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A Comparative Study on Swarm-based Algorithms to Solve the Stochastic Optimization Problem in Container Terminal Design

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Abstract. This study compared swarm-based algorithms in terms of their effectiveness in improving the design of facilities in container terminals (CTs). The design was conducted within the framework of stochastic discrete optimization and involved determining the number of equipment needed in CTs by considering variations in demand and the productivity of facilities—issues that are rarely elaborated in CT design. Variations were identified via Monte Carlo simulation characterized by a particular distribution. The conflicting issue due to increments in equipment investment that possibly cause the distribution delays was also modeled, specifically in relation to the increasing number of trucks used in terminals. Given that the optimization problem is typified by numerous combinations of actions, the swarm-based algorithms were deployed to develop a feasible solution. A new variant of glowworm swarm optimization (GSO) was then proposed and compared with particle swarm optimization (PSO) algorithms. The numerical results showed that the performance of the proposed GSO is superior to that of PSO algorithms.

Keywords: Design of container terminal facilities; Glowworm swarm optimization; Particle swarm optimization; Stochastic optimization.

1. Introduction

As an essential part of annually expanding global trade, the container shipping industry has been compelled to extensively develop container terminals (CTs) by investing in large-scale equipment and advanced hardware for tackling container flows (Mishra et al., 2017). This development has correspondingly increased the complexity of CT operations, which encompass interactions among resources, entities, and activities. Such interactions begin at the seaside, where a vessel requires assistance from a tugboat for berthing. After berthing, quay cranes (QCs) simultaneously handle containers and transport them to a loading dock or transport vehicles. Multiple transport vehicles then convey the containers to a stacking yard, where smooth distribution is considerably facilitated by the existence of an internal road network. Cumulatively, these interactions reflect seaport performance, which is manifested in different forms that range from operational performance (Cartenì 2012 Luca, 2012) to environmental performance (Budiyanto et al., 2019).

The above-mentioned interactions equally contribute to the complexity of CT operations, which is hardly represented in analytical models (Dragović et al., 2017).

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This deficiency prompted researchers to pay increasing attention to the use of simulation models in depicting how CTs are run. In line with this trend, the current research constructed a simulation model on the basis of the Monte Carlo (MC) framework. As part of a stochastic-based procedure, the MC framework can uncover the expected values of components through randomization processes. These processes generate a random number iteratively, thereby creating various event scenarios that illustrate the stochasticity that characterizes CT operations.

The complexity of CT operations can likewise be viewed as an optimization problem, whose resolution lies in selecting the action that best enhances the performance of CTs. Given that CTs operate under uncertainties (i.e., variations at the demand and supply sides), this study also established a stochastic optimization model that directly incorporates uncertainty into the decision-making process. In this model, variations in vessel size are the uncertainties manifested in the demand side, whereas fluctuations in equipment productivity represent the uncertainties in the supply side. The stochastic modeling also considered the QCs, container truck-trailer units (TTUs), and container yard equipment [i.e., rubber tyred gantry crane (RTGC)] employed in CT operations. Because an increment in TTUs used potentially causes delays at land-side area, this research integrated estimations of delays in travel time by applying the Bureau of Public Roads (BPR) function.

Optimization in CTs may be embodied by an enormous number of problem combinations, so the issue was resolved in this research through a metaheuristic approach, which comes in several types, such as genetic algorithms, tabu search, simulated annealing, and swarm-based algorithms. Swarm-based algorithms are grounded in the natural behaviors of swarm entities, such as a flock of birds [i.e., particle swarm optimization (PSO)] and a colony of glowworms [i.e., glowworm swarm optimization (GSO)]. Because of the excellent performance of these algorithms, they have been widely used in solving various optimization problems. However, to the best of our knowledge, little research has been devoted to the performance comparison of swarm-based algorithms intended to address the CT optimization problem, specifically the stochastic type. To fill this void, the present study evaluated the effectiveness of these algorithms in enhancing the design of CT facilities. The comparison revolved specifically around the latest variants of PSO and a version of GSO within the framework of a binary optimization problem.

The rest of the paper is organized as follows. Section 2 describes CT operations and discusses the optimization modeling framework. Section 3 elaborates on swarm-based algorithms and presents the case study on the performance of these approaches. Section 4 concludes the paper with a summary.

2. Optimization Modeling Framework

In formulating a design of CT facilities, this work considered minimizing total passage time because in practice, time-related parameters serve as primary indicators of CT performance (e.g., Yun and Choi, 1999; Cartenì and Luca, 2012; Cimpeanu et al., 2017). Total passage time is defined as the time elapsed before shipment arrival at a container yard after handling by QCs.

CT operations involve uncertainty issues that stem from variations in demand- and supply-related parameters, and these issues are acted on to a limited extent by deterministic optimizations. This is where the potential of stochastic optimization comes into play as it incorporates uncertainty modeling explicitly into the optimization process. Stochastic optimization therefore enables researchers to elucidate uncertainties through probabilistic interpretations. Efforts have been exerted to integrate matters of uncertainty in explorations of multimodal transportation (e.g., Andersen et al., 2009; Sim et al., 2009;

Hoff et al., 2010; Frazila and Zukhruf, 2017), but scant attention has been paid to such an incorporation in the case of CT operations. The stochastic optimization of CT design covers decision making as regards the improvement of facilities, for which modeling involves the use of the MC framework to discover the uncertainty parameters applicable to CT operations. A stochastic model also integrates swarm-based techniques, namely, PSO and GSO algorithms, which are employed to identify an optimal solution. The stochastic optimization model established in this work is expressed in Equations 1 to 5, which reflect the model's similarity to deterministic optimization, except that the objective of the former is expressed in the form of an expectation (see Equation 1).

$$\max\left(\frac{\alpha\left(\mathrm{E}_{\tau\in\Omega}\left[z_0(\tau)-z(Y,\tau)\right]\right)}{c_y}\right) \quad y\in Y \tag{1}$$

$$z(Y,\tau)=$$
$$\min\left[\frac{1}{M}\sum_{m=1}^{M}W_m^1\left(q_m^1(\tau),p\left(n_m^1,\tau\right)\right)+\frac{1}{M}\sum_{m=1}^{M}W_m^2\left(q_m^2(\tau),p\left(n_m^2(y),f_g(y),\tau\right)\right)+W^3\left(q^3(\tau),p\left(n^3(y),\tau\right)\right)\right] \tag{2}$$

subject to

$$\sum_{m=1}^{M}q_m^1\geq\sum_{m=1}^{M}q_m^2 \tag{3}$$

$$\sum_{m=1}^{M}q_m^2\geq q^3 \tag{4}$$

$$q_m^1,q_m^2,q^3,n_m^1,n_m^2,n^3,\geq 0 \tag{5}$$

where

$z_0(\bullet)$: Total passage of time (hours) before arrival at a container yard, with no actions implemented
$z(\bullet)$: Total passage of time (hours) before arrival at a container yard, with actions implemented
y : Vector set of implemented actions
α : Time value of a container (Rp./hours)
c_y : Cost incurred from implementing action y (Rp.)
W_m^1 : Time required by a QC at dock m to transport a container to TTU (hours)
W_m^2 : Time required by a TTU at dock m to move to a container yard (hours)
W^3 : Time required by an RTGC to handle a container at a container yard (hours)
q_m^1 : Quantity of containers handled by a QC at dock m in twenty-foot equivalent units (TEUs)
q_m^2 : Quantity of containers handled by a TTU at dock m (TEUs)
q^3 : Quantity of containers handled by an RTGC (TEUs)
p : Equipment productivity (TEUs/hour)
n_m^1 : Number of available QCs at dock m
n_m^2 : Number of available TTUs for servicing dock m
n^3 : Number of available RTGCs
f_g : Flow of TTU at link g (TTU/hour)
M : Number of available docks at a CT

A random parameter from a space of probability (Ω, A, θ) is denoted by τ, in which E represents an expected value. Uncertainty is illustrated by a random process, where Ω denotes a set of outcomes. The outcome combination is defined as events wherein A represents a collection of random events, and it is related to θ as the probability variable.

Given that the action for improving CT facilities intended to minimize total time should be evaluated on the basis of investment cost, the objective function is set in such a way that maximizes the benefit–cost ratio (BCR). Benefits define the time value of savings acquired from the expected decrement in the total passage of time after action execution, and costs are the investments required to implement action. The BCR has been extensively employed in the field of transportation (e.g., Yamada et al., 2009; Yamada and Zukhruf, 2015) to identify the economic effectiveness of improvement actions. Equation 2 explains the processing time involved in QC conveyance to a container yard; such a period also reflects demand uncertainty and variations in equipment productivity, which is denoted by the random parameter τ. Equations 3 and 4 illustrate container flow conservation, and Equation 5 shows the non-negativity constraint. As the number of equipment used in a CT affects the productivity of facilities, its establishment is regarded as equivalent to the execution of improvement actions. The solution techniques then generate the number of equipment to be assigned, which is denoted by n_m^2 and n^3.

Unloading is first modeled by randomly assigning demands on a dock. The model is configured to consider variations in ship size and QC allocations, wherein two or three QCs can simultaneously handle a single ship. Variations in service time are used to reflect uncertainties in equipment productivity, and such ambiguities are subsequently used to construct the time at which containers are expected to be moved to a TTU.

Containers are further transported by a TTU to container yard using the transport link in a CT area. To illustrate actual conditions, this research accounted for the relationship between the increment in trucks used and the time required for travel from a dock to a container yard. The relationship was modeled using the BPR function (see Equation 6), which has been extensively used to describe increasing delay due to fluctuations in traffic flow (see, e.g., Di et al., 2014; Watling et al., 2018). Because delays may influence entire port operations, the optimization technique should uncover the optimal number of TTUs employed in the process.

$$a = \sum_{g}^{G} \left(v_g^0 \left(1 + 0.5 \left(\frac{f_g(y)}{C_g} \right)^{1.5} \right) \right) \tag{6}$$

where a is the travel time of a TTU (hour), v_g^0 is the free travel time condition of link g (hour), and C_g is the capacity of link g (TTU/hour).

The final stage of CT operations incorporates the maneuvering of an RTGC, which handles containers at a container yard. The time spent handling a container is determined on the basis of queuing theory.

3. Solution Techniques

Problem complexity practically determines a way to choose a technique for solving an optimization problem. Because of its stochastic characteristics and problem size, an exact approach is not always available for solving the problem. To address this dilemma, researchers traditionally deploy a metaheuristic procedure, which covers the use of swarm-based algorithms adopted by researchers to deal with various optimization problems. Govindan et al. (2019), for example, developed a hybrid swarm-based algorithm using PSO, the electromagnetism-like mechanism algorithm, and artificial bee colony to optimize a bi-objective sustainable distribution network. Yamada and Zukhruf (2015) proposed a new variant of PSO to deal with the multimodal supply chain transport supernetwork equilibrium problem. Other applications of swarm-based algorithms include exploring social aware cognitive radio handovers (Anandakumar and Umamaheswari, 2018), wind farm decision systems (Zhao et al., 2019), load balancing for long-term evolution-advanced heterogeneous networks (Summakieh et al., 2019), and molten pool detection (Baskoro et al., 2011). As can be seen, swarm-based algorithms have been substantially exploited to solve numerous engineering problems, yet few such initiatives have been directed toward transportation challenges, specifically in the CT domain, as was done in the current work. This section explains two variants of swarm-based algorithms for CT optimization: PSO and GSO.

PSO, which was invented by Kennedy and Eberhart (1995), was initially developed for continuous and discrete optimization (Kennedy and Eberhart, 1995; Kennedy and Eberhart, 1997). Its short computational time and fast convergence motivated the creation of several discrete PSO variants, such as modified binary PSO (Shen et al., 2004), probability discrete binary PSO (PBPSO) (Menhas et al., 2012), and modified probability discrete PSO (MPBPSO) (Zukhruf et al., 2014). Another recently proposed version is GSO (Krishnanand and Ghose, 2005; Krishnanand and Ghose, 2008), which was preliminarily based on the behavior of glowworms; these insects use brightness to attract other glowworms. GSO has been employed (e.g., Krishnanand and Ghose, 2009; Zhou et al., 2014; Li et al., 2014; Marinaki and Marinakis, 2016), along with PSO, to address various optimization issues. For instance, GSO was used to design a routing algorithm for wireless sensor networks (Xiuwu et al., 2019) as well as optimize a job shop and the transportation of cranes in heavy industries (Liu et al., 2019). PSO was employed to solve the hub location problem, which features capacity restrictions (Özgün-Kibiroğlu et al., 2019) and a routing challenge (Chen and Shi, 2019; Chen et al., 2019).

3.1. PSO

PSO is a metaheuristic approach composed of particles (Kennedy and Eberhart, 1995; Kennedy and Eberhart, 1997), each characterized by a position that determines the fitness value of a particle. Hence, particle position can be regarded as a candidate solution to the optimization problem. Vector velocity acts as an input that updates particle position, for which this particle's own experiences and those of its neighbors are considered. The experiences of the particle are represented by *pbest,* which reflects the best position of this particle. The best position that is visited by any particle in a swarm (i.e., *gbest*) then denotes the experiences of neighbors. PSO was first invented to address continuous problems, but several binary PSOs have since been developed to handle discrete optimization problems. This research tested two of the latest binary versions of PSO with respect to their performance in addressing a stochastic discrete optimization problem.

3.1.1. PBPSO

PBPSO, which was proposed by Menhas et al. (2012), entails replacing the sigmoid function with the probabilistic linear function. The sigmoid function in the original discrete binary PSO (DBPSO) converts a continuous position into a binary position. A similar concept underlies PBPSO, which has a velocity function (i.e., Equations 7–8) and a continuous position (i.e., Equations 9–10). It is distinguished from DBPSO in that it uses the probabilistic linear function (i.e., Equation 11) to update the binary position (i.e., Equation 12).

$$w_{ih}^{t} = \omega w_{ih}^{t} + e_1 rand\left(pbest_{ih}^{t} - u_{ih}^{t}\right) + e_2 rand\left(gbest_{h}^{t} - u_{ih}^{t}\right) \tag{7}$$

$$w_{ih}^{t}=\begin{cases}vel_{\min} & \text{if } w'^{t}_{ih}\le vel_{\min}\\ w'^{t}_{ih} & \text{if } vel_{\min}<w'^{t}_{ih}<vel_{\max}\\ vel_{\max} & \text{if } vel_{\max}\le w'^{t}_{ih}\end{cases} \tag{8}$$

$$x'^{t}_{ih}=x_{ih}^{t}+w_{ih}^{t} \tag{9}$$

$$x_{ih}^{t}=\begin{cases}prob_{\min} & \text{if } x'^{t}_{ih}\le prob_{\min}\\ x'^{t}_{ih} & \text{if } prob_{\min}<x'^{t}_{ih}<prob_{\max}\\ prob_{\max} & \text{if } prob_{\max}\le x'^{t}_{ih}\end{cases} \tag{10}$$

$$prob_{ih}=\left(x_{ih}^{t}-prob_{\min}\right)/\left(prob_{\max}-prob_{\min}\right) \tag{11}$$

$$u_{ih}^{t}=\begin{cases}1 & \text{if } rand\le prob_{ih}\ \left(0\le prob_{ih}\le 1\right)\\ 0 & \text{else}\end{cases} \tag{12}$$

In the equations above,

w_{ih}^{t} : Velocity of particle *i* at iteration *t* in the *h*th dimension

w'^{t}_{ih} : Velocity of particle *i* at iteration *t*+1 in the *h*th dimension

u_{ih}^{t} : Binary position of particle *i* at iteration *t* in the *h*th dimension

u'^{t}_{ih} : Binary position of particle *i* at iteration *t* +1 in the *h*th dimension

$pbest_{ih}^{t}$: Personal best of particle *i* at iteration *t* in the *h*th dimension

$gbest_{ih}^{t}$: Global best at iteration *t* in the *h*th dimension

ω : Inertia weight

$e_1\ e_2$: Learning factors for local best and global best solutions, respectively

$rand$: Uniform random numbers between 0 and 1

$prob_{ih}$: Linear function falling in the range [$prob_{\max}$, $prob_{\min}$]

x_{ih}^{t} : Pseudo position of particle *i* at iteration *t* in the *h*th dimension

x'^{t}_{ih} : Pseudo position *i* at iteration *t* +1 in the *h*th dimension

3.1.2. MPBPSO

A recent update to PBPSO was carried out by Zukhruf et al. (2014), who added an updating rule on changing positions in existing PBPSO algorithms. Equations 13 to 16 define the updating rule for MPBPSO (refer as well to the general procedures in Figure 1). Equations 13 and 14 represent the exploitation strategy for maintaining the current best solution, and Equations 15 and 16 reflect the exploration meant to extend the search space.

$$\text{if } (0\le rand<\tau) \qquad u''^{t}_{ih}=gbest_{h}^{t} \tag{13}$$

$$\text{if } \left(\tau\le rand<\left(2\tau+1\right)/3\right) \qquad u''^{t}_{ih}=pbest_{ih}^{t} \tag{14}$$

$$\text{if } \left(\left(2\tau+1\right)/3\le rand<\left(\tau+2\right)/3\right) \qquad u''^{t}_{ih}=irand \tag{15}$$

$$\text{if } \left(\tau+2\right)/3\le rand\le 1 \qquad u''^{t}_{ih}=u_{ih}^{t} \tag{16}$$

where $irand$ is a binary random number (0 or 1).

3.2. GSO

The behavior of glowworms motivated Krishnanand and Ghose (2005, 2008) to design GSO as a swarm-based technique. It incorporates the luciferin that describes the illumination level of a glowworm, with each glowworm discovering high luciferin values within its scope. An increase in luciferin value directly induces the attraction of glowworms within their range. This process also denotes the range of local decisions. Luciferin is therefore an essential variable for identifying solutions. Because GSO was initially aimed at settling continuous problems, some revision is undoubtedly needed, specifically in terms of position updates. This work formulated a GSO variant that addresses binary optimization by invoking the probabilistic function, which has been successfully implemented in PSO variants (i.e., Menhas et al., 2012; Zukhruf et al., 2014; Yamada and Zukhruf, 2015). The procedure for executing the GSO variant is delineated as follows:

Step 1. Initial stage ($t = 0$)

- Determine the initial values of N, *iter*, ρ, γ, β, o, s $prob_{\min}$, $prob_{\max}$, $r_{\max}$.
- Set initial random position (x_i^t) for $i = 1, 2, \ldots, N$.
- Similarly initialize the value of luciferin (l_i^t) and its distance range (r_i^t) for each glowworm $i = 1, 2, \ldots, N$.
- In accordance with glowworm position (x_i^t), calculate the Euclidean distance of glowworms i and j ($d1_{ij}^t$).
- Estimate the probability of movement to a nearby glowworm for each glowworm i. This probability is given by

$$b_{ij}^t = \frac{l_i^t - l_j^t}{\sum_{k \in N_i^t} l_k^t - l_j^t} \tag{17}$$

where $j \in N_i^t, N_i^t = \left\{ j : d1_{ij}^t < r_i^t, l_i^t < l_j^t \right\}$ are the neighbor set of i at iteration t.

- Set the movement direction by considering the highest movement probability, and renew the glowworm position on the basis of the following formula:

$$x_i^{t+1} = x_i^t + s\left(\frac{x_j^t - x_i^t}{\left\| x_j^t - x_j^t \right\|} \right) \tag{18}$$

in which s (>0) denotes the size of step

Step 2. Determine the glowworm binary position by following the probability function thus:

$$prob_{ih} = \left(x_{ih}^t - prob_{\min} \right) / \left(prob_{\max} - prob_{\min} \right) \tag{19}$$

$$prob_{ih} = \left(x_{ih}^t - prob_{\min} \right) / \left(prob_{\max} - prob_{\min} \right) \tag{20}$$

$$u_{ih}^{t+1} = \begin{cases} 1 & \text{if } rand \le prob_{ih} \ \left(0 \le prob_{ih} \le 1 \right) \\ 0 & \text{else} \end{cases} \tag{21}$$

where $u_i^{t+1} = \left[u_{i1}^{t+1}, u_{i2}^{t+1}, u_{i3}^{t+1}, \ldots, u_{ih}^{t+1}, \ldots u_{iH}^{t+1} \right]$, and *rand* is a random number ranging from 0 to 1.

Step 3. Calculate the glowworm's fitness (z_i^{t+1}), and update the luciferin using the following equation:

$$l_i^{t+1} = (1 - \rho)\, l_i^t + \gamma z(u_i^{t+1}) \tag{22}$$

where ρ and γ are constants that represent the decay and enhancement of luciferin, respectively.

Step 4. Update the range of local decision (r_i^t) using

$$r_i^{t+1} = \min\left\{ r_{\max}, \max\left\{ 0, r_i^t + \beta\left(o - \left| N_i^t \right| \right) \right\} \right\} \tag{23}$$

where r_{max} is the maximum value of r_i^t, and o denotes a variable that limits the number of glowworms within the range of their scope.

Step 5. Update the distance and calculate the movement probability using Equation 17.

Step 6. Compute $t = t + 1$. Terminate the process when the criterion for stopping is satisfied; otherwise, revisit **Step 2**.

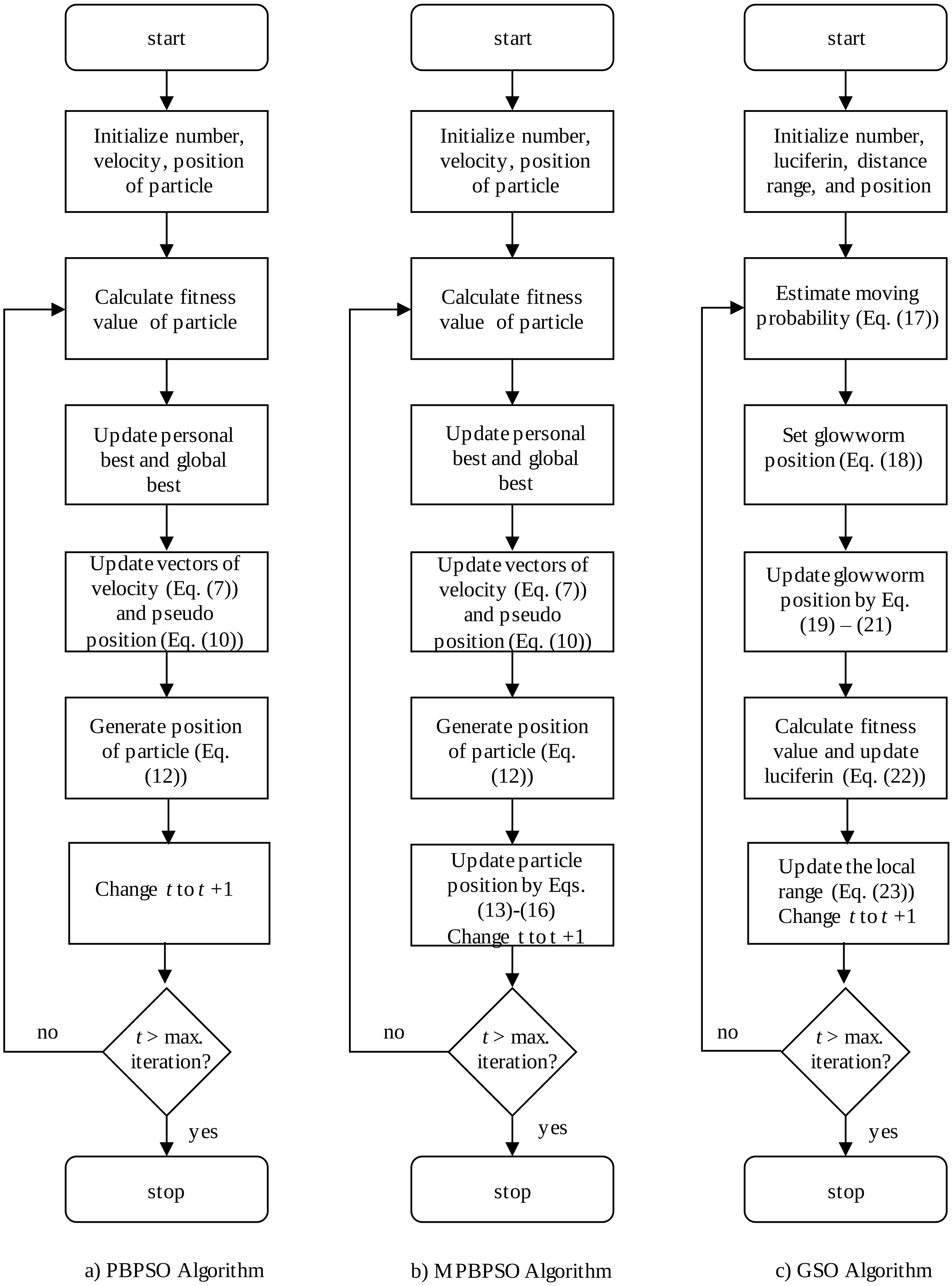

Figure 1 PBPSO, MPBPSO, and GSO operations

4. Performance Comparison

4.1. Case Study and Optimization Problem

This section discusses the evaluation of the performance of the swarm-based algorithms in improving the design of CT facilities within the framework of stochastic optimization. CT operations involve the container transportation process, which begins in vessels and ends in container yards. The design of facilities hence include decision making on quantity assignments for TTUs and RTGCs (Figure 2). The facility characteristics analyzed in this work, namely, the number of equipment used and the time to service a container (Table 1), were obtained from actual data on CT operations in Indonesia (Burhani et al., 2014). These data served as the primary input in the simulation of CT operations, for which the data ranges (i.e., minimum, mean, and maximum values) was employed to work out distribution under a stochastic process. In a CT, three docks are available for the handling of vessels and the containers that they transport, and each dock has three QC units that can be operated simultaneously. On land, the CT is equipped with 45 and 10 units of TTUs and RTGCs, respectively. Variations in vessel type and the frequency with which they visit each dock were configured to follow a certain distribution to represent uncertainty at the demand side.

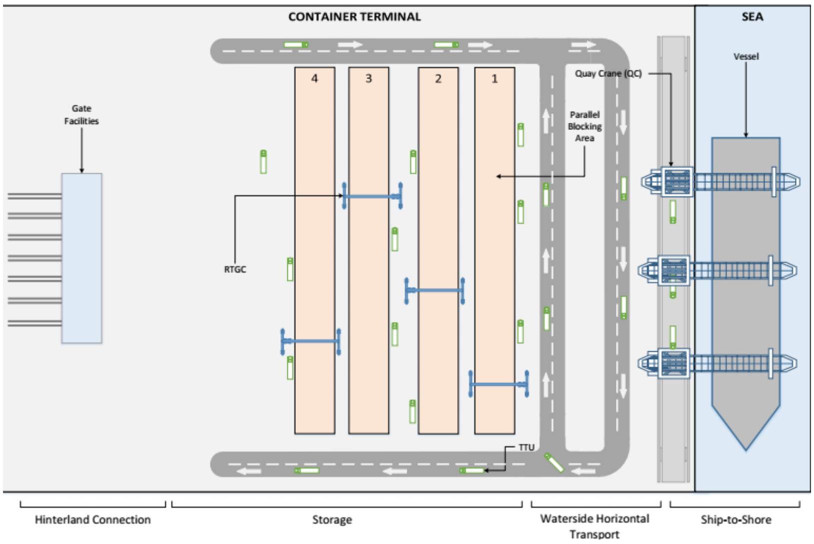

Figure 2 Handling process at CT

A random number was established to follow the triangular distribution that demonstrates the stochastic condition of CT operations. The MC simulation entailed repeatedly generating a random process to produce multiple problem scenarios. The random process was run for 1000 event times, each representing 30 days of CT operations.

Table 1 Input variables for simulation

Variables	Units	Minimum	Maximum	Mean
Ship Capacity	TEUs	500	3200	2000
Arrival Frequency	Vessel/dock/day	0	3	1
Service Time of QC	Minute/TEUs	2	3	2.5
TTU Travel Velocity	Km/hour	10	25	15
Service Time of RTGC	Minute/TEUs	5	8	7

Before more comprehensively discussing the optimization problem of CT design, an important task is to present the base conditions of CT performance. As illustrated in Figure 3, the arrival and stacking of a container in a container yard entail an average of 33.63 hours. The optimization problem centers on resolving the optimal decision problem to determine the number of equipment and equipment combinations needed (i.e., TTU and RTGC). Given that the total passage of time is a function of equipment productivity, an increase in equipment expectantly reduces such time. However, because an increment in TTUs possibly increases delays, an essential step is to seek the optimal quantity of TTUs necessary to reduce delays.

The swarm-based algorithms were used to decide on the optimal number of equipment needed. As the objective function considers the BCR, the container value of time was set to 1.95 million Rp./TEUs per hour, and the equipment purchase costs were set to 500 million and 1.5 million Rp./unit for TTUs and RTGCs, respectively. It was also assumed that the pattern of demand consistently occurred within five years of operation.

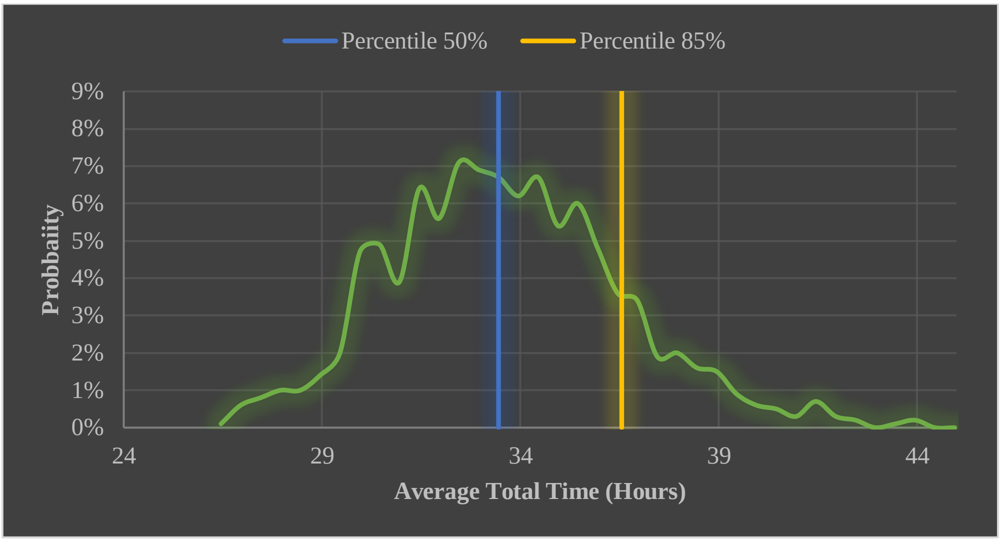

Figure 3 Total passage of time before arrival at container yard under base conditions

The swarm-based algorithms represent the addition of equipment using a binary-based representation, which accords with Equations 24 and 25:

$$n_m^2 = \left(\sum_{h=3m-2}^{h+2} 2^{h-1} x_h \right) \quad \forall h \in H \tag{24}$$

$$n^3 = \left(\sum_{h=10}^{12} 2^{h-10} x_h \right) \quad \forall h \in H \tag{25}$$

4.2. Performance Comparison Results

The performance of the swarm algorithms was evaluated on the grounds of the optimization results and running times that they generated because these items are the most important concerns. The optimization result is defined as a fitness value of the objective function, which is assessed from 10 runs on the basis of the maximum, average, and minimum values of solutions. To ensure a fair comparison, the possible number of solutions across all the algorithms was set to 4500, which was a value considered in practical applications in previous optimization works (i.e., Yamada et al., 2009; Yamada and Zukhruf, 2015). The best parameter values of GSO were preliminarily determined by conducting parameter tuning analysis. With respect to the parameter settings of GSO, the range of "*N*×iterations" was set to 10×450, 20×225, 30×150, and 50×90. The ranges of other parameters were set from 0.1 to 1 for ρ and γ, from 0.01 to 0.04 for β, from 1 to 50 for $r_{\max}$, from 1 to 10 for o, from 0.1 to 1 for s, and from 10 to 150 for $prob_{\max}$. The best parameters identified were as follows: 20 for *N*, 225 for iteration, 0.5 for ρ, 0.3 for γ, 0.04 for β, 30 for $r_{\max}$, 6 for o, 0.2 for s, and 100 for $prob_{\max}$. In terms of PBPSO and MPBPSO, parameter setting was carried out in accordance with the results of Yamada and Zukhruf (2015), who conducted sensitivity analysis to select the best parameter set.

Table 2 presents the findings on the performance comparison of GSO, PBPSO, and MPBPSO. The best value results suggested that GSO generates better outcomes than those achieved by the other swarm-based algorithms. The MPBPSO results are superior to those produced by PBPSO, similar to what was discovered in previous research (e.g., Zukhruf et al., 2014; Yamada and Zukhruf, 2015). As indicated in Table 2, however, all the swarm algorithms were still confronted with a stability issue as they resolved the stochastic optimization problem. This issue prevented them from delivering the same quality of results in 10 runs, highlighting the need for further research. The computational times involved in algorithmic operation were also compared on a PC with an Intel Core i5 processor, a 2.2 GHz CPU, and 16.0 GB RAM. The fastest computation was exhibited by GSO, followed by MPBPSO. This result was driven not only by the simpler process of GSO but also by the fact that it reached the best value at the 81st iteration (i.e., 1620 combinations evaluated). These results lead to the conclusion that the binary version of GSO presents the potential of the algorithm to eliminate the stochastic optimization problem, despite room for improvement in its stability.

Table 2 Performance comparison of swarm algorithms

	GSO	MPBPSO	PBPSO
Best	1.01	1.00	0.94
Average	0.90	0.85	0.84
Worst	0.73	0.71	0.74
Computational Time (seconds)	8,372	14,264	17,345

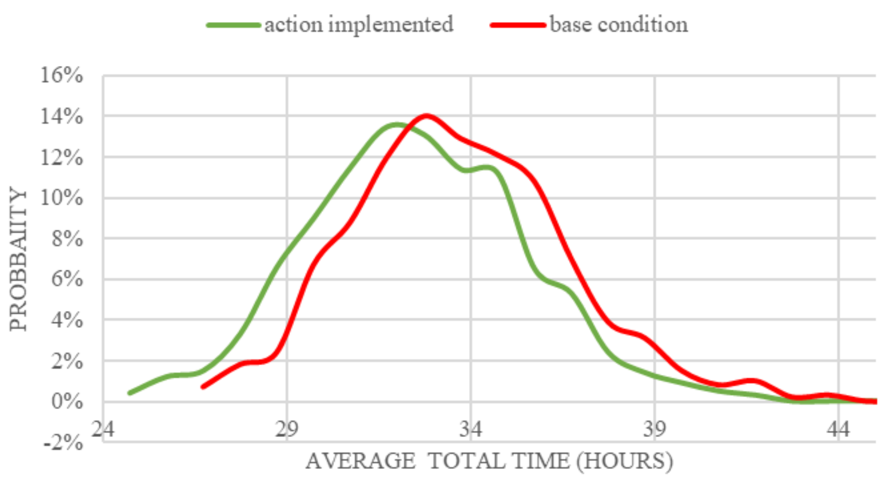

Figure 4 Average total time, with action implemented

On the basis of the GSO optimization results, the optimal action for improving CT performance is the addition of 11 and five units of TTUs and RTGCs, respectively. This measure directly reduces the total passage of time before arrival at a container yard by up to 5% from existing conditions. In addition, the distribution graph in Figure 4 shows a shift to the left-hand side, implying that a container is transported at less time than that occurring in the base conditions.

5. Conclusion

This research investigated the performance of swarm-based algorithms in the design of CT facilities. To this end, a new variant of binary GSO and the latest types of binary PSOs (i.e., PBPSO and MPBPSO) were incorporated into the framework of stochastic discrete optimization. Taking into account uncertainty issues and possible additional delays due to increments in the number of facilities, the swarm-based algorithms were used to determine the number of additional facilities required for CT operations. The results revealed that an increase in the number of trucks and gantry cranes improves CT performance. The numerical experiment showed that the binary version of GSO realizes better optimization results and computational times than those achieved by the comparison algorithms. However, its stability needs to be carefully considered in future works. Another essential issue of stochastic optimization is computational time because MC simulation requires massive repetitions, albeit the proposed algorithm can reduce this requirement significantly. Further efforts may be needed to inquire into the development of a more efficient algorithm.

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