. 2018), while MicroCity and $O^2DES.NET$ are commonly used in port and shipping network simulation (Sun and Zhu 2022; Li et al. 2022).

Beyond mere 3D animated demonstrations or commercial software-backed simulation models, digital twinning offers the ability to monitor real-time operations, analyze "what-if" scenarios, and make informed decisions (Zhou et al. 2021). To address the challenges of designing complex systems, a simulation-optimization-powered toolbox has been developed for aiding logistics park layout planning. This toolbox is supported by Particle Swarm Optimization with Optimal Computing Budget Allocation (PSO-OCBA) (Zhang et al. 2017) and the discrete event simulation framework $O^2DES.NET$ (Li et al. 2015). Aimed at achieving optimal performance with lower costs, the toolbox simplifies the optimization of the warehouse design and allocation by requiring only a designated land space as input. This innovative approach streamlines the planning process while ensuring efficient and cost-effective logistics park designs.

The remaining paper is organized as follows: Section 2 introduces the framework of the toolbox followed by technical details in Section 3. A case study is discussed in Section 4. Finally, the conclusion is made in Section 5.

## 2 TOOLBOX FRAMEWORK

The toolbox is designed to help planners efficiently and effectively obtain a good layout design for the logistics park. Following the digital twinning concept raised by Zhou et al. (2021), the toolbox is built with several essential functions, including evaluating the expected operation performance, analyzing setup and operation costs, and eventually suggesting the best candidate designs. Different from existing approaches, the toolbox merges simulation and numerical analysis into a single platform, and provides park planners with rigorous decisions to make.

The toolbox, developed in *.Net Core*, has three layers as illustrated in Figure 1: the infrastructure layer defines application programming interfaces and data structure, which are vital to data exchange between models, algorithms, and web-based interface; the core-function layer consists of three engines to simulate the park operations, to optimize layout design, and to calculate the operation and construction costs of the park, respectively; the user-interface layer is built as a web service which offers to planners an easy approach to setup and analyze test cases.

### 2.1 Core Function

As the core of the toolbox, this layer consists of three engines in response to the various needs of the planners. To simulate and evaluate the system performance of the candidate park design, the discrete event simulation (DES) method is applied and enabled through an open-source package $O^2DES.NET$. The package provides basic definitions of elements in the DES, such as events, dynamic and static entities, and the logic of the simulation. Our engine is built on top of the package. By parameterizing the design factors, such as facility locations, dimensions, orientations, handling capabilities, and traffic network, the engine can be easily configured to various park designs and output corresponding simulation models and can model the operation uncertainties in detail, such as truck arrival, cargo handling, traffic congestion, etc.

The cost analysis engine provides an intuitive evaluation of the layout design which transforms both design factors and operation performance into a single factor, i.e., cost. A candidate layout is created, and the simulation engine will be activated first to make sure that the layout is operationally feasible and also

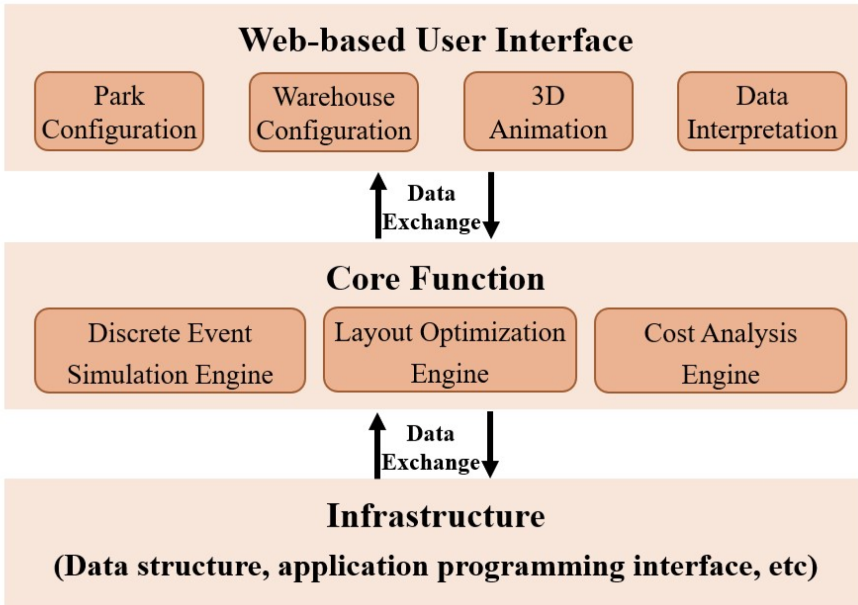


Figure 1: Toolbox framework illustration.

to evaluate its throughput. Then the cost analysis engine will be triggered to estimate layout performance in terms of setup cost and operation cost.

The layout optimization engine is proposed to optimize the layout design of the logistics park, which can also be formulated as a two-dimensional bin packing problem. The flexibility of the simulation engine further allows the optimization engine to search for the best layout design according to simulation outputs, which are represented by a total cost. As such, the PSO-OCBA, one of the simulation-optimization methods, is implemented, which guarantees the convergence of the optimization through the particle swarm optimization (PSO) algorithm, and accelerates simulation evaluation through the optimal computing budget allocation (OCBA) algorithm.

### 2.2 Web-based User Interface

In order to provide park planners with easy-to-use and convenient access to the desired information, four modules are set up, which are *Park Configuration*, *Warehouse Configuration*, *3D Animation*, and *Data Interpretation*.

*Park Configuration* (presented in Figure 2) allows the users to import or setup parameters such as park dimensions, truck speed, the minimum road width, etc, while *Warehouse Configuration* defines the parameters of the possible warehouse designs, such as warehouse dimension, number of docks, throughput in terms of dock number and internal resources, etc.

*3D Animation* (presented in Figure 3) and *Data Interpretation* (presented in Figure 4) provide intuitive interpretations of the candidate layouts derived from the core-function layer. Specifically, *3D Animation* offers a dynamic demonstration of how the logistics park is operated in the given layout, which can also be used for debugging, and *Data Interpretation* summarizes key indicators of the candidate layouts, which allows the planners to make the final decision on which layout to be adopted.

## 3 DECISION-MAKING THROUGH SIMULATION-OPTIMIZATION

Given the demands of the toolbox above, a formal description of the research problem that supports the decision-making capability of the toolbox is as follows: We consider a logistics park of a rectangular area with $w^l \times l^l$, where $w^l$ denotes the vertical length and $l^l$ denotes the horizontal length. The park has a

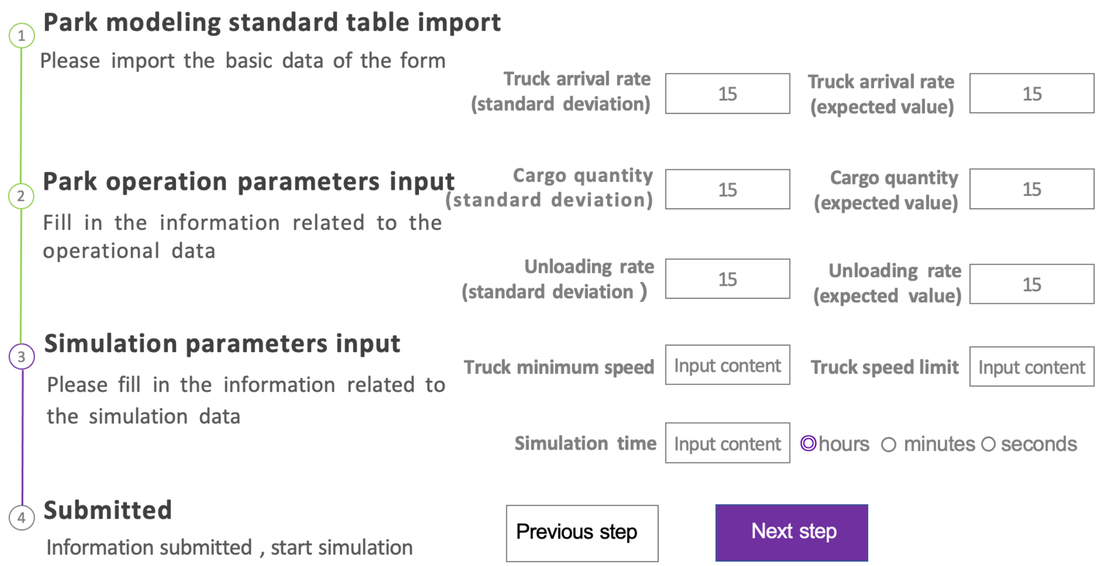


Figure 2: Portal-based park configuration.

parking area (a rectangle area of $w^p \times l^p$) located at the lower left corner with parking capacity $c^p$. The warehouse to be built in the park is not free to shape. Instead, there are $\gamma$ warehouse designs to be chosen from and let $\mathbf{I} = \{1, 2, \ldots, \gamma\}$ denote the set of design. Each design $i \in \mathbf{I}$ takes a rectangle area of $w_i \times l_i$ with $p_i$ docks on one side of the warehouse, $k_i$ transport equipment inside such as forklifts or workers, and the daily construction cost per unit area is $c_i$. Once chosen the warehouse design, the traffic network is established and the distance between warehouses within the park should not be less than the minimum road width $d$.

In previous studies (Gonçalves and Resende 2015; Paes et al. 2017), the number of warehouses to be laid out is predetermined. However, our toolbox loosens this restriction. Instead, the maximum number of warehouse design $i$ in the given scale of the park, denoted by $|\mathbf{S}_i|$, can be estimated by Formulation (1). The term $\lfloor (w^l - d)/(w_i + d) \rfloor$ represents the maximum number of vertical warehouse design $i$, and the term $\lfloor (l^l - d)/(l_i + d) \rfloor$ represents the maximum number vertically.

$$|\mathbf{S}_i| = \lfloor (w^l - d)/(w_i + d) \rfloor \times \lfloor (l^l - d)/(l_i + d) \rfloor \tag{1}$$

The number of design $i$ that needs to be built is converted into the decision on whether to build warehouse $v$ of design $i$, $v \in \{1, 2, \ldots, |\mathbf{S}_i|\}$. Figure 5 presents an illustration of the problem. Therefore, let $u_{iv}$ be a binary decision variable, and $u_{iv} = 1$ if warehouse $v$ of design $i$ is built, otherwise $u_{iv} = 0$. In the meanwhile, we need to determine the location of the warehouse $v$ of design $i$ in the park, denoted by $(x_{iv}, y_{iv})$.

### 3.1 Simulation Modeling

The logistics park is essentially coordinated and operated based on operational rules and protocols, which makes the discrete event simulation the most suitable for our toolbox.

Without losing generality, it is assumed that all trucks entering the park are for unloading operations, and each truck needs to travel through the entrance, parking area and arrives at the target warehouse. Once the operation is finished at the warehouse, the truck will depart from the exit directly without hanging

Figure 3: Illustration of the *3D Animation* module.

out in the logistics park. The variable uncertainties within the simulation model include factors like truck arrival, unloading operation, cargo handling, etc.

The simulation model consists of three modules, i.e., a generator, a parking area, and corresponding warehouses. The model is implemented on top of $O^2DES.NET$ and its conceptual diagram is illustrated in Figure 6.

- **Generator:** This module is designed to describe the event of trucks arriving at the logistics park. In addition, the event within the module can trigger events in other modules. Once a truck arrived, then *OnArrived* will be triggered.
- **Parking area:** This module is modeled as a limited capacity queue and describes truck waiting upon arrival. *AttemptEnGate* acts when a truck attempts to enter the parking lots, and if the parking lots have additional capacity, the truck will be transferred from "Generator" to "Parking Lots", otherwise, the truck will be waiting outside the entrance. Once the truck entered the parking lots, *EnPLed* will be triggered. Finally, when the truck leaves the parking lots, *DePL* will be triggered.
- **Warehouse:** Each warehouse is modeled as a limited capacity server and describes the truck unloading operation. When a truck waiting at the parking lots attempts to enter the target warehouse, *AttemptEnWH* will be triggered, and if the target warehouse has an idle dock, the truck will depart to the corresponding path. In addition, *EnPathed* will also be triggered, which feedback to the "Parking Lots" module, such that the truck will be transferred from "Parking Lots" to "Path and Warehouse".
- **Traffic Network:** To simulate truck movement within the park, a traffic network sub-module is developed and integrated into "Path and Warehouse". The geometric center of each warehouse and parking area serves as a control point. Collectively, these control points create the logistics park's traffic network. The travel distance between the two control points is estimated using the Manhattan distance. Hence, truck movement in the logistics park can be viewed as traversing these control points, specifically from the entrance control point to the parking area control point, and finally to the target warehouse control point.

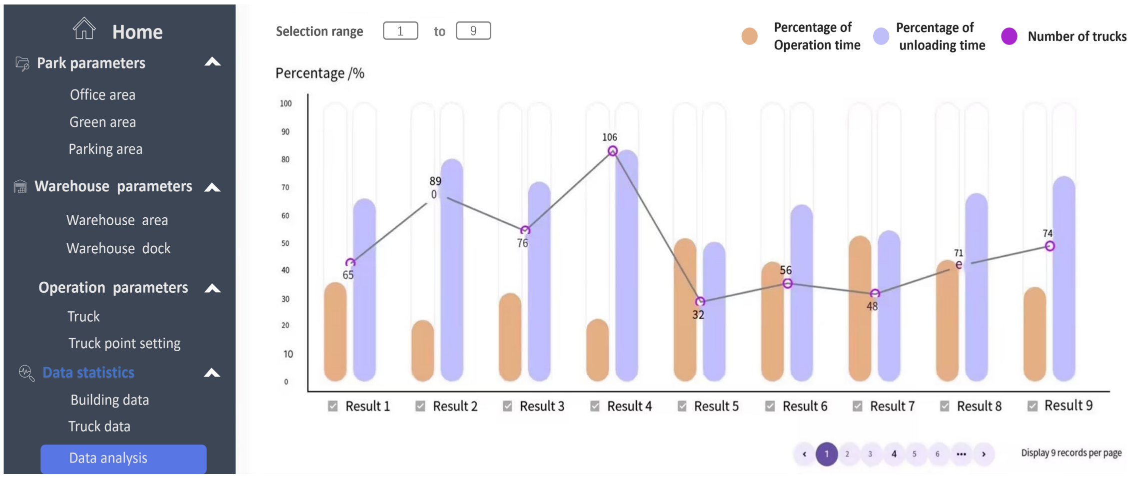


Figure 4: Illustration of the *Data Interpretation* module.

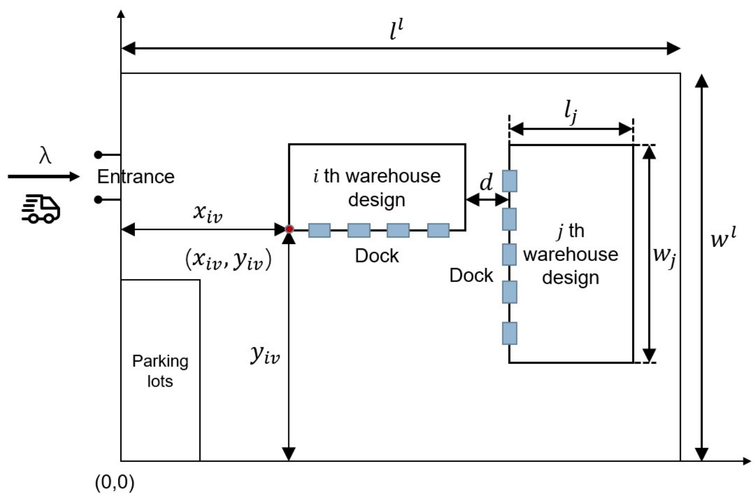


Figure 5: Problem illustration.

To estimate warehouse throughput per design, a separate simulation model is developed as shown in Figure 7. The inputs of this model encompass truck arrival rate, cargo quantities, cargo handling rate, and warehouse configuration. The outputs comprise the daily average number of trucks served by the warehouse and the associated variance. An example of the results is presented in Table 1.

## 3.2 Cost Function

The cost function consists of two parts, i.e., setup cost and operation cost. The setup cost is measured by the area occupied by warehouse designs, and the unit construction cost of the warehouse during the service life is $c_i$ Yuan per square meter per day, which can be found in Table 1. The operation cost indicates the penalty incurred from the delay of unloading trucks, where the unit cost is $c^t = 1152$ Yuan per day. Let $truck^{all}$ denote the total number of trucks arriving within a day generally, and $truck_{iv}^{processed}$ presents the number of trucks served by warehouse $v$ of design $i$ within a day. The objective is formulated by Function (2).

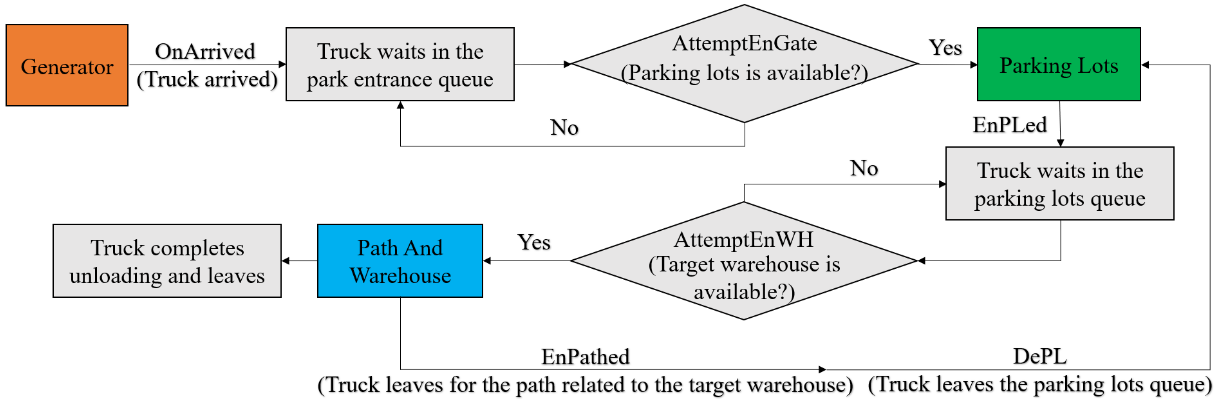


Figure 6: Logistics park simulation model illustration.

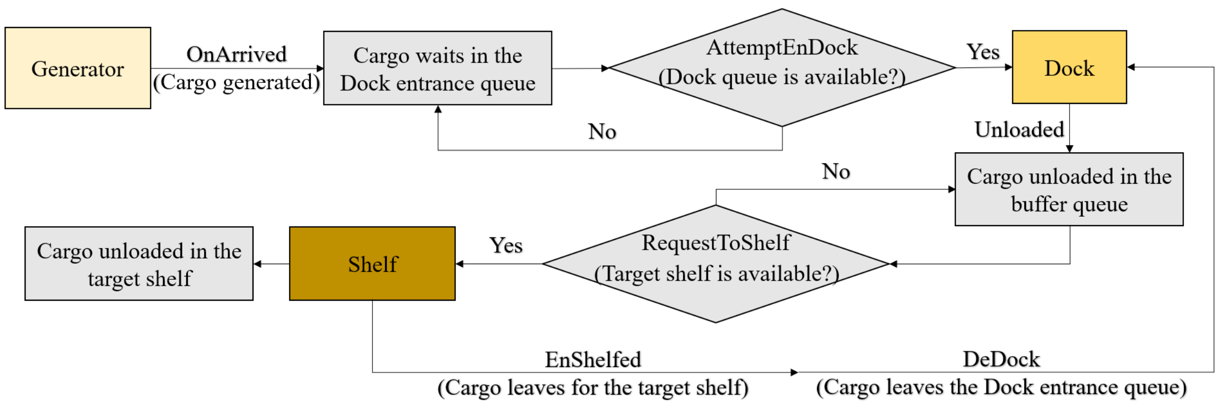


Figure 7: Illustration of warehouse simulation model.

$$\min \sum_{i \in \mathbf{I}} \sum_{v \in \mathbf{S}_i} c_i \times w_i \times l_i \times u_{iv} + c^t \times \max\{0, truck^{all} - \sum_{i \in \mathbf{I}} \sum_{v \in \mathbf{S}_i} truck_{iv}^{processed} \times u_{iv}\} \tag{2}$$

Due to many uncertain factors, the second term of the objective function can be obtained by simulation. Take the bottom left-hand corner of the logistics park as the origin, and establish the X-axis and Y-axis to the right and upward respectively.

### 3.3 PSO-OCBA Algorithm

There are two parts of the PSO-OCBA framework: the PSO procedure and the OCBA procedure. Figure 8 illustrates the framework of the PSO-OCBA algorithm.

In the PSO, each particle $n \in \{1,2,\ldots,N\}$ has a position $X_n^t$ and a velocity $V_n^t$ at iteration $t \in \{1,2,\ldots,I\}$. Then, the velocity of the particles will be updated based on the local best position $\mathbf{Pbest}_n$, global best position **Gbest**, and other random information. Finally, the new velocity will be used for changing the current position of the particle and the new fitness value will be evaluated.

A layout design of the logistics park consists of the number of warehouses in design $i$ to be built and the corresponding locations ($x_{iv}$, $y_{iv}$). Based on this idea, the solution structure of the PSO has $3\alpha$ elements, where $\alpha$ is calculated by Formulation (3), and the solution can be represented by $X_n^t = \{x_{n1}, \ldots, x_{nk}, \ldots, x_{n\alpha}, x_{n(\alpha+1)}, \ldots, x_{n(2\alpha)}, x_{n(2\alpha+1)}, \ldots, x_{n(3\alpha)}\}$ for $k \in \{1,2,\ldots,\alpha\}$, and $x_{nk}$ is a real number.

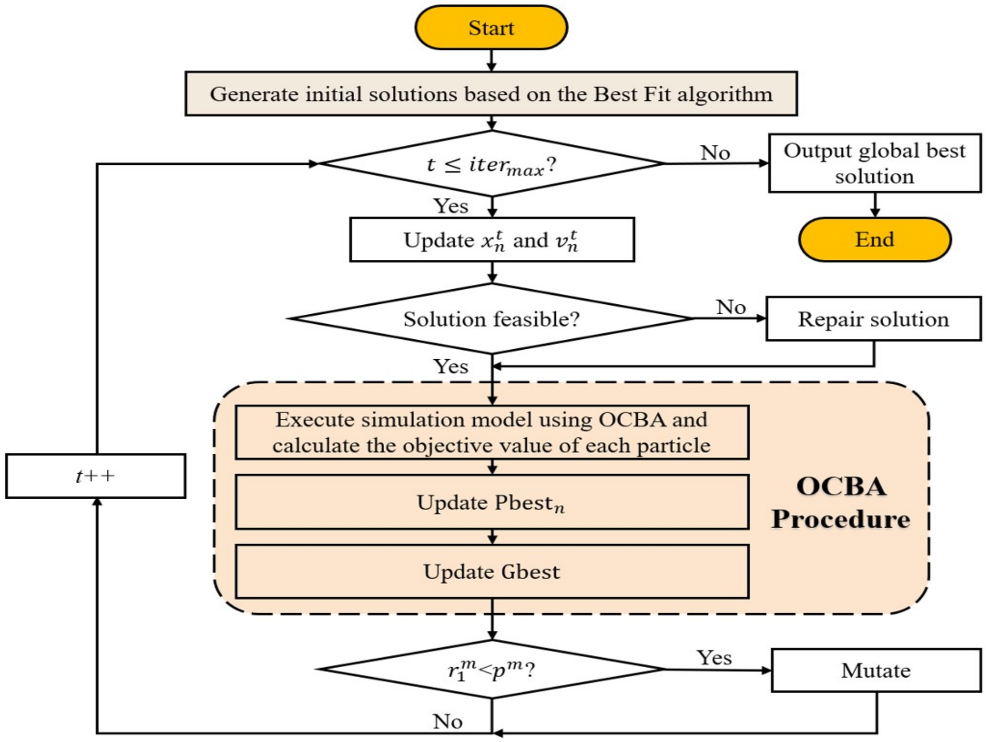


Figure 8: PSO-OCBA algorithm.

$$\alpha = \sum_{i \in \mathbf{I}} |\mathbf{S}_i| \tag{3}$$

### (i) Initial solutions

As a variant of the two-dimensional bin packing problem, a modified Best-fit algorithm is adopted to generate initial solutions for the PSO. Typically, the input for the best-fit method consists of a list of known number rectangles with preset dimensions. However, since we do not know which warehouses to arrange beforehand, we randomly sample a rectangle from $\gamma$ designs one by one into a list. This process continues until the cumulative area of all rectangles in the list slightly exceeds the logistics park's area, taking into account both the road width $d$ and the area of the parking lots. In addition, the initial solutions obtained by random sampling ensure the diversity of particles.

### (ii) Velocity and position update

Following Clerc and Kennedy (2002), the velocity and position of the particles are updated by formulations (4) and (6), respectively. Specifically,

$$V_n^{t+1} = \omega V_n^t + c_1 r_1 (\mathbf{Pbest}_n - X_n^t) + c_2 r_2 (\mathbf{Gbest} - X_n^t) \tag{4}$$

where $\omega$ is the inertia weight which can be calculated by Formulation (5); $c_1$ and $c_2$ are velocity constants related to the local best and the global best, respectively; $r_1$ and $r_2$ take a value from a uniform distribution between 0 and 1.

$$\omega = \omega_{max} - (\omega_{max} - \omega_{min}) \times t/I \tag{5}$$

where $\omega_{max}$ represents the maximum inertia weight, and $\omega_{min}$ denotes the minimum inertia weight. As the number of iterations increases, $\omega$ decreases continuously which leads to a strong global convergence ability of the PSO at the early stage and a strong local convergence ability at the later stage.

$$X_n^{t+1} = X_n^t + V_n^{t+1} \tag{6}$$

### (iii) Mutate operator

To avoid falling into the local optimum, the mutate operator is the same as Zeng et al. (2017). Let $p^m$ be the probability of mutation given by Formulation (7), and $r_1^m$ and $r_2^m$ take a uniform distribution between 0 and 1. Subsequently, if $r_1^m \leq p_m$, then perform the mutate operator in accordance with Formulation (8) or (9) by using the global best information and local best information.

$$p^m = p_m^{max} - (p_m^{max} - p_m^{min}) \times t/I \tag{7}$$

When $r_2^m \leq 0.5$,

$$X_n^t = X_n^t + r_2(1-t/I)^{\theta}(\mathbf{Gbest} - X_n^t) \tag{8}$$

When $r_2^m > 0.5$,

$$X_n^t = X_n^t + r_1(1-t/I)^{\theta}(\mathbf{Pbest}_n - X_n^t) \tag{9}$$

where $\theta$ is the scale parameter and we configure it to 4 following Zeng et al. (2017).

### (iv) OCBA

The purpose of OCBA is to use an effective allocation rule to better utilize limited computing resources and maximize the probability of correctly selecting the optimal solution from a limited number of solutions (Zhang et al. 2017; Liu et al. 2016). During iterations of the stochastic PSO, the key challenge is how to evaluate the fitness value of each particle accurately so as to update the global best and local best correctly. Therefore, we apply the asymptotic optimal allocation rule and modify the sequential allocation procedure following Zhang et al. (2017). Briefly, particles with the largest variance and particles that are closest to local or global best will be given more simulation replications. We set $T$ as the total replications per iteration. Then we set $n_0$ and $\Delta$ as the initial replications for each particle and the move step size, respectively.

## 4 CASE STUDY

To demonstrate how the toolbox can assist planners to obtain a desired layout design, the following scenario is introduced as the case study: currently, at the planning stage, a planner needs to design a logistics park within a given dimension of land space. He needs to evaluate the total cost of the candidate layouts, which consists of setup cost incurred from building the warehouses and operation cost that occurred from the penalty for the number of trucks that are rejected to enter the park due to long waiting time at the gate.

### 4.1 Experiment Setting

The size of the logistics park is planned to be $l^l = 360$ meters and $w^l = 380$ meters with a parking area of $l^p = 10$ meters, $w^p = 40$ meters and $c^p = 10$, located in the bottom left corner. The minimal road width $d$ is 24 meters. At each warehouse, let $d^{width} = 6$ meters represent the width of the dock and $d^{safe} = 3$ meters represent the safe distance between docks. There are six designs of the warehouse to be chosen as presented in Table 1.

The scenario under investigation is as follows: the number of truck arrivals per hour is assumed to follow a Poisson distribution with parameter $\lambda = 6$. The average volume of cargo carried by each truck is

Table 1: The parameters analysis with different warehouse designs.

| Design | $c_i$ | $l_i$ | $w_i$ | $p_i$ | $k_i$ | $\lvert\mathbf{S}_i\rvert$ | Served Trucks (avg.) | Served Trucks (var.) |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.148 | 90 | 55 | 9 | 3 | 12 | 16.01 | 0.75 |
| 2 | 0.148 | 55 | 90 | 9 | 3 | 8 | 16.01 | 0.75 |
| 3 | 0.123 | 60 | 100 | 10 | 5 | 8 | 23.43 | 0.86 |
| 4 | 0.123 | 100 | 60 | 10 | 5 | 8 | 23.43 | 0.86 |
| 5 | 0.115 | 60 | 200 | 21 | 10 | 4 | 33.31 | 1.05 |
| 6 | 0.115 | 200 | 60 | 21 | 10 | 4 | 33.31 | 1.05 |

20 tons. We assume that the unloading time of the truck on the dock obeys the normal distribution with the expectation of 12 tons per minute and a variance of 1 ton per minute. Motivated by Szczepański et al. (2019), the processing time of a unit quantity of cargo in the warehouse follows a normal distribution with the expectation of $distance/speed$ seconds and the variance of 10 seconds, where $distance$ is calculated by formulations (10) and (11) inspired by Huertas et al. (2007) and $speed = 1.2$ meters per second.

When the number of docks of the specific warehouse design, i.e., $p_i$, is an even number, then

$$distance = w_i - 2 \times d^{safe} - d^{width} + l_i - (p_i/2 - 1) \times (d^{safe} + d^{distance}) \tag{10}$$

And if $p_i$ is odd, then

$$distance = (w_i - 2 \times d^{safe} - d^{width}) \times (p_i - 1)/p_i + l_i - ((p_i - 1)/2 - 1) \times (d^{safe} + d^{distance}) \tag{11}$$

To determine the service rate of different warehouse designs, we conducted simulation experiments of 500 replications to estimate the number of trucks processed by design $i$ per day, using the sample mean and variance to approximate Served Trucks (avg.) and Served Trucks (var.). The result of the analysis of the parameters is presented in Table 1. Other parameters of PSO-OCBA, including $I$, $c_1$, $c_2$, $\omega_{max}$, $\omega_{min}$, $\theta$, $p_m^{max}$, $p_m^{min}$, $T$, $n_0$, and $\Delta$ are set to be 500, 2.04, 2.04, 2.1, 0.9, 4, 0.1, 0.01, 500, 10 and 100, respectively. Finally, the case study is performed on a workstation with an Intel Core i9-10900K 3.7GHz CPU and 64GB of RAM.

### 4.2 Result Analysis

The convergence of the PSO-OCBA algorithm is illustrated in Figure 9, where the objective refers to the total cost of the layout design. The objective value is no longer improved after 250 iterations, and the improvement is nearly 13%.

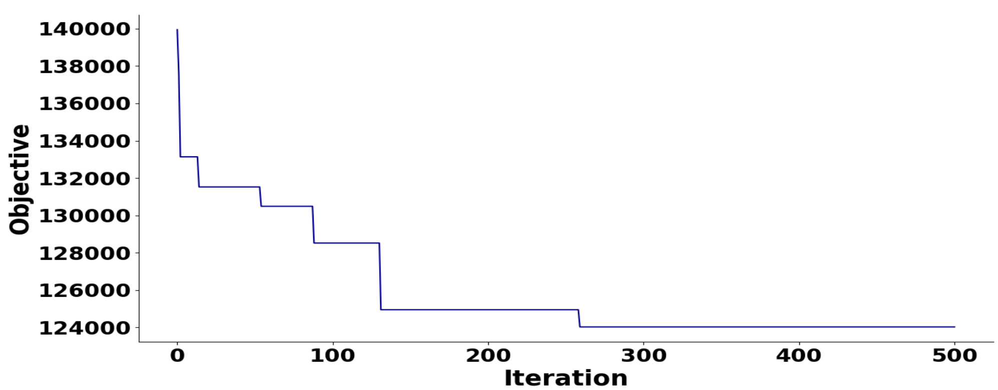


Figure 9: Convergence of the algorithm.

Table 2 compares the details of initial and optimized solutions, where *SC* represents setup cost, *OC* represents operation cost, and *DS* 1 to 6 represents the number of specific warehouse design is placed in the layout design. Despite different warehouse designs and a slight increase in the setup cost, operation cost is significantly reduced. It means that the proposed toolbox is able to find a good layout with higher throughput. These practical results and insights can only be achieved through a simulation-optimization approach.

Table 2: Output analysis between initial and optimized solutions.

| Solution | Objective | SC | OC | DS 1 | DS 2 | DS 3 | DS 4 | DS 5 | DS 6 |
|---|---|---|---|---|---|---|---|---|---|
| Initial | 139947.5 | 7824.6 | 132122.9 | 0 | 1 | 1 | 3 | 1 | 2 |
| Optimized | 124026.0 | 7904.4 | 116121.6 | 0 | 4 | 1 | 2 | 1 | 1 |

Finally, a graphic comparison between initial and optimized layouts is presented in Figure 10. A lower cost can be achieved by putting more warehouse design 2 instead of the other designs. The graphic comparison offers the planner a viable development plan, which provides detailed warehouse location and orientation information.

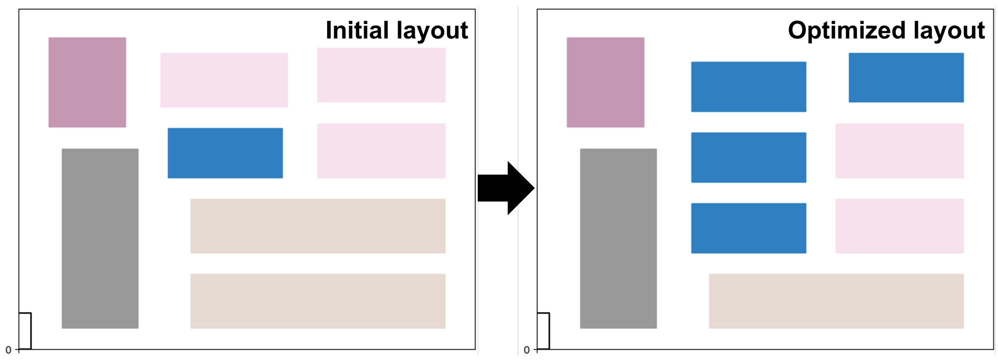


Figure 10: Graphic comparison between initial and optimized layouts.

## 5 CONCLUSION

This paper developed a digital twinning-based toolbox for assisting users in solving the layout design problem of the logistics parks, with the consideration of operation uncertainties. A three-layer framework of the toolbox was introduced, which enables the integration of system simulation and optimized decision-making. The case study, specifically the graphic comparison result, provides significant support for the benefit of this digital twinning. Rather than purely experience-driven, the toolbox could assist the park planners to make verified and validated decisions. However, note that this is still a work-in-progress project where the accuracy of the estimated uncertainty parameters is not considered, which leads to unreliable simulation outputs. It motivates the future development of the toolbox to consider the estimation of a risk measure in the simulation-optimization framework inspired by Wang et al. (2023).

## ACKNOWLEDGMENT

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## REFERENCES

Agalianos, K., S. Ponis, E. Aretoulaki, G. Plakas, and O. Efthymiou. 2020. "Discrete Event Simulation and Digital Twins: Review and Challenges for Logistics". *Procedia Manufacturing* 51:1636–1641.

Bozer, Y. A., and C.-T. Wang. 2012. "A Graph-Pair Representation and MIP-Model-Based Heuristic for the Unequal-Area Facility Layout Problem". *European Journal of Operational Research* 218(2):382–391.

Clerc, M., and J. Kennedy. 2002. "The Particle Swarm-Explosion, Stability, and Convergence in a Multidimensional Complex Space". *IEEE Transactions on Evolutionary Computation* 6(1):58–73.

Gonçalves, J. F., and M. G. Resende. 2015. "A Biased Random-Key Genetic Algorithm for the Unequal Area Facility Layout Problem". *European Journal of Operational Research* 246(1):86–107.

Huertas, J., J. Díaz-Ramírez, and F. Trigos. 2007. "Layout Evaluation of Large Capacity Warehouses". *Facilities* 25(7/8):259–270.

Li, H., X. Cao, E. P. Chew, K. C. Tan, K. Kundu, and H. Chen. 2022. "Hybrid Simulation Modeling Formalism via O2DES Framework for Mega Container Terminals". In *Proceedings of the Winter Simulation Conference*, edited by B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C. G. Corlu, L. H. Lee, E. P. Chew, T. Roeder, and P. Lendermann, 207–221. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Li, H., Y. Zhu, Y. Chen, G. Pedrielli, and N. A. Pujowidianto. 2015. "The Object-Oriented Discrete Event Simulation Modeling: A Case Study on Aircraft Spare Part Management". In *Proceedings of the Winter Simulation Conference*, edited by L. Yilmaz, V. W. Chan, I. Moon, T. M. Roeder, C. Macal, and M. D. Rossetti, 3514–3525. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Liu, Y., L. H. Lee, and E. P. Chew. 2016. "Multi-Objective Optimal Computing Budget Allocation for Multi-Objective Particle Swarm Optimisation with Particle-Dependent Weights". *International Journal of Simulation and Process Modelling* 11(3-4):167–175.

Paes, F. G., A. A. Pessoa, and T. Vidal. 2017. "A Hybrid Genetic Algorithm with Decomposition Phases for the Unequal Area Facility Layout Problem". *European Journal of Operational Research* 256(3):742–756.

Sidiropoulos, S., A. Majumdar, and K. Han. 2018. "A Framework for the Optimization of Terminal Airspace Operations in Multi-Airport Systems". *Transportation Research Part B: Methodological* 110:160–187.

Sun, Z., and T. Zhu. 2022. "Simulation Case Study: How Arctic Shipping Shares the Flow of Cargo from Traditional Routes". In *Proceedings of the Winter Simulation Conference*, edited by B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C. G. Corlu, L. H. Lee, E. P. Chew, T. Roeder, and P. Lendermann, 1899–1910. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Szczepański, E., R. Jachimowski, M. Izdebski, and I. Jacyna-Gołda. 2019. "Warehouse Location Problem in Supply Chain Designing: A Simulation Analysis". *Archives of Transport* 50(2):101–110.

Tang, J., L. Tang, and X. Wang. 2013. "Solution Method for the Location Planning Problem of Logistics Park with Variable Capacity". *Computers & Operations Research* 40(1):406–417.

Wang, T., J. Xu, J.-Q. Hu, and C.-H. Chen. 2023. "Efficient Estimation of a Risk Measure Requiring Two-Stage Simulation Optimization". *European Journal of Operational Research* 305(3):1355–1365.

Zeng, M., W. Cheng, and P. Guo. 2017. "Modelling and Metaheuristic for Gantry Crane Scheduling and Storage Space Allocation Problem in Railway Container Terminals". *Discrete Dynamics in Nature and Society* 2017:9025482.

Zhang, S., J. Xu, L. H. Lee, E. P. Chew, W. P. Wong, and C.-H. Chen. 2017. "Optimal Computing Budget Allocation for Particle Swarm Optimization in Stochastic Optimization". *IEEE Transactions on Evolutionary Computation* 21(2):206–219.

Zhou, C., J. Xu, E. Miller-Hooks, W. Zhou, C.-H. Chen, L. H. Lee, E. P. Chew, and H. Li. 2021. "Analytics with Digital-Twinning: A Decision Support System for Maintaining a Resilient Port". *Decision Support Systems* 143:113496.

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