Proceedings of the 2018 Winter Simulation Conference
M. Rabe, A. A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, eds.

CHALLENGES AND OPPORTUNITIES IN INTEGRATION OF SIMULATION AND OPTIMIZATION IN MARITIME LOGISTICS

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ABSTRACT

Maritime logistics plays an important role in the global trading scene with over 80% of global trade by volume and more than 70% of the trade value being handled by vessels and seaports worldwide. Today, the maritime industry is facing both new challenges and opportunities. Amongst the existing review papers, an in-depth and systematic summary on the integration of simulation and optimization is lacking. To fill the gap, this paper reviews dozens of papers on the integration of simulation and optimization for maritime logistics since 2010. Five modes of integration are classified according to how the two techniques interact with each other. Lastly, the paper introduces new challenges and opportunities in the maritime industry, and how the integration of simulation and optimization can help to boost the development of the next generation maritime systems.

1 INTRODUCTION

Global trade is constantly growing at a significant rate, with the majority being handled by vessels and seaports worldwide. Furthermore, with the recovery of the global shipping market, more cargoes are flowing through the chain of maritime logistics, which generally consists of the land, port, and sea side, as shown in Figure 1 (the bulk cargo and bunkering services are not shown in the figure).

Today, the maritime industry is facing both new challenges, such as higher operation efficiency standards and increasing costs of resources, and opportunities, such as the rapid development of big data, Internet of Things and various other new technologies. Meanwhile, the gap between academia and industry has become one of the major concerns in the operations research society, since good research ideas do not always guarantee impactful (social or economical) results in practice. Hence, both industry and academia are motivated to seek new solutions from advanced management and operation strategies.

The operations research field has made significant contributions to addressing the problems faced by the maritime industry. There are several reviews which provide comprehensive summaries on the specific topics relating to the maritime logistics, such as green ports and sea logistics (Davarzani et al. 2016), container liner shipping (Tran and Haasis 2013), storage yard operations (Carlo et al. 2014a), yard management (Zhen et al. 2013), transport operations (Carlo et al. 2014b), and berth allocation and quay crane scheduling (Bierwirth and Meisel 2015).

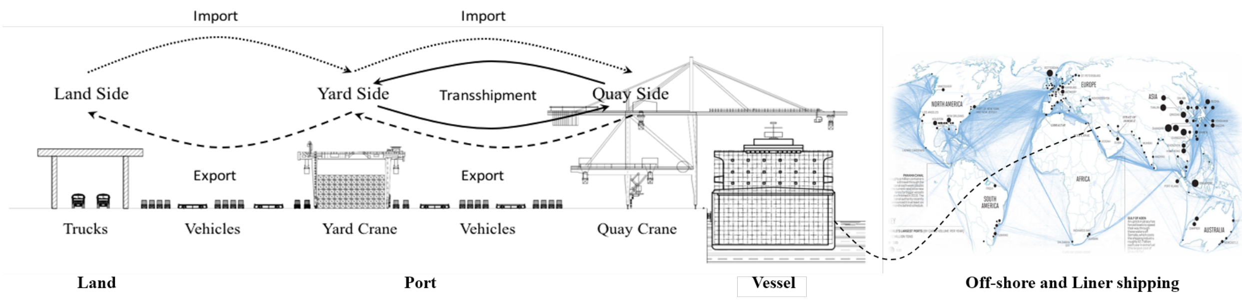

Figure 1: Illustration of the chain of maritime logistics.

Amongst these review papers, simulation and optimization are commonly used operations research techniques. However, it has been widely agreed that applying simulation or optimization alone has its drawbacks. Many have expressed their concerns that despite its usefulness in industry settings, simulation does not receive much preference from academia, and at the same time industry does not seem to readily accept the optimization approach since it is hard to obtain a closed-form analytical approach for complex systems.

From the reviews on simulation modeling (Angeloudis and Bell 2011; Dragović et al. 2017) and optimization modeling (Gharehgozli et al. 2016), we observe a trend of integrating simulation and optimization as part of the proposed method. Even though there are a number of papers cited in these reviews which contain "simulation optimization" or "simulation-based optimization" in their titles, an in-depth and systematic summary on the integration of simulation and optimization is absent, which is the motivation for writing this paper.

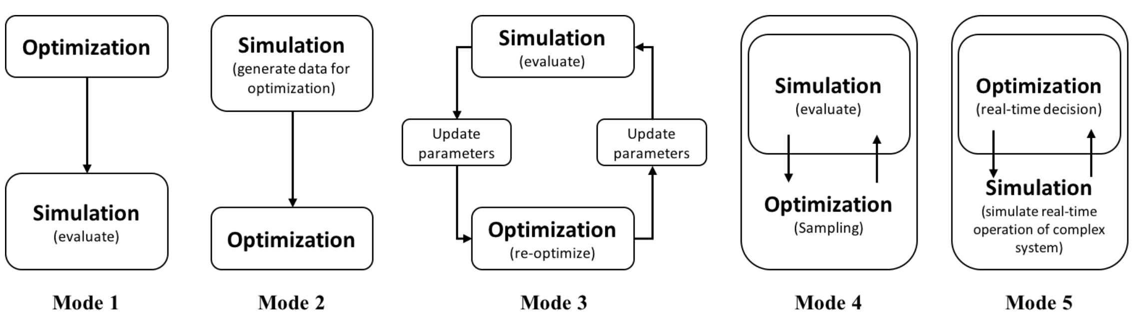

Figure 2: The five proposed modes of integrating simulation and optimization.

Table 1: Comparisons for the five proposed modes of integrating simulation and optimization.

	Output Evaluation	Input Generation	Interaction	Real-time Support
Mode 1	√			
Mode 2		√		
Mode 3	√	√	√	
Mode 4	√		√	
Mode 5	√	√	√	√

Based on our understanding of the 51 papers which we have reviewed, we categorized them into five modes of integrating simulation and optimization, as shown in Figure 2. Table 1 presents the differences and similarities between these modes:

- Mode 1: Simulation model is used to process the output of an optimization problem, which includes evaluating the results or providing a form of benchmark.
- Mode 2: Simulation is utilized to provide inputs used in the optimization problem, including the generation of an initial solution or initialization of parameters.
- Mode 3: Simulation and optimization are executed iteratively to update the respective parameters and are often run repetitively until the terminating condition is met.
- Mode 4: Simulation is used to evaluate the solution while the optimization algorithm samples or searches for the optimal solution.
- Mode 5: Simulation is utilized to simulate the operation of the complex systems and optimization is triggered by the simulation model to provide the decisions used during the simulation run.

The papers were sourced from Google Scholar with the keywords since year 2010: "maritime", "container terminal", "port operation", "gate operation", "shipping", "simulation optimization", and "simulation-based optimization". Table 2 presents the categorization of the reviewed papers according to the maritime operations for each proposed mode.

Table 2: Categorization of reviewed papers by the five proposed modes and maritime operations.

	Gate	**Port**		**Vessel**
Mode 1		Angeloudis and Bell (2010) Tang et al. (2014) Zehendner and Feillet (2014) Zehendner et al. (2015)	Wu et al. (2015) Fischer et al. (2016) Jiang et al. (2018)	
Mode 2		Zhang et al. (2014) Zhou et al. (2017) Gharehgozli and Zaerpour (2018)		Fagerholt et al. (2010) Long et al. (2012) Long et al. (2015)
Mode 3	Kulkarni et al. (2017)	Chang et al. (2010) Guo and Huang (2012)	He et al. (2013)	
Mode 4		Legato et al. (2010) Legato et al. (2014) Do et al. (2014) He et al. (2015)	Cordeau et al. (2015) Ursavas (2015) Zeng et al. (2015) Li et al. (2017)	Song et al. (2015)
Mode 5		Arango et al. (2011) Tang et al. (2014) Kavakeb et al. (2015)	Gharehgozli et al. (2017) Speer and Fischer (2017)	Halvorsen-Weare et al. (2013)

In the following sections, detailed reviews on each mode will be carried out from Section 2 to Section 5. Section 6 shares the challenges and opportunities of the future maritime logistics, and how the integration of simulation and optimization could contribute to the maritime industry.

2 SIMULATION-SUPPORTED OPTIMIZATION

Despite the popularity of optimization studies in maritime logistics, the accuracy of the models and practicality of the solutions are often questioned. For Modes 1 and 2, optimization techniques are mainly used to get the optimal solution. Optimization is also an effective tool for modeling complex systems with strong uncertainties. In this context, simulation has been a popular implementation that provides the input for the optimization model or processes the output from the optimization model. Since the dependencies between simulation and optimization in these two modes are not strong (which is to say that the simulation is dispensable to the optimization), we refer to Modes 1 and 2 as "simulation-supported optimization".

2.1 Simulation for Output

There are various ways that simulation can be employed to process the output of the optimization model. For example, simulation can be used to (1) check the feasibility of the optimal solution, (2) validate tactical level decisions in the operation level environment with stochasticity, and (3) compare the optimal solution with other strategies. This appears to be the most-common practice in operations research across various fields of studies, and there are numerous publications which adopt this mode. Due to the page limit, only the recent publications in the maritime logistics were reviewed.

Under this mode, the papers reviewed dealt with the problems faced by the port operation. Angeloudis and Bell (2010) studied job assignments for automated guided vehicles and developed a flexible dispatching algorithm, which was compared with other algorithms in the simulation. Zehendner and Feillet (2014) developed an optimization model for a truck appointment system to reduce the overall delays at the terminal, and a simulation model was employed to validate the results obtained by the optimization model. Fischer et al. (2016) developed a mathematical model of fleet deployment with several strategies for disruption management. The simulation was then developed to evaluate different strategies, i.e., the output of the model. Jiang et al. (2018) studied the multi-resource dispatching and scheduling problem of a conceptual wharf-side container delivering system. The solutions of the optimization problem were compared with two intuitive strategies on the total operation time through simulation.

The yard management problem was studied by Tang et al. (2014) who looked into the container stacking and reshuffling problem in a bay and developed several algorithms. A simulation model was utilized to test the performance of the proposed algorithms in a static environment. The tactical level allocation problem of straddle carriers was addressed by Zehendner et al. (2015). The problem was formulated as a deterministic optimization model, and was then validated at an operational level in a stochastic environment via simulation. In another study, Wu et al. (2015) investigated the multiple yard crane scheduling problem within a generic yard block considering the operational restrictions, and simulation runs validated the robustness and stability of the proposed algorithm.

To further enhance the efficiency of the simulation in validating and comparing the optimal decisions, variance reduction techniques can be incorporated into the simulation models. In addition, ranking and selection procedures can also be adopted to determine the allocation of the simulation budget for the evaluation of different candidate solutions so that the best solution can be identified with a high probability.

2.2 Simulation for Input

Due to the uncertain nature of real-world problems, and in cases where the system of interest does not even physically exist, it is often difficult to obtain or estimate the input values for the optimization problem. As a practical approach, simulations are commonly used to simulate complex systems and output data as initial solutions or parameters to the optimization problem.

The following papers employed the "simulation for input" approach on port operations problems. Zhang et al. (2014) developed dynamic programming models for the bay stacking problem in the container block, and adopted an approximate dynamic programming method – the roll out algorithm. The essence of the algorithm is to utilize the simulation and function approximation to replace the cost-to-go function, such as the objective function which minimizes the total punishment. Zhou et al. (2017) developed a storage allocation model for a conceptual yard-side container handling system. Since the system is still a prototype, simulation was needed to understand the performance in terms of handling capacity and relevant impact factors. The study also approximated the capacity function using sufficient simulation outputs and applied the approximated function as part of the optimization model. Gharehgozli and Zaerpour (2018) studied the container stacking problem and developed a stacking heuristic to reduce the retrieval time. Due to the difficulty of obtaining real data from the terminal operators, the authors used simulation to generate various data points to perform sensitivity analysis on the proposed method.

There were also studies on vessel operations utilizing this mode, such as the paper by Fagerholt et al. (2010), who proposed a decision support system that can deal with a large number of strategic planning problems in maritime transportation. Such a strategic-level problem includes the analysis of long-term contracts and the optimal fleet for a certain market situation. A Monte Carlo simulation method is used to generate a number of scenarios which might represent the real case, and a solver is developed to find the optimal decisions to a series of short-term routing and scheduling problems for different scenarios and a rolling time horizon. Then, the sample averages of the simulation and optimization results are analyzed to evaluate each strategic decision. Long et al. (2012) proposed a two-stage stochastic programming model based on the sample average approximation (SAA) to minimize the expected operational cost for the empty container repositioning (ECR) problem. A large number of scenarios considering different combinations of demand, supply, ship weight capacity, and ship space capacity, are randomly generated from a pre-specificed simulation model. This ECR problem was further examined by Long et al. (2015) who developed two methods to further improve the efficiency of the previous SAA method. First, a Latin hypercube design and a supersaturated design were introduced to reduce the number of scenarios and maintain an acceptable approximation to the true underlying expected objective. Second, several non-independent and identically distributed sampling methods are adopted with the numerical experiments demonstrating their superior performance.

Apart from the above literature, one recent trend of the "simulation for input" mode is to consider the uncertainties of the input parameters for either the simulation or the optimization model itself. Therefore, there is a growing interest on risk-aware approaches and the generation of representative inputs to these types of problems. For some recent theoretical papers on input uncertainty, one can refer to Zhou and Xie (2015), Gao et al. (2016), Hong et al. (2016), Lam (2016), and Liu et al. (2017).

3 SIMULATION OPTIMIZATION ITERATION

Whenever the simulation is used to provide the initial solution or to evaluate the result of an optimization problem, a question worth asking is if the result of the optimization or simulation can be returned to the other model to improve its output. In some of the reviewed papers, the proposed methods use the output of the simulation as the input for optimization and then utilize optimization to generate the next inputs for the simulation model. Since the simulation and optimization models are solved iteratively, we name this method as "simulation optimization iteration" (Mode 3).

Under a multi-lane gate system, Kulkarni et al. (2017) applied the simulation optimization iteration to reduce the total gate operating time. A simulation model is employed to evaluate the system performance, in terms of the average time in the gate system for all vehicles, under a certain gate operating schedule. The optimization model then determines the operation schedules for each lane and minimizes the total lane operating time. The system performance in the simulation model is used as parameter for optimization.

Looking at the port operations, Chang et al. (2010) focused on the reduction of energy consumption in a container terminal by dealing with an integrated berth allocation and quay crane assignment problem via adopting the simulation optimization iteration approach. Optimization was carried out using a combination of the proposed heuristics algorithm, which is designed to generate a feasible initial solution, and a parallel genetic algorithm. The simulation model will perform a gene repair if required, and evaluate the solution based on the objective function, which is aimed at minimizing the energy consumption. Guo and Huang (2012) developed a hierarchical yard crane workload management scheme with time partitioning and space partitioning algorithms. The scheme is implemented using the simulation optimization iteration approach, whereby the simulation module is firstly used to provide predicted vehicle arrivals for the partitioning algorithm to produce a partitioning plan. The simulation model then takes the partitioning plan and evaluates the job waiting time incurred in different partitioning plans. Under the improved simulation optimization iteration, the optimization algorithm generates candidate partitioning plans for the simulation module to provide the lower bounds of the job waiting time, before the plan with the smallest lower bound is chosen. He et al. (2013) studied the approach of sharing internal trucks for multiple container terminals in a large port. The objective function is aimed at minimizing the overflowed workload and transfer costs. The simulation optimization iteration approach used in this study is based on a genetic algorithm as its optimization module. The simulation model is designed with a rolling-horizon approach, and is used for evaluation and repair of infeasible schedules.

It should be noted that the result of Mode 3 is not guaranteed to be optimal. Since the simulation is a black-box and each iteration will only evaluate one scenario, such as the lane operation schedule, the performance of the result may depend on the number of iterations and the quality of the initial solution.

4 SIMULATION-BASED OPTIMIZATION

Unlike the "simulation optimization iteration" (Mode 3), in this "simulation-based optimization" (Mode 4), the simulation model is used to evaluate the performance of the system for a given configuration, while the optimization algorithm explores alternative configurations in the solution space and identifies the optimal setting. In fact, many papers using "simulation optimization", "simulation-based optimization", and "optimization via simulation" can be categorized to this mode. For a comprehensive literature review on the recent development of algorithms and applications for simulation-based optimization, see Pasupathy and Ghosh (2013), Amaran et al. (2014), Chau et al. (2014), Xu et al. (2015), and Fu (2016).

There were numerous researches on the port operation problems under this mode. Do et al. (2014) proposed a new truck arrival control method to reduce emissions from waiting trucks and related crane operations. A discrete event simulation model is constructed to estimate total truck waiting times and crane moving distance, and then a genetic algorithm is applied to find the optimal solutions.

Zeng et al. (2015) investigated the quay crane dual-cycling scheduling problem. Firstly, they employed a bi-level genetic algorithm to search for the optimal operation sequence of quay cranes and the stowage plan for outbound containers. Then a simulation module is implemented to evaluate the total operation time of this schedule. If the total operation time does not satisfy the stopping criterion, a new set of schedules will be generated by the bi-level genetic algorithm until the stopping condition is met. He et al. (2015) addressed the yard crane scheduling problem with consideration of energy-savings by integrating a simulation model with an optimization algorithm. The simulation model is used to evaluate the solution based on the completion delay and energy consumptions, while the optimization algorithm searches the solutions based on the simulation results. The optimization algorithm utilizes a genetic algorithm for global search and a particle swarm optimization for local search.

The simulation-based optimization approach was adopted by Cordeau et al. (2015) to optimize the housekeeping operation of a container transshipment terminal. This housekeeping operation aims at facilitating the discharging and loading operations and mitigating the congestions in the terminal. Two meta-heuristics, including simulated annealing and tabu search, embedded in a discrete event simulation model that evaluates the congestion and throughput of the port, are used to find the optimal vehicle schedules. Legato et al. (2010) investigated the optimal assignment and scheduling problem for a set of discharging and loading jobs involving a single container ship, multiple quay cranes and vehicles. A simulation model was constructed to evaluate the efficiency of port operation, and the simulated observations are used to guide the simulated annealing search process to find the optimal discharge and loading decisions.

In a separate study, Legato et al. (2014) studied the berth allocation problem and developed a simulation-based optimization framework. Under the proposed framework, the tactical level decision is first generated using a beam search algorithm on an MIP with the same objective function as the evaluation returned by the simulation model, which captures the costs of delayed berthing and non-optimal berthing positions. In this case, the simulation optimization iteration is also built-in to tune the decision at the operational level, which uses the simulated annealing algorithm to carry out a global search by generating a neighboring solution and the simulation model to evaluate the given solution. The optimization component in the simulation-based optimization also employs a non-standard ranking and selection procedure to optimize the number of simulation runs. In another research, Ursavas (2015) aimed at providing a decision support system for the terminal managers to tackle the problem of berth allocation to vessels with different priorities. A dynamic discrete event simulation model was built to evaluate the efficiency of the terminal operation given the berth allocation derived from the scatter search algorithm. The simulation outputs are further utilized by the optimization algorithm to find new sets of decision variables (i.e., berth allocation) to be evaluated by the simulation model.

Also, Li et al. (2017) integrated several advanced simulation-based optimization algorithms into a decision-making process to solve the capacity planning problem for mega container terminals. Specifically, this planning problem is formulated as a large-scale multi-objective problem with multi-fidelity simulation models, which aims at determining the optimal number of vehicles, quay cranes, and yard cranes such that the berth-on-arrivals rate could be maximized.

A problem on the vessel operations was investigated by Song et al. (2015), who studied the operational-level planning problem with uncertain port time to find the Pareto optimal combinations of the number of ships, the planned maximum sailing speed, and the liner service schedule considering three objectives including the expected cost, the service reliability, and the shipping emission. To solve this challenge, an improved version of the non-dominated sorting genetic algorithm (NSGA II) is adopted to search for the optimal solution, while a simulation model is used to measure the three objectives for the given solutions.

One main challenge for the “simulation-based optimization” is the efficient identification of the optimal solutions from a large search space, especially when the underlying problem is not well structured. A good balance between the exploration and exploitation should be maintained to attain a desired level of optimality and efficiency from the optimization algorithm. One possible approach to further enhance the algorithm is through the adoption of simulation models with different fidelities and the identification of their relationship so as to reduce both the simulation and optimization effort (see Xu et al. 2016).

5 OPTIMIZATION-EMBEDDED SIMULATION

The concept of the “optimization-embedded simulation” (Mode 5) approach is essentially to use simulation as a digital copy of the real-world system, and utilizing optimization algorithms to make decisions and drive the digital system. Unlike Mode 3 and 4, the “optimization-embedded simulation” method does not require the iterative evaluation of alternative solutions by the simulation model. Whereas, it involves the modeling of intelligent agents that could learn from the consecutive simulation results in a single run, and improve on the operational policies that are embedded in each of the agents while the simulation is running. From another perspective, it can be seen as a way to simulate the optimization procedure in a dynamic and interactive manner.

Figure 3 shows how the optimization interacts with the simulation: while the simulation is running, specific triggers will call the optimization model to make decisions. The trigger can be an event, a time point, or any other form of programmed triggers.

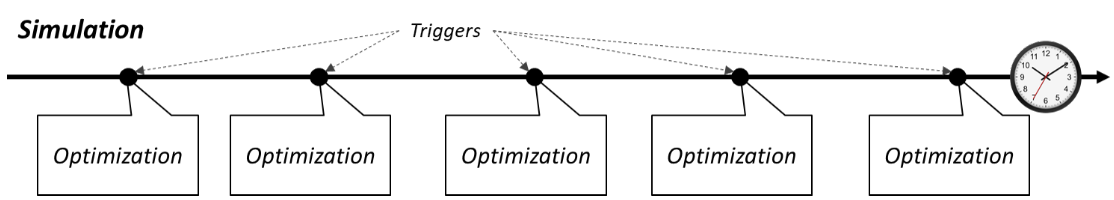

Figure 3: Illustration of optimization-embedded simulation approach.

Under the port operations, Arango et al. (2011) studied the berth allocation problem to minimize the total service time. A detailed simulation model was developed to simulate the berth operation, and whenever a new ship was created, it would trigger the optimization model to reallocate the berths. Looking at the container stacking and reshuffling problem, Tang et al. (2014) proposed algorithms that were tested in the dynamic environment using the simulation, whereby the algorithms make reshuffling and stacking decisions when retrieving or stacking a new container. In another research, a simulation model was developed by Gharehgozli et al. (2017) to study the effect of a handshake area on the performance of twin yard cranes. Since there are many complex decisions that have to be made during the simulation, such as the crane scheduling problem, several heuristics were applied to handle these sub-problems. Speer and Fischer (2017) studied the real-time yard crane scheduling problem and developed a branch-and-bound algorithm to repeatedly re-plan a limited number of known jobs. To evaluate the algorithm performance in the real-time environment, the simulation models were developed for four different automated crane systems. Kavakeb et al. (2015) utilized a discrete event simulation model to simulate micro-level port activities. Since the coordination between terminal equipment such as quay crane and vehicle is critical to the overall performance, a sophisticated dynamic vehicle dispatching strategy is "plugged" into the simulation model. The simulation model triggers the scheduler frequently and passes the required input parameters to the scheduler, while the scheduler will provide the optimal schedules for the vehicles that are simulated in the simulation model. Halvorsen-Weare et al. (2013) considered a liquified natural gas vessel fleet routing and scheduling problem where the output data are more robust with respect to uncertainty, such as the sailing times due to changing weather conditions. The simulation model developed would trigger the re-optimization of the schedule when a when a specified conditions occurs.

Note that the challenge of implementing the "optimization-embedded simulation" lies in the computational efficiency. Since the simulation is a digital copy of the real-world system, it is not practical to make the simulation or the real system pause and wait for the optimization to solve for a long time. Hence the optimization algorithm has to be very efficient, either by the utilization of heuristics, or solving a small-scale model with commercial software such as CPLEX.

6 FUTURE OF MARITIME LOGISTICS

The previous sections provided a comprehensive literature review on the recent papers in maritime logistics that integrated simulation and optimization. Five modes of integration have been identified including simulation-supported optimization (simulation for output/input), simulation optimization iteration, simulation-based optimization and optimization-embedded simulation. The reviewed literature has shown how integration of simulation and optimization can provide practical solutions to the current problems. However, new challenges and opportunities are constantly appearing in the field of maritime logistics, which will be further discussed below.

6.1 Future Challenges in Maritime Logistics

New technologies are emerging every year in maritime logistics. For example, drones have been implemented for terminal surveillance, and automation and autonomous technology have been applied to AGVs and automated cranes, which helped to upgrade conventional manual equipment into semi-automatic equipments. Also, the Internet of Things (IoT) technology, which includes digital sensors, can be found almost everywhere, such as on the containers, vehicles, cranes, and vessels. These new technologies add a multitude of data sources on top of the Terminal Operating System (TOS). Thus, the question on how to effectively utilize this massive amount of data to improve the port efficiency, capacity, safety, and profitability is an interesting one which can be explored.

In order to evaluate these emerging technologies, a digital twin of the maritime system is needed. Digital twin refers to a digital replica of the physical assets, processes, and systems which can be used for various purposes. Simulation has proven to be an effective tool to model a complex system with strong uncertainty, and can be utilized as a digital twin, which not only replays the historical events, but also tests "what-if" scenarios. Using the historical data, simulation can be employed to test different strategies or layouts for systems, while optimization methods can be used to further improve the operation efficiency of the terminals. Therefore, potential integration of simulation and optimization in Mode 1-4 can be applied to solve a similar type of problems in an offline manner. In addition, the development of emerging technologies mentioned above will further support the connectivity between the real-world system with its digital twin. For example, the simulation model can directly read real-time data from IoT sensors, and simulate some "what-if" scenarios. Furthermore, the digital twin of the terminal can also be an interface between different emulators, such as a TOS emulator that is more precise than a simulation model on TOS. In this case, methods in Mode 5 might be appropriate to solve this type of problem in an online manner.

6.2 Opportunities with Simulation Analytics

Even though the digital twin can simulate the real-world system in real-time, it may not be able to assist in making real-time decisions. In the context of real-time decision making, both simulation and optimization procedures are still computationally expensive. Future research can be directed to filling the existing gaps by re-engineering the simulation-based analytics and enable it to carry out real-time decision making.

Under the simulation analytics framework, simulation is used to generate "what-if" scenarios that might happen in the future, while the optimization is employed to find the best decisions for that particular scenario. Even if advanced algorithms can improve the speed of the simulation optimization process, the efficiency gain is far less than the requirement for sub-seconds or sub-milliseconds real-time decision making. Therefore, learning models of either statistical meta-modeling or machine learning methods should be developed to identify the relationship between scenarios and the respective best decision. In contrast to the conventional simulation-based decision tool, the proposed method decouples the process of decision-making from the process of optimization, so that any delay during decision-making will not occur due to the time spent on the simulation-based optimization.

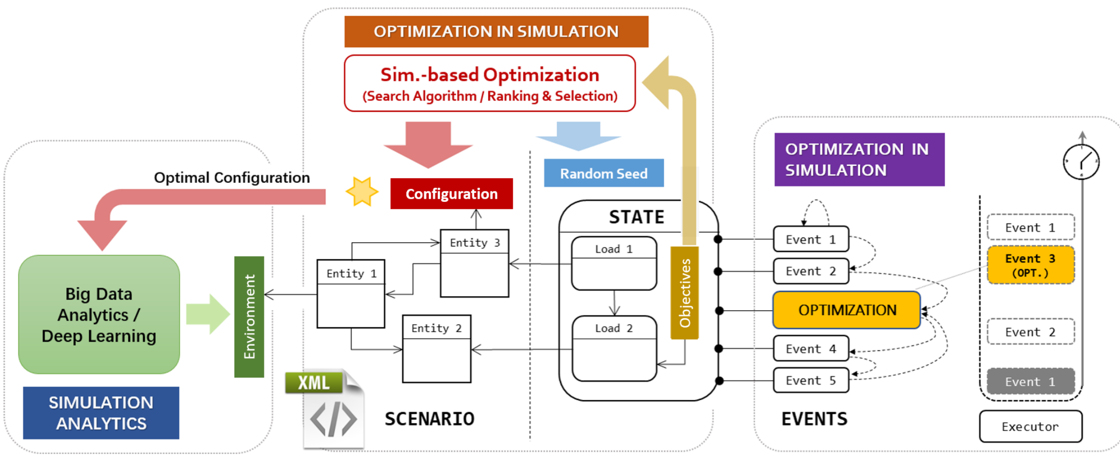

Figure 4: Illustration of O^{2}DES.Net framework.

To claim this improvement opportunity, the object-oriented simulation modeling paradigm, e.g., O^{2}DES.Net (Li et al. 2015) as illustrated in Figure 4, is critical due to its capability of 1) seamless integration of discrete event simulation modeling, optimization algorithms, and other analytical tools; and 2) flexible model decomposition or modularization for large-scale complex systems.

ACKNOWLEDGMENTS

This research has been made possible with the funding support from Singapore Maritime Institute.

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