Proceedings of the 21st International Conference on Modelling and Applied Simulation (MAS), 005
19th International Multidisciplinary Modeling & Simulation Multiconference

2724-0037 © 2022 The Authors.
doi: 10.46354/i3m.2022.mas.005

A generic framework for simulation-based optimization using high-level architecture

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Abstract

Simulation optimization has been the focus of numerous studies in the area of operations research, with many studies integrating optimization algorithms with simulation models to improve decision-making. Although useful, these studies target particular applications and are built for specific problems. As such, their interoperability and reusability remain limited, with the incorporation of new optimization components or simulation models requiring a complete redesign of the entire simulation-optimization system. To enhance system flexibility, a novel, generic framework that can be easily applied to any simulation model and can accompany any optimization algorithm is proposed. Using high-level architecture (HLA), the proposed framework is able to provide a communication channel between a simulation model and an optimization algorithm, facilitating the reuse of system components for different problems. A case study was used to demonstrate the functionality of the proposed framework. Flexibility of the system was demonstrated by combining a simulation model (discrete-event simulation) with an optimization algorithm (genetic algorithm).

Keywords: High-level architecture; optimization; distributed simulation; genetic algorithm; metaheuristic methods

1. Introduction

Successful decision-making requires a thorough understanding of a system's underlying behavior. As the complexity, uncertainty, and constraints of a system expand, decision-makers must increasingly rely on computational power for decision-making. For decades, simulation has allowed researchers and decision-makers to analyze and evaluate conditions of complex systems that would otherwise be impossible to investigate (Shannon 1998). By mimicking the overall logic of a system's various activities, computer simulation models allow analysts to simulate a specific system and to configure the environmental conditions and the resources required to achieve system requirements (AbouRizk, 2010). Computer simulation, therefore, has become a fundamental component of many decision-support systems, remaining one of the most powerful techniques for designing and analyzing complex processes and systems (Azadivar, 1999; Shannon, 1998).

Simulation is often used to identify ideal combinations of model specifications (i.e., input parameters and/or statistical assumptions) that lead to optimal system performance (April et al., 2003), which can be accomplished using one of two possible approaches (Cheng et al., 2006). The first establishes a fixed simulation model and examines the impact of changing a variable's input values (e.g., task duration, different resource combinations) on system outputs (i.e., sensitivity analysis) (Cheng et al., 2005). The second approach involves testing each possible scheme of the model by building various simulation components and evaluating the performance of all resource combinations in each modeling scheme. Various performance outcomes (e.g., cost and time) derived for each experimental scenario are then compared and used for decision-support (Cheng & Yan, 2009).

The use of simulation to identify ideal system conditions, however, becomes limited as system complexity expands. Increasing the number of system resources will expand the number of possible resource combinations, in turn resulting in an exponential rise in the number of experimental scenarios (i.e., simulation alternatives) that must be evaluated. Additional techniques capable of reducing the time and effort required to identify ideal system conditions have, consequently, been developed (Cheng & Yan, 2009). Several research studies have investigated the integration of simulation models with metaheuristic algorithms (e.g., genetic algorithms) to solve optimization problems, where system resources are input as optimization decision variables (Salimi et al., 2018) into metaheuristic algorithms (Alshibani & Moselhi, 2012; Cheng et al., 2005, 2006; Cheng & Yan, 2009; Marzouk & Moselhi, 2004; RazaviAlavi & AbouRizk, 2017; Salimi et al., 2018; Zhang & Li, 2004).

Although an improvement over previous methods, such as those developed by Salimi et al. (2018), many hybrid simulation-optimization models are specific in nature and built to solve particular problems. As a consequence, these hybrid models are inflexible, often requiring a complete redesign of the model if changes to either the optimization or simulation components are required. The inability to easily modify models in response to real system changes has considerably hindered the practical application of simulation-based optimization, particularly in sectors where analysts' knowledge of simulation is limited. A flexible, generic framework that can be applied to any simulation problem, however, has yet to be developed.

With the aim of facilitating the use of hybrid simulation in practice, this study has developed a novel, generic framework capable of improving the flexibility of traditional hybrid simulation-optimization models. Using a high-level architecture (HLA)-based approach, the proposed framework makes use of a newly-developed federation object model (FOM) to facilitate information exchange between separate simulation and optimization federates (i.e., components). Simulation models or optimization algorithms are easily updated or changed without the need to redesign both system components which facilitates testing different combinations.

2. Literature review

2.1. Simulation optimization

A typical optimization problem has a mathematical objective function and constraints used to formulate and evaluate candidate solutions. However, certain complex systems cannot be modeled mathematically. In these instances, optimization can be achieved by replacing the objective function with a simulation model. This results in a hybrid simulation-optimization model that is capable of finding "the best input variable values from among all possibilities without explicitly evaluating each possibility" (Carson & Maria, 1997).

Effective in applications with multiple criteria as well as non-parametric objectives, simulation optimization has been extensively applied to assist with decision-making across a variety of engineering fields, including transportation (Chong & Osorio, 2017; Osorio & Bierlaire, 2013; Osorio & Chong, 2015; Osorio & Selvam, 2017; Xi et al., 2013), agriculture (Diaz & Perez, 2000; Gates et al., 1992), reservoir operation (Neelakantan & Pundarikanthan, 2000; Rani & Moreira, 2010; Simonovic, 1992), civil and environmental engineering (Ayvaz & Karahan, 2008; Fikar et al., 2018; Gaur et al., 2011; Shin et al., 2011), and project management (Cheng et al., 2005, 2006; Lu et al., 2018; Zhang & Li, 2004).

2.2. High-level architecture

Distributed simulation, also known as the High Level Architecture (HLA) standard (IEEE, 2010b), was designed to enhance system operability by facilitating the integration of autonomous simulation models and other analytical components into a single, distributed simulation system. The high-level architecture standard is comprised of three elements. The first, a run-time infrastructure (RTI), ensures synchronicity between various system components and manages the exchange of information between them. The second are the individual components (e.g., simulation models, optimization algorithms, and databases), hereafter referred to as federates. The final element is a federation object model (FOM), which stipulates which information should be shared and exchanged between the federates. By facilitating communication and coordination between individual federates, HLA reduces the time and cost required to develop a synthetic environment for new purposes, as each federate can be modified without the need to redesign all components of the system. Readers are referred to IEEE (2010b, 2010a) for a detailed review of the HLA standard.

The HLA standard has been used to develop distributed simulation models across a number of sectors, including transportation (Zacharewicz et al., 2011), supply chain (Jian et al., 2017), and disaster management (Hwang et al., 2016). In the construction domain, for example, HLA has been used to develop a variety of decision-support systems. Azimi and colleagues (2011) applied HLA to integrate different types of simulation models to improve real-time decision making in steel fabrication projects. Their model resulted in the generation of a graphical representation of the steel structure, allowing project managers to easily visualize which portions of the structure were over/under budget or behind/ahead of schedule. An HLA-based approach was also used by Alvanchi and colleagues (2012) to combine discrete-event simulation (DES) with system dynamic models to evaluate productivity in construction operations. Also, Al-Bataineh (2013) used HLA to simulate tunneling operations for rapid scenario-based planning. Although HLA has been used to integrate simulation models with each other as well as with a number of additional components, the use of HLA to integrate simulation models with optimization algorithms has yet to be reported in literature. Indeed, an HLA-based framework for generating flexible simulation-based optimization models has yet to be developed.

3. Methodology

This study has developed a novel, HLA-based framework for increasing the flexibility and reusability of simulation-based optimization models. The proposed framework neither presumes a specific simulation technique nor does it model a specific optimization algorithm. Rather, it provides a generic communication proxy that works with any optimization algorithm, any simulation technique, or any combination thereof. At the core of the framework is an RTI that provides standard HLA services, including publishing, subscription, and simulation-time management. The RTI creates a simulation federation that contains two federates. The optimization federate encapsulates an optimization algorithm, and the simulation federate encapsulates a simulation model. The two federates communicate with one another based on a predefined federation object model (FOM). The FOM defines two interaction classes: (1) parameters (time-stamped), which contain a variable array parameter, and (2) results (time-stamped), which contain a float variable.

The communication workflow is illustrated in **Figure 1** and detailed as follows. It is important to note that the communication flow does not rely on the HLA's time-stamped messages, but on the "next message request."

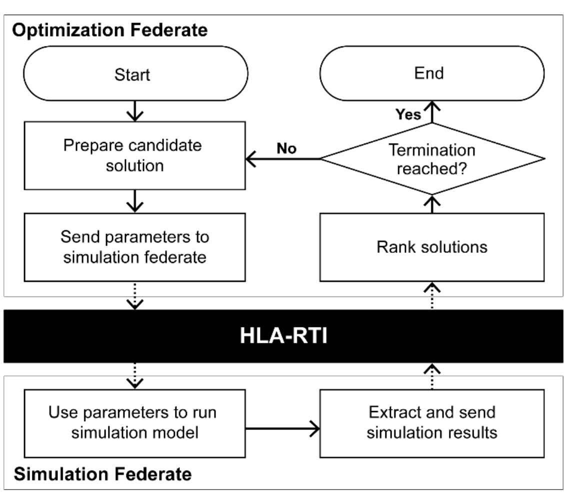

Figure 1. Proposed framework and communication workflow; dotted lines represent communication between federates and the RTI

4. Case study

To demonstrate the full functionality of the framework, the proposed approach was applied to a real-world case study. Many real-world problems are non-deterministic polynomial-time hard (NP-hard) problems, which require the use of simulation models to solve. To demonstrate the ability of the framework to propose solutions for complex, NP-hard problems, the case study presented herein describes a problem incapable of being modeled using closed-form mathematical equations. This is in contrast to many of the studies described in simulation-optimization literature, which focus on simple, deterministic problems with exact solutions.

4.1. Snow removal

A snow removal project, based in Alberta, Canada, was used to demonstrate the functionality of the proposed approach. A DES model and a genetic algorithm optimization model were input into the framework to optimize the fleet size for snow removal operations. Snow removal projects are often outsourced to contractors. Contractors are provided with a map of the contract maintenance area (CMA), which illustrates the boundaries and scope of the CMA as well as truck shop locations (i.e., depots). A request for proposal (RFP), which mandates the maximum snow accumulation amount, is also provided. Contractors must then develop their own fleet size and truck allocation plans to ensure a project is completed in a cost- and time-efficient manner while achieving performance requirements mandated by the RFP (Jafari et al., 2018). Project efficiency can increase considerably if resources are optimized.

This project involves the removal of snow on a major, bi-directional highway with three traffic lanes in each direction and two depot locations. The highway is divided into four sections: AB, BC, BA, and CB. Shop 1 is located at one end of the highway (near point A), and Shop 2 is located at the midpoint of the highway (near point B). Accordingly, Section AB is assigned to Shop 1, while sections BA, BC, and CB are assigned to Shop 2. Road sections, section length, and section priority, as mandated in the RFP, are summarized in **Table 1**; the total accumulation of snow cannot exceed 2 centimeters for class A+ roads. One loader is available at each shop for loading sand. A toe-plow is attached to one truck to plow two lanes, and a single truck is assigned to plow the third lane. Plowing and sanding operations occur simultaneously. Trucks are loaded with sand at their assigned shop. Travel speed from the shop location to the road is triangularly distributed with most-likely, minimum, and maximum values of 40, 35, and 45 km/h, respectively. Similarly, plow speed is triangularly distributed with values of 50, 40, and 60 km/h, respectively.

A DES model was built using the aforementioned configurations. The simulation model was developed using an in-house simulation engine, *Simphony.NET* (AbouRizk et al., 2016).

Table 1. Road specifications

Road	Route	Length (km)	Class	Priority[a]
1	AB	20	A+	4
2	BC	17	A+	4
3	BA	20	A+	4
4	CB	17	A+	4

[a]Based on traffic volume

The time period with the greatest precipitation per hour over the last 10 years was chosen for optimization, as the fleet size optimized under these conditions is expected to meet RFP requirements for a majority of snowfall events. *Darkskylib*, an open-source python wrapper for the DarkSky API (Kubis, 2016), was used to extract weather data for Calgary, Alberta, Canada. Three weather stations were positioned along the highway, and precipitation levels recorded by each station were compared over a 5-year period. Because differences in precipitation levels along the highway were minimal (**Figure 2**), one weather station (Location 2) was selected for input into the model.

Peak snowfall per hour was determined to have occurred on February 13, 2018, where 20 cm of snow accumulated on the road over 5 hours with an average hourly accumulation of 4 cm. Maximum snowfall mandated by the RFP is 2 cm, requiring plowing to be performed every half hour to meet requirements. The objective function was designed to minimize the inter-arrival time of trucks so that each segment is cleared within approximately 30 minutes. Here, the optimization federate takes the simulation result (i.e., mean inter-arrival time) from the DES model, alters the fleet size, and returns the updated fleet size to the simulation model as input. As the optimization algorithm analyzes various fleet sizes, the optimal solution is approached.

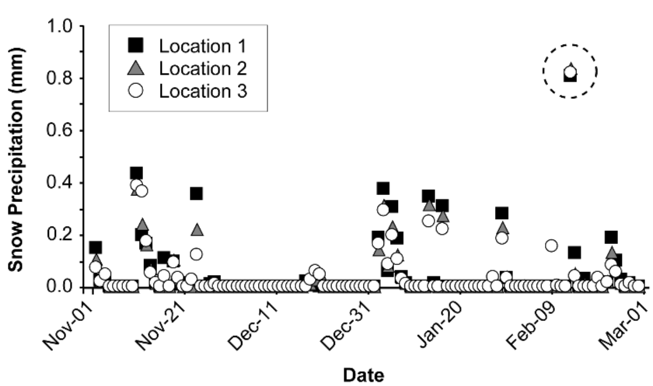

Figure 2. Precipitation at weather station location 1 (squares), 2 (triangles), and 3 (circles) from November 1, 2017 through March 1, 2018; peak snowfall event indicated by dashed circle

5. Results and discussion

The model was run with various resource combinations, as detailed in Table 2. Results obtained using the framework are presented in **Table 2** and illustrated in **Figure 3**. Additional loaders (Scenario 4 vs. Scenario 3) did not have a notable impact on overall performance, reducing mean inter-arrival time by a maximum of 5.4 minutes (Scenario 4: BC). Additional trucks, however, had a considerable impact on performance (Scenario 1 vs. Scenario 7), reducing mean inter-arrival time by 17.8 minutes for Section AB and at least 122 minutes for Sections BA, BC, and CB. Improved performance was observed up to a maximum of 10 and 4 trucks for Shops 1 and 2, respectively (Scenario 7). Further increasing the number of trucks (Scenario 8 vs. Scenario 7) did not have a notable impact on performance, reducing mean inter-arrival time by less than 2.0 minutes. The results demonstrate that the framework is capable of coupling simulation with optimization to propose reasonable solutions for industrially-relevant problems.

Table 2. Resource combination scenarios; optimized solution indicated in grey

Scenario	Shop 1		Shop 2		Mean Inter-Arrival Time (min.)			
	Trucks	Loaders	Trucks	Loaders	AB	BA	BC	CB
1	2	1	2	1	47.8	162	162	162
2	4	1	4	1	29.9	79.1	91.4	79.9
3	6	1	4	1	29.9	54.8	58.1	64.7
4	6	2	4	2	29.9	51.4	52.7	59.9
5	8	1	6	1	29.9	42.7	43.1	44.8
6	8	1	4	1	29.9	42.4	42.7	44.6
7	10	1	4	1	30.0	35.9	37.3	39.4
8	12	1	4	1	29.8	34.7	35.5	37.5

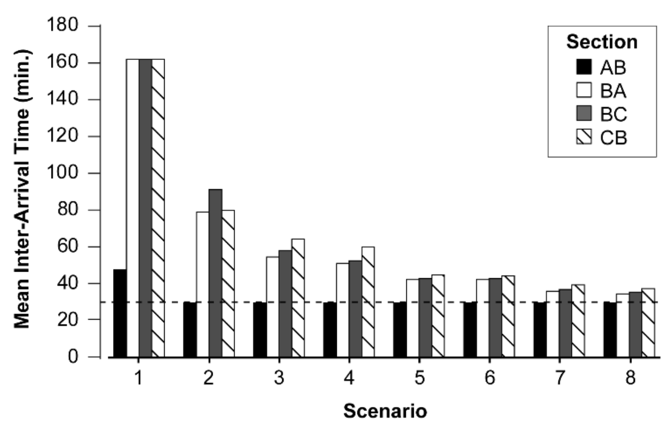

Figure 3. Mean inter-arrival time for road sections AB (solid bar), BA (white bar), BC (grey bar), or CB (hatched bar); target inter-arrival time (in minutes) indicated by dashed line

6. Conclusion

Integration of simulation and optimization within decision-support systems is essential for facilitating what-if and sensitivity analyses to identify near-optimum solutions for complex processes. Integration of the two systems was not previously feasible due to incompatibility, and researchers instead relied on custom integrations for specific problems or domains.

We developed a simulation-based optimization framework using HLA to enable practical and effective communication between simulation and optimization components. A C#-based prototype system, which improves decision-making by drastically reducing the development effort required for each practical problem, was also developed. Practicality, feasibility, and functionality of the framework and prototype were demonstrated following their application to solve an NP-hard case study. A benefit over existing hybrid simulation-based optimization approaches, the flexibility offered by the proposed method is anticipated to not only spur theoretical advancements in the field, but also to facilitate the application and use of simulation-based optimization in practice.

While the proposed method offers considerable advantages over previously developed methods the findings of this study should be interpreted in consideration of the following limitations. First, the framework uses an optimization engine to update parameters in the simulation model without changes to simulation behavior/topography. Future work investigating the ability of simulation model topography to be modified based on optimization candidate solutions has yet to be explored. Second, only discrete-event simulation was investigated here. Although it is expected that other types of simulation models (e.g., system dynamics) can be easily accommodated by the framework, their interoperability with the proposed approach should be evaluated.

Acknowledgements

This work was funded by a Collaborative Research and Development Grant from the Natural Sciences and Engineering Research Council of Canada (CRDPJ 492657). Data for the snow removal case study was generously provided by Ledcor Constructors Inc. The authors would like to thank Stephen Hague for developing code allowing HLA to be written in *Simphony.NET*.

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