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Tactical and strategic planning for a container terminal: Modelling issues within a discrete event simulation approach

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ABSTRACT

In this paper different microscopic discrete event simulation models for a container terminal are presented. The focus is on the best approach to adopt to simulate handling activity time duration and on which level of detail should be pursued with respect to different planning horizons that a decision maker have to face. The models share the same logical architecture but differ in the approaches pursued to estimate handling activity time duration. Terminal operations were broken down into elementary activities pursuing a level of disaggregation not usual in the literature; time duration of each elementary handling activity was modelled through a stochastic approach, distinguishing container type; validation was carried out with respect to different planning horizons (real-time/short-term, long-term) through the definition of local and global indicators and a before-and-after analysis. Modelling issues are discussed for tactical and strategic planning, and operational guidelines are given.

1. Introduction

Design and project appraisal of container terminals (CTs) may be carried out through two main approaches: optimization or simulation. Although the approaches based on optimization models allow a more elegant and compact formulation of the problem, simulation models are mainly based on Discrete Event Simulation (DES) models and help to achieve several aims: overcome mathematical limitations of optimization approaches, support computer-generated strategies/policies and make them more understandable, and support decision makers in daily decision processes through a "what if" approach.

Several applications of DES models have been proposed and simulation results confirm that such an approach is quite effective at simulating CT operations. Most of the contributions in the literature develop object-oriented simulation models; system discretization depends on case study size (one terminal vs. multiple terminals), data available (aggregate vs. disaggregate; historical data vs. experimental data), on the problem to be addressed (e.g. vessel loading/unloading vs. whole system simulation) and/or on the planning time horizon (short term vs. medium term).

Although the DES approach is a well-consolidated approach in CT simulation, it should be pointed out that most of the contributions in the literature pursue a macroscopic approach, activity duration is often assumed to be deterministic, and those authors that estimate specific stochastic handling equipment models do not clearly state how they were calibrated, what data were used and what the parameter values are. Moreover, effects of container types (e.g. 20′ vs. 40′, full vs. empty) are neglected, as well as the incidence of different handling activities that may seem similar but show different a time duration and variability/dispersion (e.g. crane unloading a container to dock or to a shuttle) and differences within the same

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handling activity (e.g. stacking/loading/unloading time with respect to tier number). Finally, few have carried out specific experimental campaigns that observe single container trips, none have performed *before-and-after* analyses and models are often validated on the calibration data-set through global performance indicators that seem too aggregated to point out the strengths or weaknesses of approaches pursued.

In this paper most of the cited remarks are addressed investigating those modelling issues that may arise when different planning horizons (real-time, short/medium term, long-term) must be simulated and evaluated. In particular, the focus is on the best approach to adopt to simulate handling activity time duration and on what level of detail should be pursued.

Four microscopic DES models for the Salerno Container Terminal (a major CT in southern Italy) are proposed. Each model presents the same modelling architecture – level of detail – but different approaches to estimating handling activity duration. The models are specified with a level of detail not usual in literature. They pursue an approach in which single container movement is explicitly simulated and in which each elementary (homogeneous) activity occurring inside the terminal is identified, analysed individually and explicitly modelled. The handling equipment in question consisted of quay cranes, yard cranes and reach stackers. The elementary activities taken into account were: as regards quay cranes: loading time from dock to vessel, loading time from shuttle to vessel, unloading time from vessel to dock, unloading time from vessel to shuttle; as regards yard cranes: unloading time (to shuttle/truck), loading time (from shuttle/truck), unloading time (to stack), loading time (from stack), trolley speed (with container), free trolley speed, crane speed; for reach stackers: unloading time from shuttle/truck, loading time to shuttle/truck, stacking time (to tier). All of the cited handling activities were analysed for the following container types: undifferentiated, 20′, 40′, $2 \times 20'$, full and empty.

For each type of handling equipment and for each container type (if significant), starting from an extremely detailed survey, mean values were estimated and different probability distribution functions (Gamma, Normal, Weibull, Beta, Log-Normal and Exponential) were calibrated and compared, and different estimation methods (Moment and Maximum Likelihood) were investigated. Finally, 51 handling activities were monitored, and 153 stochastic handling equipment models were calibrated. Effectiveness and robustness were assessed by estimating global and local terminal performance with respect to a pre-scenario (before) and a post-scenario (after). The former is the scenario representing the terminal configuration in 2003 and in which the handling equipment models were calibrated; the latter represents the present configuration, appreciably different from that observable in 2003. Global performance of the whole CT was analysed by measuring terminal operation time; local performance was analysed through indicators measuring model capability to simulate handling equipment performance and single container trip time. From the proposed set of indicators, interesting guidelines for application are drawn.

The paper is divided into four sections. A state-of-the-art review is provided in Section 2; the model is described in Section 3 and validated in Section 4. The main conclusions are drawn in Section 5.

2. State of art

The existing literature reports approaches to either managing a CT as a system and trying to simulate all elements or managing a sub-set of activities (simultaneously or sequentially following a predefined hierarchy). The most widely followed approaches are based on deterministic optimization methods, although recently stochastic optimization models were proposed by Murty et al. [33]. Such approaches schematize CT activities through single queue models or through a network of queues. Following a stochastic approach, both modelling solutions may lead to analytical problems and/or unsatisfactory results if the probability distribution of activities involved does not belong to the Erlang family [35,38]. Moreover, the resulting network could be very complicated and a theoretical solution might not be easy to obtain.

In such a context, an effective and challenging alternative approach for CT system analysis may be discrete simulation (a detailed literature review in [8]. Simulation can help to achieve various aims: overcome mathematical limitations of optimization approaches, allow more detailed and realistic representation of terminal characteristics, support decision makers in daily decision processes through assessment of "what if" scenarios and make computer-generated strategies/policies more understandable. System discretization depends on case study size (one terminal vs. multiple terminals), data available (aggregate vs. disaggregate; historical data vs. experimental data), on the problem to be addressed (e.g. vessels loading/unloading vs. whole system simulation) and/or on the planning time horizon (short term vs. medium term). In the discrete event simulation approach, two modelling solutions may be pursued: macroscopic discrete event models or microscopic discrete event models.

Macroscopic discrete event models aggregate elementary handling activities (e.g. using cranes, reach stackers, shuttles) into a few macro-activities (e.g. unloading vessels: crane–dock–reach stacker–shuttle–yard), simulate the movement of an "aggregation" of containers. Microscopic discrete event models simulate the movement of each container: each handling activity should be considered and the corresponding time duration should be estimated or modelled. An intermediate approach between microscopic approach and macroscopic approach was proposed by de Luca et al. [15] through an approach based on a diachronic network representation of terminal activities. Cartenì [7] carry out an analysis on the prediction reliability between microscopic and macroscopic approaches, suggesting that the microscopic approach is suitable (from a cost-benefit point of view) for the disaggregate performance indicator estimations, especially for simulating single container movements; whereas the macroscopic approach, due to lower implementation costs, is more suitable for all aggregate performance indicator estimations, especially to simulate global container terminal performance.

Simulation is not a new methodology in port operations. Several works have been presented since the 1980s, most of them concerning port operations management [13,1,45,16,36,11,10]. Many of the proposed models do not focus on the details regarding the model set-up, its calibration and its validation, but on the application and/or simulation of design scenarios. Moreover, although the estimation of handling activity models should be one of the main issues of all CT applications, this problem does not seem to be treated in depth in most applications. While many contributions fail to present any information on handling activity models used, the remainder carry out very simple approaches (deterministic) and/or give scant information on the estimation approach adopted, the experimental data used, the parameters estimated and on parameter values.

In the 1990s much effort was spent on simulating terminal containers: the number of applications based on simulation increased, terminals were modelled more realistically through disaggregation of the main operations in several elementary activities, and much more attention was laid on real case studies. The focus of most contributions was on developing practical tools to simulate terminal operations, on software issues and/or on model validation. Less attention was focused on modelling handling activities and/or model details [23,40,2,25,18,44,31,17,30,34,4,22,19,38].

Since the end of the 1990s, the most important ports in the world have been modelled through DES models, and greater interest is shown in the calibration of handling activity models [24,14,42,28,41,39,20,37,3] [5,12,27,15].

Of the contributions introduced so far, only ten papers give information on the handling equipment models used. Half of them adopt a stochastic approach and show estimated parameter values. Most of the contributions deal with vessel loading/unloading operations. There is substantial heterogeneity regarding the level of aggregation of activities involved and how such activities are aggregated in a single macro-activity: El Sheikh et al. [16], Choi and Yun [14], Kia et al. [20] and Shabayek and Yeung [39] analyse the entire time to load (unload) a vessel (vessel cycle time); Koh et al. [22] and Bugaric and Petrovic [5] investigate the crane cycle time (time needed to: lock onto the container, hoist and traverse, lower and locate, unlock and return); crane loading time to/from a vessel is analysed by Tugcu [45], Thiers and Janssens [43], Yun and Choi [24], Merkuryeva et al. [32], Korea Maritime Institute [21], Parola and Sciomachen [37], Bielli et al. (2006), and Lee and Cho [27].

As regards vessel cycle time, a stochastic approach is unanimously proposed. In particular, El Sheikh et al. [16], Kia et al. [20] and Shabayek and Yeung [39] suggest using Erlang random variables, whereas Choi and Yun [14] propose normal random variables for two crane types (quay, yard). As regards crane cycle time, Koh et al. [22] advise the use of a Weibull random variable; Bugaric and Petrovic [5], for a bulk cargo terminal, propose normal random variables and report the estimated parameters.

With regard to crane loading/unloading time, Tugcu [45], Thiers and Janssens [43], Korea Maritime Institute [21] and Bielli et al. [3] follow a deterministic approach, contrasting with the stochastic approach adopted by Yun and Choi [24], Merkuryeva et al. [32], Lee and Cho [27], Parola and Sciomachen [37]. Yun and Choi [24] propose the exponential distribution function both for quay crane and yard crane operation time; Merkuryeva et al. [32] propose the uniform distribution function for quay cranes and a triangular distribution function for yard gantry crane operation time; Lee and Cho [27] suggest the exponential distribution function for quay cranes and a triangular distribution function for yard gantry crane operation times. Parola and Sciomachen [37] estimated a normal random variable but do not report parameter values.

With respect to crane speed, all propose deterministic and aggregate models while only Yun and Choi [24], Choi and Yun [14], Korea Maritime Institute [21] and Legato et al. [29] report the estimated mean values.

With respect to other handling equipment, not much can be found in the literature: Sgouridis and Angelides [41] use deterministic values for a straddle carrier, whereas Merkuryeva et al. [32] propose a triangular distribution function for the forklift. As regards shuttle performance, (speed, travel time, waiting time, ...), the few models existing are hard to transfer to different case studies (due to the influence of path length, path winding, traffic vehicle congestion inside the terminal and so on). Hence they are omitted in this survey.

A synopsis of the above analysis is presented in Tables 1–3. For each type of handling equipment and for each activity simulated, probability distribution and corresponding parameters are reported.

3. The model

3.1. Discrete event modelling of a container terminal

The proposed approach schematizes a CT as a discrete event system and models its functioning through a simulator. A discrete event system can be defined as an interacting set of entities/objects that evolves through different states as internal or external events happen. Entities/objects may be physical, conceptual (information flows) or mathematical, and can be resident or transient. Resident entities remain part of the system for long intervals of time; transient entities enter into and depart from the system several times.

Entities can be characterized by parameters and/or variables. Parameters define static (stationary) characteristics that never change, variables define the state (dynamic characteristics) of each entity and may change over time and can further be classified as deterministic or stochastic.

An activity may be associated to each entity, in which case the entity is called active, otherwise passive. An activity represents a specific operation/task carried out by the entity. It is triggered by an event and is characterized by a time duration. The duration may be constant or variable, and its evolution over time may be modelled as a deterministic or a stochastic process. Active entities, resident or transient, play an active role that affects system evolution; passive entities, resident

Table 1
Survey of handling models: gantry crane (GC).

	Quay GC	Yun and Choi [24]	Exponential	Mean = 0.50 (min)
		Lee and Cho [27]		Mean = 1.00 (min)
		Merkuryeva et al. [32]	Uniform	Min. = 2.00 (min) Max. = 4.00 (min)
		Bielli et al. (2006)	Deterministic	Mean = 1.50 (min)
	Yard GC	Yun and Choi [24]	Exponential	Mean = 1.00 (min)
Crane operation time		Merkuryeva et al. [32]	Triangular	40′ Loading Mean = 6.00 (min) 40′ Unloading Mean = 4.00 (min) SD = 0.41 (min)
		Lee and Cho [27]		Mean = 1.55 (min) SD = 0.08 (min)
		Bielli et al. (2006)	Deterministic	Mean = 1.50 (min)
	Not specified	Parola and Sciomachen [37]	Normal	Not reported
		Tugcu [45]	Deterministic	Not reported
		Thiers and Janssens [43]	Deterministic	Not reported
		Korea Maritime Institute [21]	Deterministic	Not reported
Crane cycle time	Not specified	Koh et al. [22]	Weibull	
	Bulk cargo	Bugaric and Petrovic [5]	Normal	Mean = 5.00 (min) SD = 0.26 (min)
Vessel Cycle	Quay GC	Choi and Yun [14]	Normal	Mean = 112.80 (min) SD = 5.60 (min)
Time	Yard GC	Choi and Yun [14]	Normal	Mean = 87.00 (min) SD = 13.89 (min)
	Entire loading operation	El Sheikh et al. [16]	Erlang	Mean = 4.20 (day) $K = 4.33$
	Entire unloading operation	El Sheikh et al. [16]	Erlang	Mean = 7.57 (day) $K = 10.77$
	Not specified	Kia et al. [20]	Erlang	Mean = 37.85 (h) $K = 4.00$
	Not specified	Shabayek and Yeung [39]	Erlang	Mean [9.6, 16.3] (h) $K = 117$
Crane speed	Quay gantry crane	Yun and Choi [24]	Deterministic	45 (m/min)
		Legato et al. [29]	Deterministic	45 (m/min)
		Korea Maritime Institute [21]	Deterministic	45 (m/min)
	Hoist with full load	Korea Maritime Institute [21]	Deterministic	55 (m/min)
	Hoist without load			130 (m/min)
	Ship trolley			180 (m/min)
	Store trolley			75 (m/min
	Yard gantry crane	Choi and Yun [14]	Deterministic	134 (m/min)
	Not specified	Tugcu [45]	Deterministic	
	Not specified	Koh et al. [22]	Deterministic	
	Not specified	Thiers and Janssens [43]	Deterministic	

Table 2
Survey of handling models: Straddle carrier (SC).

Handling activity	Model used	Characteristic parameters	Reference
Speed	Deterministic	Inside yard: 110 (m/min) Outside yard:250 (m/min)	Sgouridis and Angelides [41]
Shuttle loading/unloading time	Deterministic	0.60 (min)	
Spreader movement	Deterministic	0.30 (min)	
Turning	Deterministic	0.02 (min)	
Container spotting	Deterministic	1.00 (min)	

Table 3
Survey of handling models: Forklift (FL).

Handling activity	Model used	Characteristic parameters	References
Loading/unloading time	Triangular	20′ Loading Mean = 4.00 (min) SD = 0.41 (min) 20′ Unloading Mean = 3.00 (min) SD = 0.41 (min)	Merkuryeva et al. [32]

or transient, are fundamental in system evolution but do not carry out any activity, such as the facilities needed to carry out an activity (e.g. dock) or what is actually moved by the active entities (e.g. containers).

Entities interact through rules. Rules can be endogenous or exogenous. Endogenous rules may reflect the hierarchy (spatial or temporal) between entities and they are derived from the building process of the logical architecture of the system. Exogenous rules may depend on exogenous phenomena, and may reflect "human" managing actions.

The entire system is characterized by a state. The state describes the entire system and is completely defined once entity attributes are known. The state of a system evolves as events occur that change the value of entity attributes, and evolution depends on the logical or physical relationship existing between entities (*hierarchy*).

A discrete event approach allows good abstraction of the phenomenon, modelling modularity and graphical representation of results. In this sense, CT operations seem a natural application of the discrete event approach, since it can be easily schematized in a finite set of entities (physical or conceptual), it has a clear hierarchy, and has an internal complexity which means that other approaches have little effectiveness (e.g. Petri nets or optimization models).

In a CT, entities represent the handling equipment, the containers and all those physical locations relevant to CT operations (dock, yard, gates, etc.).

Handling equipment is a resident and active entity and may be characterized by parameters, variables and an activity. Parameters define the main characteristics of each piece of equipment; variables define the state of the entity, such as state of occupancy, position; activity defines the time duration of the task that the entity carries out. Time duration can be deterministic or stochastic and, in either case, should be estimated on real data. Containers are transient and passive entities. The main objective of simulation concerns how they are moved through the terminal by the handling equipment. Containers are only characterized by parameters and variables. Parameters define the container type (e.g. 20′, 40′, empty or full); variables define their state (steady or in movement) or their position (through coordinates, CT areas, etc.). Physical locations are resident and passive entities. As for containers, they may be characterized by parameters and variables. Parameters define their geometrical characteristics (e.g. length, area available, number of tiers); variables define their state (occupancy, containers/trucks in the queue, etc.).

Apart from the above-described entities others can be considered. Such entities do not usually move containers but can control/manage entities that handle containers and can thus change their attributes. The change in such attributes may be driven by simple heuristic rules (e.g. if there are more than four trucks waiting for a reach stacker, use one more reach stacker) or by sub-models that change entity attributes, trying to optimize overall terminal performance in real time. The former approach can be easily implemented and is similar to what occurs in most CTs. The latter is much more complex but more stimulating, since it allows the development of "what to" procedures.

Interaction between entities is possible if events occur. In a CT system, events may be exogenous or endogenous. Exogenous events are, for example, vessel arrivals, truck arrivals and container arrivals; endogenous events are represented by the start or end of a task (activity) or by events that may happen due to real-time control/management strategies (also departures).

All the entities introduced so far can be grouped into two sub-systems:

i. Demand sub-system, represented by the number of containers to be moved inside/outside the CT.
ii. Supply sub-system, or the set of all entities and their relationships that make container movement possible. The sub-system is made up of the handling equipment, the CT physical points and their relationships.

To develop a DES model both sub-systems must be identified and modelled. Three main tasks should be carried out.

(a) Identification of the terminal's logical and functional architecture.
(b) Demand characterization and estimation.
(c) Supply characterization and calibration.

3.2. Case study and models architecture

In discrete event modelling the model is defined once the case study is defined. In this paper the Salerno Container Terminal (SalCT) is analyzed. SalCT is a major private CT operator in southern Italy, and is both small and very efficient: it handles close to 0.45 MTEUs per year in less than 10 ha (100,000 m^2), which amounts to 45 kTEUs/ha. These figures should be compared with terminals such as HIT and COSCO-HIT in Hong Kong which handle 6.6 MTEUs in 122 ha (2008), or 54 kTEUs/ha, and Delta Terminal in the Netherlands which handles 2.5 MTEUs or 9 kTEUs/ha (2008). In addition the location of Salerno harbor does not allow the terminal area to be extended. Hence the chances of any improvement to keep pace with increasing demand will depend on operation management enhancements rather than an increase in land occupation.

The SalCT can be divided into three subsystems: enter/exit port gates (land-side), container yards, and berths (sea-side). Container handling equipment comprises storage cranes, loading/unloading cranes, yard tractors, trailers and reach stackers. The basic activities occur simultaneously and interactively, and can be grouped into four main operations: receiving (gate–yard), delivery (yard–gate), loading (yard–berth) and unloading (berth–yard).

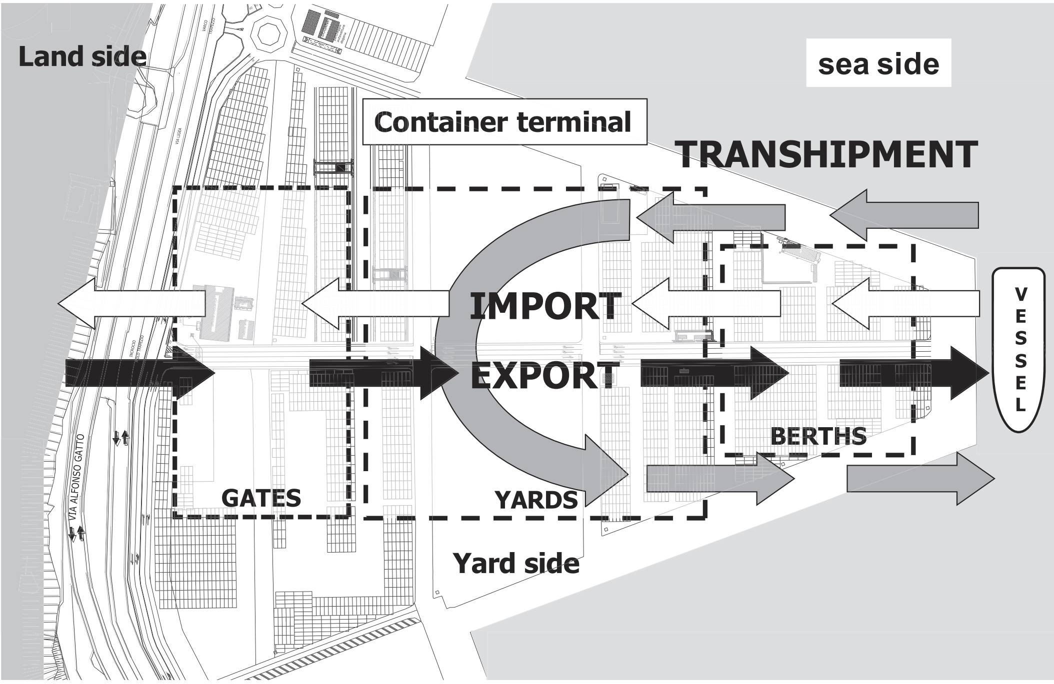


Fig. 1. SalCT lay-out and main operations.

Planning of the SalCT includes berth planning, yard planning, storage planning and logistics planning. Berth planning controls container loading and unloading. Yard planning optimally allocates storage areas for import, export and transhipment containers. Storage planning assigns storage locations to the containers in the vessel bays. Logistics planning assigns and coordinates the operations of container handling equipment such as gantry cranes, transfer cranes and yard tractors for transferring containers between vessel bays and the container yard.

In Fig. 1 SalCT lay-out is proposed and main operations are graphically schematized.

The developed logical and functional model architecture is represented in Fig. 2.

In particular, three different macro-activities are carried out in SalCT and were taken into account in the DES model: import, export and transhipment. Apart from vessel arrival and berthing (not relevant to our case study) and apart from truck arrival, all the typical activities of a CT are explicitly simulated. In export operations, containers enter the CT from the landside through the road network and, after gate-in activities, are stacked in the export yard, where they wait for their turn to be loaded on the corresponding vessel. Each container may be loaded directly or through the use of a buffer area. In the former case, containers can reach the corresponding berth on a reach stacker or on a shuttle. In the latter case, containers are stacked in a specific area and moved to the berths through reach stackers. Once they have arrived at the berth, containers are directly loaded onto the vessel, if on the shuttle, or left on the dock, if on reach stackers, and subsequently loaded on the vessel. In import operations, containers are unloaded on the berth and moved towards the import yard, if full, or towards the empty yard, if empty containers. Empty containers are loaded to shuttles through reach stackers and are stacked in the empty yard through forklifts. Full containers may reach the import yard through reach stackers or through shuttles and they are stacked with a gantry crane. Once stacked, full containers may pass through customer activities or just wait to leave the terminal. Containers can leave the terminal by rail or road; in the former case they are transferred onto railway cars and leave the terminal after the train has been composed; in the latter case they are directly displaced on trucks and leave the terminal immediately.

In transhipment operations (unusual in the CT analyzed), containers are unloaded on the berth and can be directly loaded on a vessel or moved towards a specific buffer area. In both situations reach stackers, shuttles or a combination can be used.

3.3. Demand characterization

Demand is represented by single containers. For each macro-operation the demand flows may be characterized over space, time and type. As regards spatial characterization, container flow can be subdivided by origin and destination zone and can be arranged in origin–destination matrices (*O-D* matrices). In particular, for each operation we can distinguish macro-origin and macro-destination zones (quays, yards, gates), the generic entry gives the number of containers moving

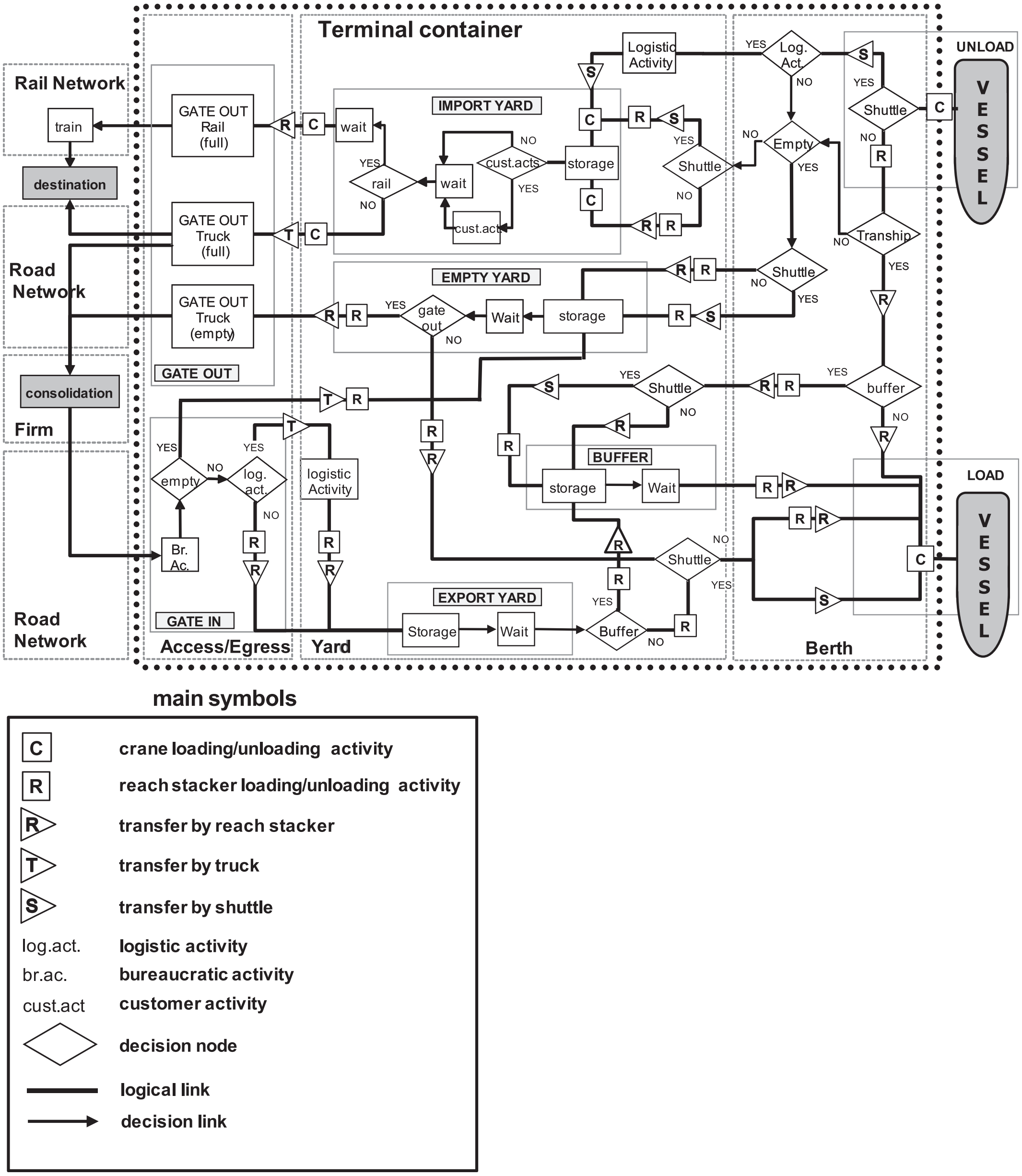


Fig. 2. Logical and functional model architecture.

in the simulation time interval from each origin and destination pair. Different *O*–*D* matrices should be estimated for each operation and container type (20 feet vs. 40 feet, full vs. empty, ...).

Finally, in order to carry out the simulation, each demand flow is characterized by its distribution over time. In general, two conditions may be distinguished:

(i) if the containers arrive over time (e.g. by truck),
(ii) if the total demand is already present at a physical point of the CT (e.g. vessel or yard) and ready to be handled.

In the first condition a demand profile for each container class should be estimated. In general, we will assume that the demand profiles are *a priori* known and independent of any variations in any characteristic of the supply system. Such a hypothesis is realistic since the number of containers entering/exiting in/from a CT is usually known in advance.

In the second condition, since total demand is ready to be handled, temporal distribution does not depend on container flow arrival, but on the capacity supplied by the services involved with respect to the chosen time segmentation.

3.4. Supply characterization and calibration

In a CT macro-operations (import, export, transhipment), operations (unloading vessels: crane–dock–reach stacker–shuttle–yard) and handling activities may be distinguished. Macro-operations are set up by operations; operations are set up by elementary handling activities. In such a classification, depending on the level of aggregation chosen, the different entities (e.g. equipment handling activities) involved must be characterized by parameters, variables and time duration (activity).

In this section, equipment handling times are estimated. For each elementary handling activity sample means are estimated and random variable probability distributions are explored. Two different estimation methodologies and different distribution functions were tested on experimental data taken from a survey carried out between January 2003 and July 2005 inside the SalCT. More than 3000 containers were monitored (20% of the containers loaded/unloaded per month and 1% of the containers loaded/unloaded per year), each of which was traced from the origin to its final destination; each trip was subdivided into homogeneous activities (see Table 4).

For each activity the time duration was measured and the resulting data were classified according to the following classes: 20′ (full and/or empty), 40′ (full and/or empty), 20′ × 20′ (full).

Four different handling models were estimated:

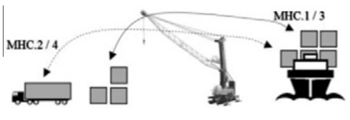
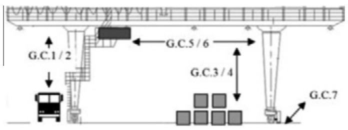
- *sample mean* as estimation of activity time duration;
  - Sample Mean Undifferentiated (**SMU**) model (undifferentiated per container type);
  - Sample Mean Container Type (**SMCT**) models (20′ full and/or empty; 40′ full and/or empty; 2 × 20′ full);
- *random variable* as representative of activity time duration;
  - Random Variable Undifferentiated (**RVU**) model (undifferentiated per container type).
  - Random Variable Container Type (**RVCT***)* models (20′ full and/or empty; 40′ full and/or empty; 2 × 20′ full).

The analyses are divided into a preliminary descriptive analysis of experimental data and statistical analysis.

In the descriptive analysis, the mean values and corresponding standard deviations are estimated. Such values are useful to develop/implement a discrete event model based on sample mean variables, and allow the need for a stochastic approach to be appreciated. From the methodological point of view standard errors and confidence intervals were estimated for each handling activity type. Moreover, since each handling activity (e.g. loading or unloading) was analyzed taking into account different classes of container and distinguishing different means to handle/move a container (e.g. loading from dock vs from shuttle), specific statistical tests were carried out to evaluate if differences among mean values were statistically significant (e.g. if the mean loading time of the 20′ full container is equal to that of the 20′ empty container). At this aim, statistical tests were performed assuming observed values independently (realistic hypothesis) and normally distributed (acceptable hypothesis).

By contrast, statistical analysis aims to estimate the theoretical continuous cumulative distribution function that best fits the sample distribution function. Following a non-parametric approach, two estimation methods were compared: Moment Estimation (M-E) and Maximum Likelihood (M-L) estimation. Several distribution functions (Normal truncated, LogNormal, Gamma, Weibull, Exponential, Beta) were tested for each handling activity involved (Table 4) and for different container type. The Kolmogorov–Smirnov (K–S) statistic was used to evaluate the quality of the estimation methodology and the random variables tested. Once identified the most performing statistical distribution and with respect to two sample distributions, the Kolmogorov–Smirnov statistic was used to evaluate whether two sample distributions are statistically different (e.g. if the sample distribution of the 20′ full container loading time is different from that of the 20′ empty container loading time).

Table 4
Analyzed activities.

Mobile harbour crane (MHC)	Gantry crane (GC)	Reach stacker (RS)
		
Loading time from dock to vessel	Unloading time (to shuttle/truck)	Unloading time from shuttle/truck
Loading time from shuttle to vessel	Loading time (from shuttle/truck)	Loading time to shuttle/truck
Unloading time from vessel to dock	Unloading time (to stack)	Stacking time (to tier)
Unloading time from vessel to shuttle	Loading time (from stack)	
	Trolley speed (with container)	
	Free trolley speed	
	Crane speed	

Estimation results indicated that both M-E and M-L estimation lead to statistically significant results, but M-L estimations showed always better results than the Moment one (apart for Normal distribution, for which the two methods are equivalent).

Comparison among probability distributions tested showed that only Normal (truncated), Gamma and Weibull random variables were statistically significant and, in particular, that the Gamma random variable produced the best results.

For brevity's sake, in the following sections only results regarding descriptive analysis and Maximum Likelihood estimation concerning Gamma random variable are reported. For more on statistical test made in the descriptive analysis, on the comparison between M-E and M-L estimations and on the comparison between the different distributions functions tested, the reader may refer to Cartenì and de Luca [9] and to Cantarella et al. [6] technical paper.

In the following, estimation results are shown for those equipments introduced in Table 4.

3.4.1. Mobile harbour cranes (MHCs)

The MHCs operating in the SalCT are three Gottwald HMK 260 mounted on rubber-tyres; these are particularly popular in ports and terminals frequented by feeders and other vessels with widths of up to 25 m. This equipment is also suitable for twin-lift ($2 \times 20'$ full) containers cargo. MHC activities are mainly devoted to loading/unloading containers to/from berthed vessels.

The analyses carried out concern loading activities from shuttle to vessel or from dock to vessel, and unloading activities from vessel to dock. The following container types were considered: undifferentiated containers, 20′, 40′ and $20 \times 20'$. Since most SalCT loading/unloading activities concern full containers, the analysis is mainly focused on full containers, whereas results on empty containers are proposed only for activities that systematically involve empty containers. Mean values and standard deviations are shown in Table 5a, standard errors and confidence intervals in Table 5b.

As regards undifferentiated containers, the results reported in Table 5a show a mean MHC unloading time of 0.871 min and a corresponding standard deviation of 0.263 min, 30% less than the mean. For loading activities the standard deviation (0.657 min) is 46% less than the mean (1.426 min). Such results highlight that loading activities such as container alignment in the hold are more subject to unexpected events (e.g. problems with the spreader and poor visibility during stowing).

Distinguishing loading from dock to vessel and from shuttle to vessel, it is worth noting that mean loading time from dock (1.398 min) is 3% less than the mean loading time from shuttle (1.435 min). For both activities, the standard deviation is more than 50% less than the mean value. Furthermore, the standard deviation related to the loading time from dock (0.562 min) is 17% less than that for the mean loading time from the shuttle (0.678 min). In this case the statistical test on mean values confirms that they are not statistically different.

The same analysis carried out for container type (20′, 40′ and $2 \times 20'$) shows that MHC performance changes as the container size changes. For *loading from dock*, loading time is 1.316 min for 20′ full containers and 1.494 min for 40′ full containers (14% greater). Standard deviations differ from zero and are about 60% lower than the corresponding means, appreciably varying with container type: 0.485 min for 20′ full containers and 0.632 min for 40′ full containers (30% greater). Such results, validated by the statistical test on mean values, confirm that differences between container types should be taken into account, confirm the need for a stochastic approach and show that such an approach is more desirable if we wish to explicitly simulate container type.

As regards *loading time from shuttle*, the estimates show a mean loading time of 1.193 min for the 20′ full container (with a standard deviation of 0.387 min) and 1.272 min for the 40′ full container (with a standard deviation of 0.389 min). Irrespective of container type, standard deviations differ from zero and are about 60% less than the mean values. Unlike *loading time from dock*, no significant differences can be observed between 20′ full and 40′ full, mean loading time differs by about 6%, standard deviations are almost the same and the null hypothesis of equal mean values was not rejected.

Comparing *loading time from dock* and *from shuttle*, it should be pointed out that mean values are statistically different, in particular *loading time from dock* needs more time ($\approx$+17%) both for the 20′ full and 40′ full, and show higher dispersions: +20% for 20′ full containers, +40% for 40′ full containers.

Table 5a
Mobile harbour crane: means and standard deviations.

Activity	Undifferentiated		20′				40′				$2 \times 20'$	
			Empty		Full		Empty		Full		Full	
	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s
Loading	1.426	0.657	1.102	0.385	1.257	0.444	1.121	0.386	1.332	0.476	2.214	0.926
Unloading	0.871	0.263	0.768	0.216	0.856	0.221	N.p.	N.p.	0.867	0.230	0.971	0.366
Loading from dock	1.398	0.562	N.p.	N.p.	1.316	0.485	N.p.	N.p.	1.494	0.632	N.p.	N.p.
Loading from shuttle	1.435	0.678	1.102	0.385	1.193	0.387	1.121	0.386	1.272	0.389	2.214	0.926
Unloading to dock	0.871	0.263	0.768	0.216	0.856	0.221	N.p.	N.p.	0.867	0.230	0.971	0.366

[a] $\bar{x}$: Mean value, s:standard deviation, n.p.: not present in the terminal, and n.a.: data not available.

Table 5b
Mobile harbour crane: standard errors and confidence intervals.

Activity	Undifferentiated		20′				40′				2 × 20′	
			Empty		Full		Empty		Full		Full	
	SE	Int	SE	Int	SE	Int	SE	Int	SE	Int	SE	Int
Loading	0.015	[1.397, 1.455]	0.022	[1.059, 1.145]	0.019	[1.220, 1.294]	0.021	[1.079, 1.163]	0.019	[1.295, 1.369]	0.083	[2.051, 2.377]
Unloading	0.009	[0.854, 0.888]	0.019	[0.731, 0.805]	0.011	[0.834, 0.878]	N.p.	N.p.	0.014	[0.839, 0.895]	0.031	[0.910, 1.032]
Loading from dock	0.028	[1.343, 1.453]	N.p.	N.p.	0.033	[1.250, 1.382]	N.p.	N.p.	0.046	[1.403, 1.585]	N.p.	N.p.
Loading from shuttle	0.017	[1.401, 1.469]	0.022	[1.059, 1.145]	0.021	[1.151, 1.235]	0.021	[1.079, 1.163]	0.018	[1.237, 1.307]	0.083	[2.051, 2.377]
Unloading to dock	0.009	[0.854, 0.888]	0.019	[0.731, 0.805]	0.011	[0.834, 0.878]	N.p.	N.p.	0.014	[0.839, 0.895]	0.031	[0.910, 1.032]

$^{*}\overline{int} = \bar{x} \pm t^{*}_{0.025} SE$.

Table 6
Mobile harbour crane statistical results: parameters of Gamma distribution function.

Activity	Undifferentiated		20′				40′				2 × 20′	
			Empty		Full		Empty		Full		Full	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
Loading	1.366	0.514	1.084	0.387	1.238	0.405	1.101	0.340	1.288	0.402	2.083	0.690
Unloading	0.862	0.214	0.664	0.139	0.825	0.183	N.p.	N.p.	0.835	0.188	0.933	0.326
Loading from dock	1.389	0.441	N.p.	N.p.	1.252	0.407	N.p.	N.p.	1.372	0.485	N.p.	N.p.
Loading from shuttle	1.350	0.549	1.084	0.387	1.227	0.405	1.101	0.340	1.244	0.375	2.083	0.690
Unloading to dock	0.862	0.214	0.664	0.139	0.825	0.183	N.p.	N.p.	0.835	0.188	0.933	0.326

Finally, since MHCs can move two 20′ containers at the same time (2 × 20′), the loading time for 2 × 20′ full containers was estimated. Estimates show a mean loading time of 2.214 min and a standard deviation of 0.926 min. Interestingly, the loading time is 8% less than the time required to load two 20′ full containers in succession, and the standard deviation is 60% greater than the standard deviation of loading time of a 20′ full container.

There is essentially one activity that involves empty containers: *loading from shuttle*. It is worth noting that standard deviation is similar to those estimated for 20′ full and 40′ full, while the mean loading time is 13% less than 40′ full and only 6% less than 20′ full; in this case null hypothesis of equal mean values was rejected.

Similar analyses were carried out for vessel unloading activities. In this case we refer only to the unloading time from vessel to dock, since activities from vessel to shuttle are not frequent in the SalCT. The estimates (see also Table 5a) show a mean unloading time of 0.856 min for the 20′ full container (with a standard deviation of 0.221 min), 0.867 min (≈+1%) for the 40′ full container (with a standard deviation of 0.230 min) and 0.971 min for 2 × 20′ containers. Clearly, there are no significant differences between 20′ full and 40′ full containers, standard deviations differ from zero and, for all types, 30% less than the corresponding means. Unlike loading activities, unloading time of 2 × 20′ containers is not substantially different (+12%) from the unloading time of a single container; in this case, the movement of two containers at the same time is much more effective. Comparison of loading with unloading shows that means are always 40% less than those for loading for 20′ full and 40′ full containers, and 129% less for 2 × 20′ full containers.

Finally, unloading times for 20′ empty containers were estimated. While the mean unloading time is 11% less than the time to unload a 20′ full or a 40′ full, the standard deviation (0.216 min) is 2% smaller than the corresponding standard deviations of both 20′ full or a 40′ full.

Statistical analysis for undifferentiated containers shows that the Gamma distribution function is always statistically significant, while Normal and Weibull distribution functions do not always verify the K–S test. The same random variable seems to be the best approximation for loading and unloading activities that involve 20′ and 40′ (full or empty) containers. In Table 6 means and standard deviations are reported for each activity (related to M-L estimation and Gamma distribution). Values are consistent with those introduced in the descriptive analysis and may be interpreted in the manner discussed above.

3.4.2. Gantry cranes (GCs)

The GCs operating in the SalCT are four rubber-tyred gantry cranes used both for movement/storage of containers and for loading of shuttles/trucks. This crane type usually consists of three separate movements for container transportation. The first movement is performed by the hoist, which raises and lowers the container. The second is the trolley gear, which allows the hoist to be positioned directly above the container for placement. The third is the gantry, which allows the entire crane to be moved along the working area.

The analyses carried out concern loading and unloading to the shuttle/truck, and loading and unloading to the stack (sometimes called pile). Each activity was analysed distinguishing undifferentiated containers from 20′ and 40′ containers. Moreover, loading time from stack was analysed, further distinguishing the tier. The analysis is focused on full containers, since these activities are the most frequent in the SalCT. Mean values and standard deviations are shown in Table 7a, standard errors and confidence intervals in Table 7b.

As regards loading time of undifferentiated containers (see Table 7a), the differences between loading time from shuttle and from stack (all tiers) are smaller. Mean loading time from shuttle (0.888 min) is 13% greater than the loading time from stack, while loading time from shuttle standard deviation (0.352 min) is 10% smaller than loading time from stack standard deviation. Both values are statistically different. In terms of loading time from stack for each tier, it can be pointed out that the mean decreases as the tier number increases. In particular, if the means increase slightly for each tier and statistical significant differences arise between 1st tire and the others, a not negligible difference (>30%) can be observed for the standard deviations between the 1st and 2nd tiers. From the 2nd to 5th tiers, the standard deviation increase can be considered negligible.

Only for loading time from stack there are data available for container type. As for undifferentiated containers, mean loading time from stack decreases as the tier number increases. This trend holds both for 20′ full and 40′ full containers. Comparing the means for each tier number, small differences (about 1% or 2%) can be observed among container type and do not turn out statistically significant. More appreciable and statistically significant differences exist among the different tiers. With respect to tier 1, loading time increases more than 30% for tier 2, more than 34% for tier 3 and more than 40% for tiers 4 and 5. It can be concluded that there are large differences between tier 1 and the others, while the differences are negligible among tiers from 2 to 5.

As regards the standard deviations, considerable differences can be observed between container type and between the different tiers. With respect to 40′ full containers, 20′ full container standard deviation is 46% less for tier 1, 81% less for tier 2, and more than 100% less for tiers 3–5. With respect to undifferentiated containers, smaller standard deviations can be observed for 20′ full containers (−20% for tier 1, −30% for tier 2, −40% for tier 3), whereas greater standard deviations can be observed for 40′ full containers (+20% for tier 1, +26% for tier 2, +24% for tier 3).

As regards unloading of undifferentiated containers, the results (see Table 7a) show an mean unloading time to shuttle (equal to 1.331 min) statistically different from unloading time to stack and, in particular, 40% greater than the unloading time to stack (mean on all tiers). For both activities the standard deviations are different from zero and about 30% smaller than the corresponding mean values. In particular, the unloading time to shuttle shows a 30% greater standard deviation (0.434 min) than the standard deviation of unloading time to stack (0.309 min). These results confirm that unloading to a shuttle/truck or to stack should be analysed through a stochastic approach; furthermore, unloading to a shuttle/truck requires more time than loading due to the time required to align the container to the shuttle, and show higher dispersion due to the greater number of unexpected events that may occur in such operations.

Carrying out the same analyses for 20′ and 40′ full containers, the estimation results show a mean unloading time to shuttle/truck of 1.303 min for the 20′ full container (with a standard deviation of 0.460 min) and 1.367 min for the 40′ full container (with a standard deviation of 0.402 min). The differences are not statistically significant for mean values, but more appreciable for standard deviations (13%).

As regards unloading time to stack, no differences were observed among container types and the analyses were carried out distinguishing the unloading activities with respect to the tier number. The results show that mean unloading time, as expected, decreases as the tier number increases: it is 1.101 min for tier 1 (with a standard deviation of 0.236 min), 0.753 min for tier 2 (with a standard deviation of 0.339 min), 0.699 min for tier 3 (with a standard deviation of

Table 7a
Gantry crane empirical results (minutes): means and standard deviations.

Activity	Undifferentiated		20′ Full		40′ Full	
	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s
Loading (from shuttle)	0.888	0.352	N.a.	N.a.	N.a.	N.a.
Unloading (to shuttle)	1.331	0.434	1.303	0.460	1.367	0.402
Loading (from stack)	0.769	0.380	0.758	0.283	0.774	0.422
Unloading (to stack)	0.760	0.309	N.a.	N.a.	N.a.	N.a.
Loading (from stack) – tier 1	1.025	0.431	1.019	0.348	1.031	0.509
Loading (from stack) – tier 2	0.713	0.270	0.706	0.188	0.721	0.340
Loading (from stack) – tier 3	0.672	0.290	0.658	0.169	0.683	0.361
Loading (from stack) – tier 4	0.625	0.374	0.618	0.236	0.636	0.401
Loading (from stack) – tier 5	0.614	0.376	0.605	0.261	0.623	0.415
Unloading (to stack) – tier 1	1.101	0.236	N.a.	N.a.	N.a.	N.a.
Unloading (to stack) – tier 2	0.753	0.339	N.a.	N.a.	N.a.	N.a.
Unloading (to stack) – tier 3	0.699	0.312	N.a.	N.a.	N.a.	N.a.
Unloading (to stack) – tier 4	0.647	0.309	N.a.	N.a.	N.a.	N.a.
Unloading (to stack) – tier 5	0.640	0.307	N.a.	N.a.	N.a.	N.a.

* $\bar{x}$: Mean value, s: standard deviation, n.p.: not present in the terminal, n.a.: data not available.

Table 7b
Gantry crane empirical results: standard errors and confidence intervals.

Activity	Undifferentiated		20′ Full		40′ Full	
	SE	Int	SE	Int	SE	Int
Loading (from shuttle)	0.035	[0.820, 0.956]	N.a.	N.a.	N.a.	N.a.
Unloading (to shuttle)	0.029	[1.275, 1.387]	0.040	[1.225, 1.381]	0.040	[1.288, 1.446]
Loading (from stack)	0.014	[0.742, 0.796]	0.015	[0.729, 0.787]	0.022	[0.732, 0.816]
Unloading (to stack)	0.014	[0.732, 0.788]	N.a.	N.a.	N.a.	N.a.
Loading (from stack) – tier 1	0.036	[0.955, 1.095]	0.041	[0.939, 1.099]	0.060	[0.913, 1.149]
Loading (from stack) – tier 2	0.024	[0.666, 0.760]	0.023	[0.662, 0.750]	0.044	[0.635, 0.807]
Loading (from stack) – tier 3	0.023	[0.627, 0.717]	0.020	[0.619, 0.697]	0.038	[0.608, 0.758]
Loading (from stack) – tier 4	0.029	[0.568, 0.682]	0.026	[0.568, 0.668]	0.044	[0.550, 0.722]
Loading (from stack) – tier 5	0.031	[0.554, 0.674]	0.030	[0.546, 0.664]	0.048	[0.529, 0.717]
Unloading (to stack) – tier 1	0.024	[1.053, 1.149]	N.a.	N.a.	N.a.	N.a.
Unloading (to stack) – tier 2	0.035	[0.684, 0.822]	N.a.	N.a.	N.a.	N.a.
Unloading (to stack) – tier 3	0.032	[0.636, 0.762]	N.a.	N.a.	N.a.	N.a.
Unloading (to stack) – tier 4	0.033	[0.582, 0.712]	N.a.	N.a.	N.a.	N.a.
Unloading (to stack) – tier 5	0.033	[0.576, 0.704]	N.a.	N.a.	N.a.	N.a.

0.312 min), 0.647 for tier 4 (with a standard deviation of 0.309 min) and 0.640 for tier 5 (with a standard deviation of 0.307 min). There are no significant differences from tier 3 to tier 5, while the differences between tiers 1 and 2 (46%) and tiers 1 and 3 (58%) shown to be statistically significant. Unlike means, standard deviations increase between tiers 1 and 2 while they decrease among tiers greater than 2.

Finally, means and standard deviations were estimated for trolley speed and crane speed (see Table 8a and 8b). As reported in Table 8a, the mean full trolley speed (trolley with a container) is equal to 13 m/min (with a standard deviation of more than 6 m/min) and it is 74% lower than the free trolley speed (50 m/min, with a standard deviation of more than 30 m/min). With respect to crane speed, the estimation results show a mean speed of about 13 m/min (with a standard deviation of about 6 m/min).

Distinguishing by container type, a mean trolley speed of 13.2 m/min (with a standard deviation of more than 4.1 m/min) can be observed for 20′ full containers and of 12.5 m/min (with a standard deviation of 6.9 m/min) for 40′ full containers. While the difference between means is negligible (≈6%), the differences between standard deviations (≈65%) point to the need for a stochastic approach.

For all the described activities and for each container type, in-depth analysis was developed to find out the statistical distribution which best fitted the data. Three distribution functions were statistically significant: Gamma, Normal and Weibull. As regards undifferentiated containers, the Gamma distribution function proved the best solution for all analysed activities. Similar results were achieved on analysing activities for each container type and each tier number. In Tables 9 and 10 means and standard deviations are reported for each activity (related to K–S estimation and Gamma distribution). Values are consistent with those introduced in the descriptive analysis and may be interpreted in the manner discussed above.

3.4.3. Reach stackers (RSs)

Eleven RSs operate in the Salerno Container Terminal, equipped with a twin-lift spreader able to move two full 20′ containers. They are used both to transport containers very quickly over short distances and to pile/stow them in various rows.

The analyses concern: loading to shuttle/truck, unloading from shuttle/truck and stacking. Each activity was analyzed distinguishing undifferentiated containers from 20′ and 40′ containers. Moreover, stacking was analyzed distinguishing the tier number. The analysis focused on full containers since the main activities in Salerno Container Terminal concern full containers. Mean values and standard deviations are shown in Table 11a, standard errors and confidence intervals in Table 11b.

As regards undifferentiated containers (Table 11a), reach stacker unloading activities show a mean unloading time from shuttle/truck of 0.215 min and a standard deviation of 0.114. With respect to stacking time, the estimation results show a mean (calculated wrt tier, up to five, in which a container is stacked) stacking time of 0.288 min and a standard deviation of 0.157 min. For all the activities, the standard deviation values confirm the need of a stochastic approach.

Table 8a
Gantry crane empirical results (mt/min): means and standard deviations.

Activity	Undifferentiated		20′ Full		40′ Full	
	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s
Trolley speed (with container)	12.663	6.416	13.243	4.142	12.508	6.902
Free trolley speed	49.076	30.202	–	–	–	–
Crane speed	12.916	5.515	N.a.	N.a.	N.a.	N.a.

* $\bar{x}$: Mean value, s:standard deviation, n.p.: not present in the terminal, n.a.: data not available.

Table 8b
Gantry crane empirical results (mt/min): standard errors and confidence intervals.

Activity	Undifferentiated		20′ Full		40′ Full	
	SE	Int	SE	Int	SE	Int
Trolley speed (with container)	0.472	[11.738, 13.588]	0.663	[11.943, 14.543]	0.571	[11.388, 13.628]
Free trolley speed	3.201	[42.801, 55.351]	–	–	–	–
Crane speed	1.007	[10.942, 14.890]	N.a.	N.a.	N.a.	N.a.

$^*\overline{int} = \bar{x} \pm t^*_{0.025} SE$; n.a.: data not available.

Table 9
Gantry crane statistical results: parameters of Gamma distribution function.

Activity	Undifferentiated		20′ Full		40′ Full	
	μ	σ	μ	σ	μ	σ
Loading (from stack)	0.752	0.406	0.741	0.311	0.769	0.457
Unloading (to stack)	0.766	0.352	N.a.	N.a.	N.a.	N.a.
Loading (from stack) – tier 1	1.022	0.449	1.011	0.353	1.060	0.561
Loading (from stack) – tier 2	0.687	0.250	0.658	0.222	0.712	0.256
Loading (from stack) – tier 3	0.668	0.323	0.659	0.246	0.673	0.383
Loading (from stack) – tier 4	0.592	0.325	0.583	0.261	0.606	0.390
Loading (from stack) – tier 5	0.571	0.355	0.560	0.280	0.584	0.399
Unloading (to stack) – tier 1	1.097	0.231	N.a.	N.a.	N.a.	N.a.
Unloading (to stack) – tier 2	0.703	0.308	N.a.	N.a.	N.a.	N.a.
Unloading (to stack) – tier 3	0.671	0.256	N.a.	N.a.	N.a.	N.a.
Unloading (to stack) – tier 4	0.638	0.245	N.a.	N.a.	N.a.	N.a.
Unloading (to stack) – tier 5	0.613	0.240	N.a.	N.a.	N.a.	N.a.

Table 10
Gantry crane statistical results: parameters of Gamma distribution function.

Activity	Undifferentiated		20' Full		40' Full	
	μ	σ	μ	σ	μ	σ
Trolley speed (with container)	11.653	4.597	12.740	4.275	11.203	4.530
Free trolley speed	46.609	29.892	–	–	–	–
Crane speed	11.498	4.586	N.a.	N.a.	N.a.	N.a.

Table 11a
Reach stacker empirical results.

Activity	Undifferentiated		20′ Full		40′ Full	
	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s
Loading to shuttle/truck	0.357	0.250	0.344	0.205	0.365	0.272
Unloading from shuttle/truck	0.215	0.114	0.153	0.055	0.236	0.119
Stacking time	0.288	0.157	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 1	0.201	0.062	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 2	0.186	0.077	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 3	0.238	0.098	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 4	0.355	0.148	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 5	0.542	0.164	N.a.	N.a.	N.a.	N.a.

$^*\bar{x}$: Mean value, s:standard deviation, n.p.: not present in the terminal, n.a.: data not available.

Interesting results can be observed on distinguishing between container types. With regard to loading, a mean time of 0.365 min was observed for the 40′ full container (with a standard deviation of 0.272 min) and 0.344 min for the 20′ full container (with a standard deviation of 0.205 min). It can be concluded that no statistical significant differences were observed, thus means and corresponding standard deviations are independent of container type.

Table 11b
Reach stacker empirical results.

Activity	Undifferentiated		20’ Full		40′ Full	
	SE	Int	SE	Int	SE	Int
Loading to shuttle/truck	0.011	[0.335, 0.379]	0.016	[0.314, 0.374]	0.015	[0.336, 0.394]
Unloading from shuttle/truck	0.009	[0.197, 0.233]	0.005	[0.142, 0.164]	0.016	[0.204, 0.268]
Stacking time	0.006	[0.277, 0.299]	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 1	0.004	[0.193, 0.209]	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 2	0.005	[0.176, 0.196]	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 3	0.009	[0.220, 0.256]	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 4	0.014	[0.328, 0.382]	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 5	0.017	[0.509, 0.575]	N.a.	N.a.	N.a.	N.a.

$^{*}\overline{int} = \bar{x} \pm t^{*}_{0.025} SE$; n.a.: data not available.

Table 12
Reach stacker statistical results: parameters of Gamma distribution function.

Activity	Undifferentiated		20′ Full		40′ Full	
	μ	σ	μ	σ	μ	σ
Loading to shuttle/truck	0.307	0.170	0.304	0.155	0.311	0.188
Unloading from shuttle/truck	0.186	0.074	0.144	0.056	0.200	0.087
Stacking time	0.260	0.146	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 1	0.185	0.056	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 2	0.167	0.071	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 3	0.212	0.086	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 4	0.334	0.118	N.a.	N.a.	N.a.	N.a.
Stacking time – tier 5	0.542	0.140	N.a.	N.a.	N.a.	N.a.

As regards unloading, the mean time for a 20′ full container is 0.153 min (with a standard deviation of 0.055 min), whereas it is double and statistically significant for the 40′ full container in terms of mean (0.236 min) and standard deviation (0.119 min). For this activity, mean values and standard deviations differ considerably (almost 50%) from undifferentiated values and, along with the high number of activities in which RSs are involved, show that different hypotheses on aggregation levels may lead to very different results and that such an issue should be carefully weighed up in the micro-simulation of a terminal container.

For stacking time, the time duration for each tier (up to 5) was computed, but it was not possible to distinguish container type. With respect to tier 1, the mean estimated stacking time is 0.201 min (with a standard deviation of 0.062 min), 0.186 min for tier 2 (with a standard deviation of 0.077 min), 0.238 min (with a standard deviation equal to 0.098 min) for tier 3, 0.355 min (with a standard deviation of 0.148 min) for tier 4 and 0.542 min (with a standard deviation of 0.164 min) for tier 5. Mean values are statistically different, activity duration increases as the tier increases except for tier 2 which shows the lowest time duration since the arm of the RS is positioned at the same height as tier 2. The standard deviations are independent of the tier in which a container is stacked.

Starting from the same data, several random variables were tested. For RS loading and unloading, only Gamma and Weibull variables met the statistical significance tests: the Gamma random variable fits the data better due to better values in the validation test. In Table 12, the results are shown and comments may be made similar to those proposed before for empirical analysis.

As regards RS speed, the authors suggest estimating the time duration of these activities directly. In this case, statistical models are not easily transferable since they depend on peculiarities of the CT: geometrical characteristics (path winding, . . .), traffic congestion, etc.

4. Model implementation, validation and application

4.1. Model implementation

The DES model was developed in Witness® software. Witness® is the one of the world’s leading software products in the field of visual interactive simulation. It allows simulation of operations of different kinds, is flexible and easily modifiable. It also provides animation which can be very useful for analysts and seaport planners.

Starting from the lay-out of the port proposed in Fig. 1 (Section 3.2) and from the logical architecture proposed in Fig. 2, implementation of Witness® requires a graph model to be built. In particular the following elements have to be identified:

– nodes, that represent all the activities possibly involving container movements. The following were implemented (see Section 3.1): physical (service nodes simulating handling activities, buffer nodes simulating buffer zones, where queuing may occur), conceptual (e.g. logical conditions) and mathematical (model elaborations);
– links, representing node connections and indicating the routes that may be followed by containers.

A performance function among those proposed in Section 3.4 must be associated to each node/activity.

As introduced in Section 3.2, three main operations were distinguished: export, import and transhipment. Operations share the same space and the same handling equipment, for each operation, nodes, links and performance functions were defined. In Figs. 3–5, the corresponding graphs are shown. In Table 13 acronyms for activities concerning container terminal physical flows are listed.

In particular, a rhombus represents a logical condition, a rectangle a physical activity.

In our DES model, logical conditions are introduced when:

– a logistic activity may or may not occur,
– if a container is empty or full, whether or not the operation is transhipment or not,
– if a buffer is used in an operation, whether or not a container is directly loaded onto a shuttle,
– if customs activity is carried out,
– if the gate out is on the rail network,
– if an empty container exits from the CT,
– if an unloaded container from a vessel is directly loaded onto a departing vessel.

Physical activities may be: bureaucratic, logistic, container movement on specific handling equipment, container transfer between two different pieces of handling equipment, storage, wait, customer activity, gate in/out.

In all, the graph model is formed by 87 nodes, 17 represent logical conditions, 71 physical activities, 22 nodes simulate container movement, and 27 container transfer. The import operation graph (Fig. 3) is made up by 39 nodes, 8 representing logical conditions and 31 physical activities. Of these, 9 represent container movement, 10 container transfer, the remaining are activities such as: gate out, wait, customs activity, storage and logistics. The export operation graph (Fig. 4) comprises 31 nodes, 4 representing logical conditions and 27 physical activities. Of these, 9 represent container movement, 9 container transfer, and the remaining are activities such as logistics, wait and storage. The transhipment operation graph (Fig. 5) consists of 17 nodes, 4 representing logical conditions and 13 physical activities. Of these, 3 represent container movement, 8 container transfer, the remaining wait and storage activities.

Operations start when a vessel is assigned to a berth or when a truck enters the terminal. Both vessel and truck arrivals depend on the previously estimated temporal demand profiles.

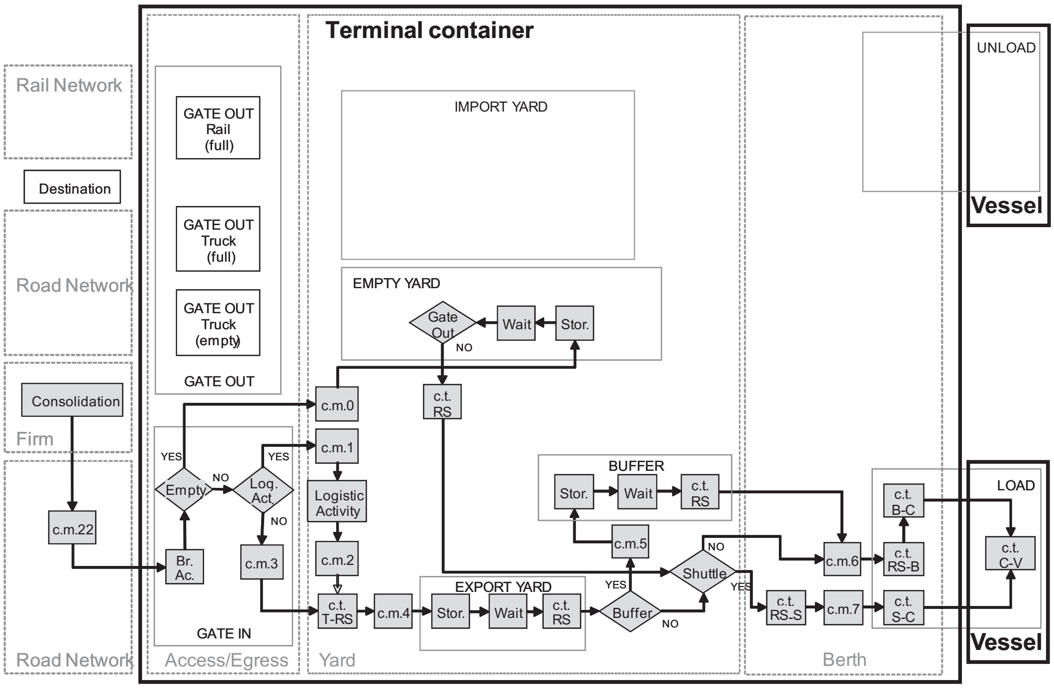


Fig. 3. Export operation: Witness® activity diagram.

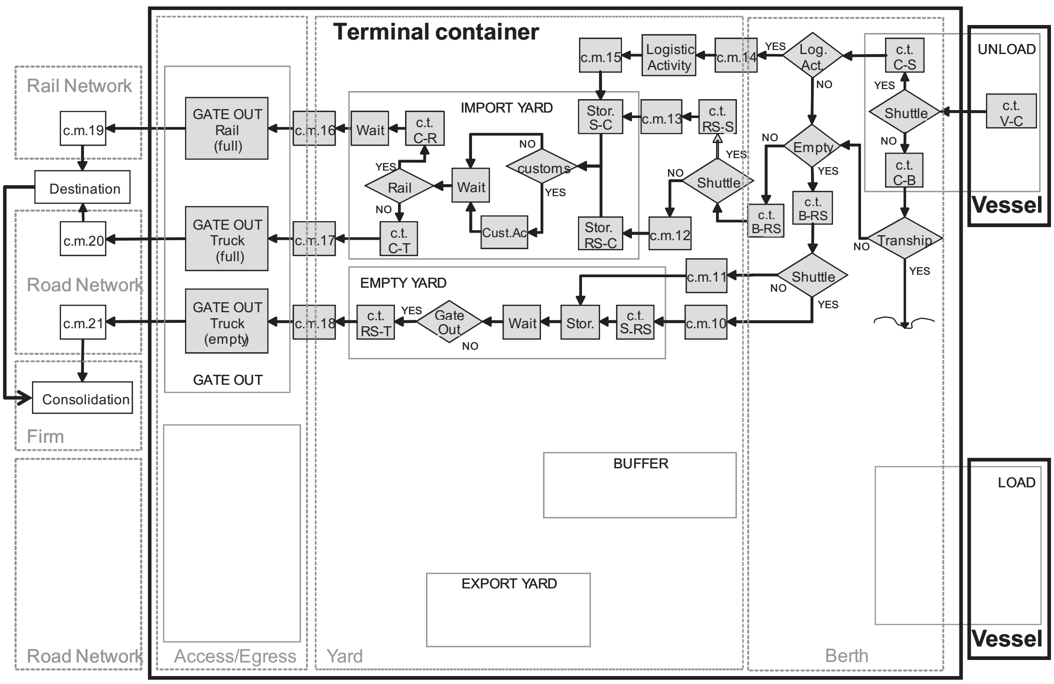


Fig. 4. Import operation: Witness® activity diagram.

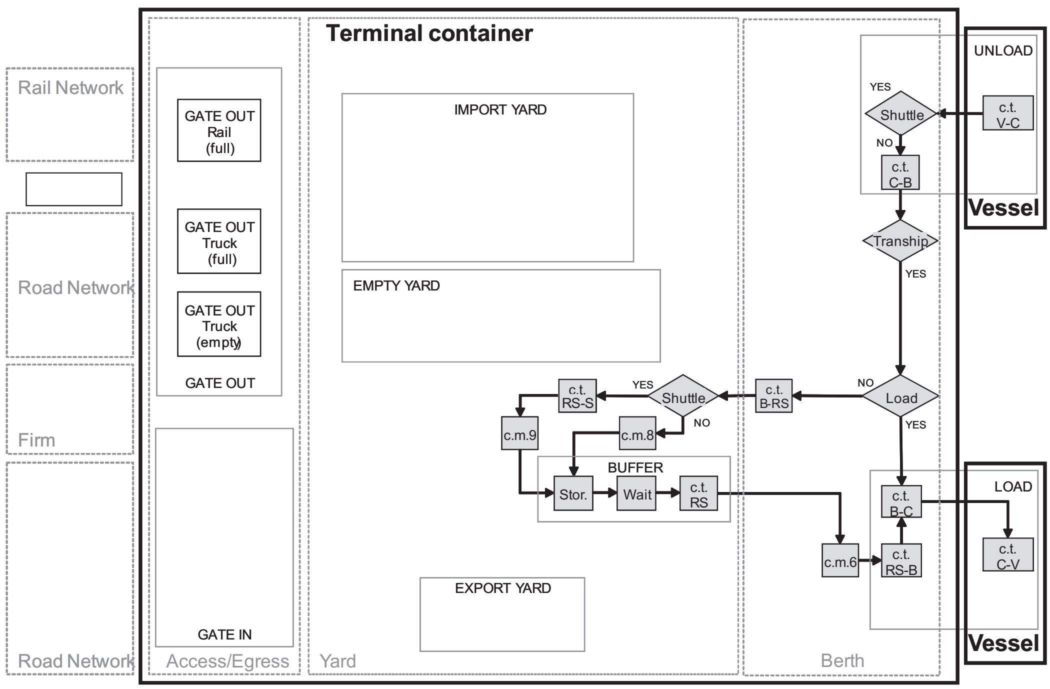


Fig. 5. Transhipment operation: Witness® activity diagram.

Since the time associated to each single activity is the realization of a random variable, random samples (replications) from probability distributions are used to drive the simulation model. In this case a single replication or a small number of replication can lead to erroneous inferences about the system under study. At this aim, several simulations should be run and the mean values should be determined. In our case study each replication started from the same initial conditions without a warm-up period (not significant in our application). In particular, a prefixed number of independent replications

Table 13
Container terminal physical flow activities.

ID	Activity description
c.t. T-RS	Container transfer from Truck to Reach Stacker
c.t. RS-S	Container transfer from Reach Stacker to Shuttle
c.t. S-C	Container transfer from Shuttle to Crane
c.t. RS-B	Container transfer from Reach Stacker to Berth
c.t. RS-C	Container transfer from Reach Stacker to Crane
c.t. B-C	Container transfer from Berth to Crane
c.t. C-V	Container transfer from Crane to Vessel
c.t. V-C	Container transfer from Vessel to Crane
c.t. C-B	Container transfer from Crane to Berth
c.t. B-RS	Container transfer from Berth to Reach Stacker
c.t. B-S	Container transfer from Berth to Shuttle
c.t. S-FL	Container transfer from Shuttle to Fork Lift
c.t. FL-T	Container transfer from Forklift to Truck
c.t. C-R	Container transfer from Crane to Rail
c.t. C-T	Container transfer from Crane to Truck
c.m.*j*	*j* Container movement (*j* [1, …, 16])
Br. Ac.	Bureaucratic activities
Stor.	Storage
Wait	Container waiting time
Cust. Ac.	Customer activities
Rail Br. Ac.	Rail bureaucratic activities
Truck Br. Ac.	Truck bureaucratic activities

were carried out, mean values for involved activities were estimated, as well for performance measures that will be introduced in the following section. Pursuing such procedure, also known as fixed-sample-size procedure, it is possible to obtain point estimate and "approximate" confidence interval (since random variable are hypothesized normally distributed).

In order to minimize sampling error and then to allow comparison among different handling equipment models and different CT configurations, variance-reduction techniques should be applied. In this paper we considered the Common Random Numbers (CRN) approach [26]. It applies when two or more alternative system configurations have to be compared, since it allows comparison of different configurations under similar experimental conditions. The CRN technique is based on the possibility of using the same basic random numbers to drive each simulation, in order to introduce correlation among random variates of different system configurations. An effective implementation of the CRN technique requires positive correlation of simulation results and synchronization. As regards correlation, it should be assumed that generated variates react monotonically to basic random numbers and it should be assumed that measures of performance react monotonically to the generated variates. As regards synchronization, random numbers should be synchronized across the different system configurations and with respect to each replication. In our case study, for each replication a random stream vector was generated for each handling activity, and the same stream vectors were used for each scenario simulated.

Finally, the number of used replications was 25, such a number showed to be sufficient to obtain stable mean values and stable confidence interval at a confidence level of 90%. Simulations were carried out on Intel Core 2 CPU 2.00 GHz, 2.00 GB RAM.

4.2. Model validation and application

4.2.1. Indicators

Comparison of different planning strategies/investments for a CT need the comparison of several scenarios through estimation of performance indicators. CT managers usually have to tackle different issues as the planning horizon changes: real-time (resources allocation), short/medium term (tactical decisions, such as yard lay-out, gate-in/out management, quay/gantry crane position, etc.), long-term (strategic decisions, such as quay/gantry crane number, etc.). Real-time strategies may involve a smaller part of the terminal and need high accuracy in container movement time estimation; short/medium term strategies may involve a single part of the terminal or the whole terminal and require accuracy on a daily basis: errors in container movement time can be more acceptable since compensation between single handling equipment simulation errors can arise. Furthermore, because the daily container dwelling times are greater than the handling times, errors in handling equipment simulation are sometimes not significant; long-term strategies usually involve the whole terminal and can be less affected by single container movement times or single handling equipment movement times. In such a context, either a model should be able to address all the issues at the same time, or different models might be specified and calibrated.

The aim of this section is twofold: (i) investigate model goodness-of-fit and (ii) point out how different modelling hypotheses may be effective in the same way but with respect to different planning horizons. For this purpose, model validation was carried out, estimating goodness of fit for each of the proposed models with respect to:

(i) Single container movement time. This allows measurement of the model's ability to simulate single container activity/movements. Such validation could be insightful in the event of the need to implement a short-term/real-time planning strategy, where simulation of single container movements should be as realistic as possible.
(ii) Handling equipment operation time. This allows measurement of the model's ability to simulate handling equipment operation time. Such validation could be useful to understand which handling equipment is most affected by different modelling hypotheses and could be insightful for implementing short/medium term planning strategies.
(iii) Terminal operation time. This can be used to measure daily operation time of the whole terminal. Such validation could be insightful for implementing long-term planning strategies.

The indicators are introduced below.

Let

o, The generic operation set up by a sequence of elementary activities, possibly involving handling equipment, in space or time (e.g. unloading vessels: crane–dock–reach stacker–shuttle–yard);

a, the generic elementary activity;

δ_{oa}, A variable that is equal to one if operation o involves activity a. Having defined the list of operations and the sequence of activities which constitute each operation, a binary matrix (operation-activity incidence matrix) representing the relationship between operation and activities can be defined;

i, the generic container type (class);

j, the generic container;

t_{aij}, the observed time of container j, belonging to class i, moved by activity a;

g_{aij}, the simulated time of container j, belonging to class i, moved by activity a;

d_{oi}, the set of containers belonging to class i, assigned to operation o that demands to be moved.

4.2.1.1. Local indicator (container). With respect to a set of monitored terminal operations, container movement times, t_{aij}, were estimated and compared with observed times g_{aij}. Absolute percentage error was estimated for each container and a global measure was obtained by summing each percentage error

$$Err_{container} = \sum_{o}\sum_{a}\sum_{i}\sum_{j\in d_{oi}} \frac{|g_{aij} - t_{aij}|}{t_{aij}} \cdot \delta_{\mathrm{oa}}$$

The indicator allows the error to be measured in simulating single container movement. It is independent of the handling equipment involved and could be used to evaluate short-term/real-time strategies. Standard deviations can be computed in order to measure the dispersion degree among the different modelling approaches.

4.2.1.2. Local indicator (handling equipment). For each elementary activity a (handling equipment activity) and for the containers involved, the sum of estimated and observed container movement time was calculated, and the percentage error variation was estimated with respect to the sum of observed container movement time:

$$Err_a = \frac{\sum_o\sum_i\sum_{j\in d_{\mathrm{oi}}} g_{aij}\cdot\delta_{\mathrm{oa}} - \sum_o\sum_i\sum_{j\in d_{\mathrm{oi}}} t_{aij}\cdot\delta_{\mathrm{oa}}}{\sum_o\sum_i\sum_{j\in d_{\mathrm{oi}}} t_{aij}\cdot\delta_{\mathrm{oa}}}$$

Since differences between sums are estimated, the indicator is less affected by single container simulation error (compensation occurs) and enables us to understand which handling equipment is most affected by different modelling hypotheses. It could be useful to indicate for which handling equipment a more detailed approach is advisable, and could be used to evaluate short-term strategies.

4.2.1.3. Global indicator (handling equipment). Starting from a disaggregated indicator calculated for each type of handling equipment, an aggregate indicator was obtained by calculating the average error of each type of handling equipment weighted with respect to the number of activities in which the handling equipment is involved (θ_a). This indicator is affected by compensation between handling equipment errors and, therefore, should be better used to evaluate medium term strategies for the whole terminal

$$Err_{a-weighted} = \frac{Err_a\cdot\theta_a}{\sum_a\theta_a}$$

4.2.1.4. Global indicator (whole terminal). It measures the absolute percentage error ($Err_{terminal}$) in simulating the time to bring terminal macro-operations (e.g. import, export) to a close with respect to a pre-fixed time interval (days, months). The indicator is calculated simulating, for a fixed set of consecutive days (representing the simulation time), the movements of each container from the arrival to the terminal until the departure from the terminal. Therefore, duration of each operation that constitutes each macro-operation and dwelling times that occur inside the terminal are explicitly estimated. Compensation between handling equipment errors and dwelling times occur, thus the indicator can be used to evaluate long-term strategies for the whole terminal.

4.2.2. Validation results and sensitivity analysis

Starting from the model architecture proposed in the previous section, four different models based on four different handling equipment models were validated:

– Sample Mean Undifferentiated (SMU) model: sample mean values are used to estimate handling equipment time duration and there is no distinction between container types.
– Sample Mean Container Type (SMCT) models: sample mean values are used to estimate handling equipment time duration and container types are explicitly taken into account: 20′ full and/or empty; 40′ full and/or empty; 2 × 20′ full.
– Random Variable Undifferentiated (RVU) model: the time associated to each single activity is the realization of a random variable, handling equipment time is modelled as a random variable and there is no distinction between container type.
– Random Variable Container Type (RVCT) models: handling equipment time is modelled as a random variable and container types are explicitly taken into account: 20′ full and/or empty; 40′ full and/or empty; 2 × 20′ full.

The model was validated and applied in two successive steps. First, model outputs were compared with the data surveyed in 2003 in the CT and used to calibrate handling equipment models (calibration sample). The aim is to ascertain the suitability of the model for representing real conditions. Secondly, model outputs were compared with a sample of data acquired in 2008 not used for model parameter estimation referring to a different terminal configuration (before and after analysis). This validation allows a robust measure of model reliability and is rarely used in CT modelling.

The activities that were taken into account to calculate the indicators are: vessel loading and/or unloading time, quay/yard crane idle time, shuttle waiting time, shuttle transfer time, reach stacker stacking time, reach stacker idle time, gate in/out waiting time. The results for the calibration sample are reported in Table 14.

The results in terms of daily simulation time show that random variable models require a much greater computational time (40 times) than sample means. The former require about 20 min, the latter less than 1 min. Clearly, the order of magnitude is appreciably different. Such a difference should be carefully weighed up with respect to the strategies to implement.

As regards terminal performance, a global indicator was estimated for 4 weeks (28 consecutive days). In Table 14, absolute percentage estimation errors are reported for each developed model. Results for models based on sample mean estimations (SMU and SMCT) show similar absolute estimation errors (10% vs. 9%) and that the distinction between container type can be ignored. Models based on random variables (RVU and RVCT) lead to a significant decrease in absolute error (more than 50%). In this case, container type distinction significantly increases model goodness of fit. Indeed, benefits in terms of absolute errors vary from 4.5% for RVU to 2.5% for RVCT.

As regards handling equipment indicators, absolute percentage errors are slightly greater than errors for global indicators, and similar remarks may be drawn. Sample-based models show worse goodness of fit than random-based ones. Absolute percentage error decreases from 13% for SMU to 3% for RVCT. The effect of container type is much more significant for random-based models and, with respect to global indicators, becomes more significant for sample-based models.

As regards the container indicator, absolute percentage errors appreciably increase, varying from 31% for SMU to 11% for the best model RVCT. Unlike the global indicator and handling equipment indicators, SMU, SMCT and RVU models show a similar poor performance, whereas the RVCT model clearly outperforms the above three models. The results point out that only the combination of the random variable-based approach and the container-type approach lead to an acceptable simulation error.

From the cumulative diagram (Fig. 6) of absolute percentage estimation error variation plotted for local indicators and for the global indicator it may be inferred how many (what percentage) business days and/or types of handling equipment and/or containers are simulated with a percentage estimation error smaller than a fixed threshold. On the x-axis absolute percentage estimation error is reported; on the y-axis the percentage of business days, handling equipment and containers are reported for each of the developed models.

Table 14
Average absolute percentage estimation error (calibration sample).

			Daily simulation time			
			Sample			**R**andom
Undifferentiated			0.5 min			18.7 min
Container type			0.6 min			21.3 min
	$Err_{terminal}$		$Err_{a\text{-}weighted}$		$Err_{container}$	
	Sample	**R**andom	**S**ample	**R**andom	**S**ample	**R**andom
Undifferentiated	10.1%	4.6%	13.2%	6.5%	30.8%	28.5%
Container**T**ype	8.9%	2.6%	11.0%	3.0%	29.3%	11.2%

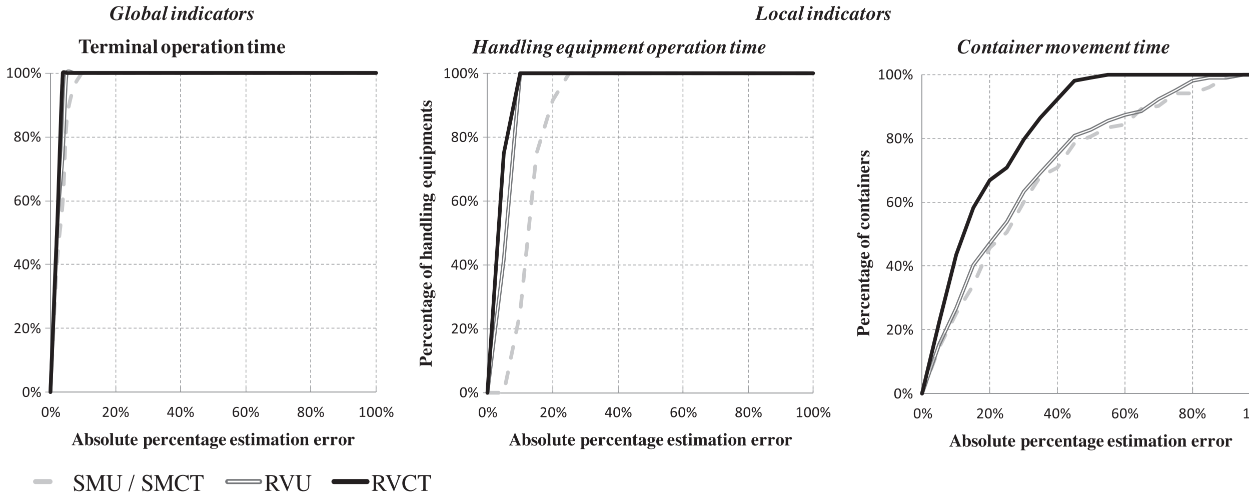


Fig. 6. Cumulate absolute percentage estimation error variation (calibration sample).

Table 15
Absolute percentage prediction error (after scenario).

	$Err_{terminal}$		$Err_{a\text{-}weighted}$		$Err_{container}$	
	Sample	**R**andom	**R**andom	**R**andom	**S**ample	**R**andom
Undifferentiated	12.0%	6.9%	15.5%	6.5%	37.5%	31.7%
Container**T**ype	9.2%	3.9%	14.2%	3.9%	32.6%	9.7%

With respect to the global indicator, more than 80% of the simulated business days show absolute percentage error lower than 10%. This result is independent of the model employed, and shows that more complex modelling approaches do not lead to proportionately better goodness of fit of terminal global performance.

Differences between the models can be observed for the local indicators. As regards the handling equipment indicator, the models based on sample means show similar cumulative diagrams and similar poor performance. Although 80% of handling equipment shows an absolute percentage error smaller than 20%, only 20% shows an error smaller than 10%. With respect to RV models, SM diagrams are translated by a quantity of 3%, meaning that there is a systematic error due to the modelling approach.

On the other hand, RV models are able to simulate 90% of handling equipment with an absolute estimation error always below 10%. Moreover, the RVCT model simulates 75% of handling equipment with an absolute percentage error below 5%.

As regards the simulation of single container movements, a greater approximation must be accepted. The best performing model (RVCT) is able to simulate only 63% of container movement times with an absolute percentage error smaller than 20%, and 90% with an absolute percentage error less than 40%. All the other models show worse goodness-of-fit and, in general, poor ability to simulate container movement time. The differences with respect to the RVCT model are significant and confirm that the only suitable model should combine the random distribution approach with differentiation in container type.

To test model robustness and reliability a before and after analysis was carried out on a large set of data (hold-out sample) acquired in 2008 (about 800 containers were monitored in all the activities involved). The test case is more significant than ever since the data differed from those used to calibrate the model and, in particular, were collected in a different terminal configuration (*after scenario*). The main characteristics of the *after scenario* are:

- a new automated gate in/out with two new gates (four gates in all);
- a new yard layout: a new location inside the terminal and increase in size;
- a new yard gantry crane (four in all);
- new shuttle paths from gate to yard and from yard to berth.

Judging from the average percentage prediction error (Table 15), the model system implemented has a good capacity to reproduce the data acquired in 2008. The simulation model with the RVU handling model has an average prediction error of more than 7% in terms of global indicators, while using RVCT handling models the average prediction error is about 4% with respect to equipment indicators and about 10% for container indicators. In conclusion, the model system applied has a good capacity to reproduce the *after scenario*, confirming the validation results reported above.

5. Conclusions

In the numerous efforts found in the literature to simulate a CT, most of the existing papers mainly focus on the application and/or comparison of design scenarios and do not pay great attention to the model set-up, its calibration and its validation. While many contributions present few information on equipment handling models used, the remaining contributions carry out mainly deterministic approaches and/or give scant information on the estimation approach pursued, on experimental data used, on parameters estimated and on parameter values. Moreover, the effects that different hypotheses on handling equipment model calibration may have on simulating CT performance have not, to date, been investigated. Such effects may well be appreciable and should be investigated with respect to strategic and tactical planning horizons.

In this paper different DES models was specified, calibrated, validated. In particular the following issues were addressed:

(a) estimation of mean and standard deviation of activity time duration for different types of handling equipment (mobile harbour cranes, gantry cranes, reach stackers) and for different container types (undifferentiated, 20 feet, 40 feet, empty, full, ...). Two DES models were derived: SMU (activity time duration: sample mean, container type: undifferentiated), SMCT (activity time duration: sample mean, container type: differentiated).
(b) Calibration of random distribution functions for each handling equipment type and for each container type (handling activity models). Two DES models were derived: RVU (activity time duration: random distribution, container type: undifferentiated), RVCT (activity time duration: sample mean, container type: differentiated).
(c) Validation of each DES model through a two-stage validation analysis: (i) on the data-set used to calibrate the handling activity models and (ii) on data monitored after significant changes in the terminal lay-out (*before and after* analysis). Three indicators were introduced in order to understand the models' ability to deal with different levels of detail (whole terminal simulation, handling equipment simulation, container simulation). Results from validation allowed us to identify the strengths and weaknesses of the proposed DES models with respect to different planning horizons: long-term planning interventions/investments, medium/short-term, short-term or real-time applications.

As regards point (a), on the basis of the results the differences between activity times may be determined if different aggregation hypotheses are made for handling activity and/or container type, such as whether and how an activity is subdivided into more elementary activities, and whether and how to distinguish container type. Sample mean values and standard deviations show that non-negligible differences can be observed and bear out the need for modelling handling activities through random variables. Particular care should be paid to container type, to correct identification of elementary activities involved, and to those activities which stack containers in different tiers.

As regards point (b), our calibration results improve the current state of the art, give some insights on the best calibration approach (Moment, Maximum Likelihood), highlight a suitable family of distribution functions to simulate handling equipment time and define the best-performing distribution functions for each type of handling equipment and each container type.

From a statistical point of view, the Maximum Likelihood estimation approach seems to be the best performing one, and Normal, Gamma and Weibull distribution functions proved statistically significant to interpret handling activity times. In particular, the Gamma random variable leads to better goodness of fit for all handling activities and for all container types involved. The whole set of distribution functions (and of their parameters) allows different simulation models to be implemented, such as changes in activity levels of aggregation and container types.

As regards point (c), specified DES models show a good reproduction capability and a good generalization ability to simulate a scenario never observed, demonstrating robustness and reliability. As expected, the DES model with random distribution of activity times and with differentiation into container type shows better goodness-of-fit for all the proposed indicators. The use of random distributions, independently of differentiation into container type, halves the absolute percentage error for global indicators. The same phenomenon does not occur for local indicator, where only the combination of random distributions and differentiation leads to a significant increase in model reproduction capability.

Differentiation into container type yields further improvements. For global indicators the marginal effect is smaller than the effect obtainable introducing random distributions; the gain in the absolute percentage error is about 2–3%. For local indicators the effect is negligible if sample means are used, whereas it is highly significant if random distributions are introduced (as pointed out above).

Such results, if analyzed from an operational point of view, provide a basis for guidelines to model strategic (long/medium term) and/or tactical (short-term, real-time, temporary) planning scenarios in the most effective way. In strategic planning scenarios, since the purpose is to simulate whole CT performance over a longer simulation time horizon (for instance 365 days), it is important to define a model which is efficient, easy to implement and realistic in simulating aggregate terminal performance (e.g. global indicator/terminal operation time). In such a context, a sample-based approach with no differentiation into container type can be pursued (SMU model): differentiation into container type (SMCT model) reduces the absolute percentage error by 2%, the random distribution approach with undifferentiated containers (RVU model) reduces the error by 5.5% but increases simulation time by a factor of 37, whereas the combination of random distribution and differentiation into container type (RVCT model) reduces the absolute percentage error by 7% but increases simulation time by a factor of 43.

In tactical planning scenarios, since benefits from real-time strategies and/or benefits from short-term/temporary investments should be estimated/simulated, having a model which is efficient and realistic in simulating shorter time periods (week, day, shift) is more important than simulation time. Unlike what happens in strategic planning, compensation phenomena (due to dwelling time) do not occur. Hence the DES model should be effective at simulating single container movements and/or single handling equipment activities. Therefore, our results show that, as regards real-time strategies, where simulation intervals can be short (one or two shifts), only the RVCT model can be used (average absolute percentage error is about 11%, about 30% for the other approaches). As regards short-term/temporary scenarios, where the simulation interval can be longer than 1 day, a realistic simulation for handling equipment activity time is sufficient. In this case both sample mean and random variable estimation can be pursued. The former guarantees lower simulation times but greater average absolute percentage errors (from 11% to 13%); the latter yields much smaller absolute percentage errors (from 3% to 6%) but simulation 40 times higher.

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