A Generic Framework For Multi-Method Modeling and Simulation of Complex Systems Using Discrete Event, System Dynamics and Agent Based Approaches.

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A GENERIC FRAMEWORK FOR MULTI-METHOD MODELING AND SIMULATION OF COMPLEX SYSTEMS USING DISCRETE EVENT, SYSTEM DYNAMICS AND AGENT BASED APPROACHES

by

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ABSTRACT

Decisions about Modeling and Simulation (M&S) of Complex Systems (CS) need to be evaluated prior to implementation. Discrete Event (DE), System Dynamics (SD), and Agent Based (AB) are three different M&S approaches widely applied to enhance decision-making of complex systems. However, single type M&S approaches can face serious challenges in representing the overall multidimensional nature of CS and may result in the design of oversimplified models excluding important factors.

Conceptual frameworks are necessary to offer useful guidance for combining and/or integrating different M&S approaches. Although several hybrid M&S frameworks have been described and are currently deployed, there is limited guidance on when, why and how to combine, and/or integrate DE, SD, and AB approaches. The existing hybrid frameworks focus more on how to deal with specific problems rather than to provide a generic way of applicability to various problem situations.

The main aim of this research is to develop a generic framework for Multi-Method Modeling and Simulation of CS, which provides a practical guideline to integrated deployment or combination of DE, SD, and AB M&S methods. The key contributions of this dissertation include: (1) a meta-analysis literature review that identifies criteria and generic types of interaction relationships that are served as a basis for the development of a multi-method modeling and simulation framework; (2) a methodology and a framework that guide the user through the development of multi-method simulation models to solve CS problems; (3) an algorithm that recommends appropriate M&S method(s) based on the user selected criteria for

user defined objective(s); (4) the implementation and evaluation of multi method simulation models based on the framework's recommendation in diverse domains; and (5) the comparison of multi-method simulation models created by following the multi-method modeling and simulation framework.

It is anticipated that this research will inspire and motivate students, researchers, practitioners and decision makers engaged in M&S to become aware of the benefits of the cross-fertilization of the three key M&S methods.

This dissertation is dedicated to my family.

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CHAPTER 1: INTRODUCTION

Modeling and simulation (M&S) can be used as a decision-making tool to provide solutions to a plethora of CS problems. Discrete Event (DE), [1], System Dynamics (SD) [2], and Agent Based (AB) [3] are three different M&S methods widely applied to enhance decision-making of CS [4], [5], [6], [7]. However, analytic and traditional single type M&S methodologies can face serious challenges in representing the overall multidimensional nature of CS [8], [6]. Such CS might be composed of models that exhibit discrete and continuous behavior and may compete or collaborate, update, change and/or adapt state during simulation run time. In addition, attempts to build holistic models with one M&S method or combination of two (hybrid M&S) for CS, may result in the design of oversimplified models excluding important factors.

Conceptual frameworks are necessary to offer useful guidance for combining and/or integrating different M&S methods. Several hybrid M&S solutions and frameworks have been proposed and are currently deployed in various domains, combining and/or integrating DE and SD [9], [10], [11], [12], SD and AB [13], [14], [15], [16] DE and AB [17], [18], as well as models produced by the three M&S methods together [19], [6], [20], [21], [22], [23]. Researching the rational possibilities for combining and/or integrating methods, first requires establishing a relevant conceptual framework, justifying the reasons for using a particular M&S method(s) and then performing simulation and obtaining results [19], [24], [25], [22]. However, in the review of the literature it has been observed that this has followed an alternative order [9], [10], [13], [18]. The importance of justifying the need to integrate and/or combine M&S

approaches and that it must be conducted prior to the development phase has been mentioned before [11], [12], [19] [24], [23], [26].

In order to overcome these challenges and provide practical guidance that will allow inclusive M&S of CS, a generic conceptual framework for applying Multi-Method Modeling and Simulation (3M&S) has been developed [27]. Currently, no reported theoretical frameworks have been identified to provide practical guidance on why, when and how to concurrently deploy DE, SD, and AB M&S to form multi-method simulation models of CS problems. The proposed 3M&S framework aims to fill this gap and provides a practical guideline on how to tackle the overall simulation of CS.

1.1 Research Motivation

Given the nascent technological advancements in Modeling and Simulation (M&S) in the last decades, there is an increasing demand for a generic multi-method modeling and simulation framework and theoretical foundation to address M&S methodologies such as Discrete Event (DE), System Dynamics (SD) and Agent Based (AB), that are used to solve problems of Complex Systems (CS) in multidisciplinary domains. Decisions about CS need to be carefully evaluated prior to implementation [11], [12], [24], [23], [26]. M&S methods, such as DE [28], SD [29], and AB [30], are widely applied to enhance decision-making of CS [6], [4], [5] and can provide solutions to a plethora of CS problems.

CS may contain non-linear relationships, internal structures with diverse interconnected and interdependent components (which may compete or cooperate with each other), causal loops, hierarchical heterogeneous subsystems and various domain behavior patterns (as well as other CS features), which are usually studied by means of M&S. Analytical solutions and traditional single type M&S methodologies face serious challenges representing the overall multidimensional nature of complexity that those systems exhibit [6]. For example, CS may be subject to both detail and dynamic complexity [2], [7], [33]. Detail complexity is related to the high combinatorial complexity among various variables and attributes, while dynamic complexity corresponds to the interaction variables of the agents, entities or stocks over time (elements of DE, SD, and AB M&S) [3].

Moreover, efforts of M&S community to expand their existing M&S approaches to advance reusability, interoperability and composability of CS, are limited to their own technical domains, or remain isolated solutions [31]. Therefore, integrating and/or combining different M&S methods has been viewed as a response to current challenges in managing, designing, and assessing CS in various domains, such as in business [32], [9], [10], and healthcare organizations [21], [33], [24].

The main aim of this dissertation is the development of a generic conceptual framework for Multi-Method Modeling and Simulation of CS, which provides a practical guideline to integrated deployment or combination among DE, SD, and AB M&S methods. The term "method" in M&S refers to a general architecture for constructing a real world system to its model [6]. Accordingly, we use the term “multi-method” to refer to all the possible architectures that can be constructed for more than two M&S methods [6], [17], [25], [25] among the three M&S methods and we mean the integration and/or combination of terms and conditions considering the three M&S methods. For brevity purposes, we define Multi-Method Modeling &

Simulation as 3M&S. In this research we use the term **M**ulti-**M**ethod **M**odeling **& S**imulation, or **3M&S**, to define combination and/or integration of more than two M&S approaches.

1.2 Research Questions

Attempts to build holistic models for CS with analytical solutions, stand-alone M&S methods, or combination of two (hybrid M&S) approaches may be impractical, or result in the design of oversimplified models, excluding important factors. On the one hand, combining or integrating methodologies may provide a more inclusive way of representing and dealing with the complexity of real world. The deployment of diverse M&S approaches presents challenges due to the different criteria and philosophical approaches that satisfy each M&S method based on problem and system perspectives. Therefore, conceptual frameworks, decision support tools and theoretical foundations are necessary to offer useful guidance for combining or integrating M&S methods within multidisciplinary domains [36], [37].

Some of the key issues that problem owners deal with are related to strategic, tactical operational levels and consider micro, meso and macro organizational matters. The 3M&S framework suggests viable solutions to strategic, tactical, and operational matters, while it contributes towards a deeper understanding of CS and multidimensional problems. In addition, the 3M&S framework is directed towards building comprehensive multi-method simulation models that can accommodate different organizational levels, while identifying the differences between them in terms of scope and level of details that are preferred and applied at each level (i.e. operational level and strategic level).

Several hybrid M&S solutions and frameworks have been proposed and are currently deployed in various domains, combining DE and SD [9], [10], [24], SD and AB [13], [33], [15], DE and AB [18], [17], and the three M&S methods together [6], [20], [21]. However, there is a lack of a practical guidance to provide an understanding of how, when and why to combine, and/or integrate the three M&S approaches. Furthermore, no reported conceptual frameworks have been identified to provide practical guidance on when, why, and how to combine DE, SD, and AB M&S to form 3M&S models. The proposed 3M&S framework aims to fill this gap and provide a generic practical guideline on how to tackle the overall simulation of CS by answering the following research questions:

Q1. Why and when CS require 3M&S?

Q2. What are the interaction points among DE, SD, and AB models?

Q3. How AB, DE and SD models interact with each other to exchange information?

1.3 Research Objectives

These research questions are addressed by the following research objectives:

- **Objective 1: Develop in depth comprehension among similar and different aspects and features of the three M&S approaches (Identification of Generic Criteria for DE, SD, and AB M&S approaches).** In order to develop the 3M&S framework, it is important to have a good understanding of the appropriateness of each of the three M&S approaches to diverse problem, methodology and system perspectives. The in depth understanding of differences and similarities among DE, SD, and AB M&S is a precondition for the selection of the appropriate approach to meet particular problem and system requirements. The process for selecting appropriate M&S approaches(s) is based on a list of identified selection criteria. The recommended criteria aid in the conceptualization as well as in the justification of using multi-method modeling and simulation or not. Furthermore, the criteria are used for the development of a conceptual framework that provides practical guideline for the combination and/or integration of DE, SD, and AB approaches. For this reason, a meta-analysis of literature on existing studies that compare, combine and integrate DE, SD, and AB models was conducted, followed by a review of literature on existing frameworks that deploy M&S approaches.

- **Objective 2: Gain knowledge through existing frameworks composed of DE, SD, and AB models.** In order to gain in depth understanding and knowledge, we reviewed existing frameworks that combine, and/or integrate M&S approaches that have been deployed in the past. In the literature, we have detected a considerable amount of published reports regarding hybrid simulation that recommend either integrated deployment or combination of two M&S approaches to address CS problems. However, most of these reports are very domain specific and limited to an integrated deployment or combination of only two M&S approaches without providing a practical guidance which the user can follow to perform different studies. The knowledge acquired through the review of this literature helped us understand different types of relationships that connect the interaction points of information exchange between models that have been implemented using different M&S approaches. This knowledge served as a basis for the development of generic interaction relationship types that are defined through the 3M&S framework and aid in the deployment of DE, SD, and AB M&S approaches.

- **Objective 3: Develop Generic Framework for Multi-Method Modeling & Simulation (3M&S).** On the basis of understanding and knowledge gained from the reviews of the literature, a generic framework capable of providing practical guidance for the implementation of multi-method modeling and simulation was proposed and developed. The framework helped us to conceptualize, understand and answer the research questions of when, why, and how to combine, and/or integrate DE, SD, and AB approaches to form multi-method simulation models.
- **Objective 4: Evaluation of the 3M&S framework:** Last but not least, one of the objectives was to evaluate the effectiveness and limitations of the developed 3M&S framework, within a various domain context including real case examples in businesses, and other organizations. The evaluation process proceeded as follows: Firstly, the framework was evaluated conceptually. This evaluation was acquired in order to address limitations. The limitations worked as a fundamental basis to adjust the developed 3M&Sframework. Then, the 3M&S framework was empirically evaluated by following it to conduct and implement real case multi-method simulation studies. The rationale of this objective was to test the framework by applying theoretical and empirical evaluation, in order to identify the strong and the weak points of it.

1.4 Overview of research

The key contributions of this dissertation are: (1) a meta-analysis literature review that identifies criteria and generic types of interaction relationships that served as a basis for the development of a multi-method modeling and simulation framework; (2) a methodology and a framework that guide the user through the development of multi-method simulation models to solve CS problems; (3) an algorithm that recommends appropriate M&S method(s) based on the user selected criteria for user defined objective(s); (4) the implementation and evaluation of simulation models (3M&S models) based on the framework's recommendation in diverse domains; and (5) the comparison of multi-method simulation models created by following the 3M&S framework's suggestions with models built based on the user's own selection.

This dissertation includes the following chapters. Chapter One contains the introduction of this research. Chapter Two provides a literature review on complex systems and M&S methods. It also includes the meta-analysis review of the literature to identify various criteria which aid in selecting an appropriate M&S approach. Chapter Three describes the research methodology and the development of the framework. In this chapter we describe an algorithm that helps in selection of appropriate M&S approach based on the established criteria as well as the generic types of interactive relationships that take place in multi-method simulation models. Chapter four describes the evaluation of the framework using three real case studies and Chapter five provides a summary of this dissertation, limitations and future work.

CHAPTER 2: REVIEW OF LITERATURE

The main objective of this chapter is to provide a review on CS and M&S methods related research. More specifically, Chapter 2 describes the three M&S approaches (AB, DE, and SD), existing frameworks and studies related to comparisons and combination of them in order to gain knowledge about similar and different aspects and features which are necessary for the development of the 3M&S framework.

2.1 Complex Systems (CS)

CS allow fuzzy multi-level and multi-disciplinary representation of a real dynamic environmental adaptation within autonomous readjustments, where control and command is emergent and not deterministic [38]. Some formal and informal definitions of the term "Complex System" are given below:

- "CS are highly structured systems, which show structure with variations" [39]
- " CS are systems whose evolution is very sensitive to initial conditions or to small perturbations, on which the number of independent interacting components is large, or those by which there are multiple pathways by which the system can evolve" [40]
- "CS are formed from few to many agents and can emerge simple to sophisticated behavior" [41]
- "CS can be adaptive collections of interacting, autonomous, learning decision agents embedded in an interactive environment" [30]

- “CS consists of many diverse and autonomous but interrelated and interdependent components or parts linked through many (dense) interconnections” [42]
- “ CS are systems that by design or function or both is difficult to understand and verify” [43]
- “A CS is one in which there are multiple interactions between many different components” [44]
- “CS are systems in process than constantly evolve and unfold over time” [45]

For interpretation purposes, the author reviewed attempts to characterize CS from various scientific fields [30], [39], [40], [41], [43], [44], [45], and listed some of the most common characteristics of CS, which are widely associated with:

- interdependence of various interacting components
- nonlinearity
- emergence, flexible, adaptive, learning and autonomous behaviors (systems have memory)
- sensitive causal relationships (positive and negative feedbacks)
- open system boundaries (exchange of input/output information)
- theory of chaos

Analytical attempts to find solutions for a CS face challenges and serious limitations compared to computer based M&S. The decomposition of a CS is even more challenging to be achieved with synthetic general laws and the existence of non-linearity which disables stand-alone analytical models and makes them impractical, or even impossible to be solved [6]. More specifically, in micro-established models the representation of the dynamics for multiple entities may happen concurrently. In this case the analytical approach would have to deal with multiple sets of differential equations that would be time consuming and a lapse could force the analyst to start the process all over again. Furthermore, non-linear differential equations are hard and sometimes even impossible to be solved analytically. Therefore analytical modeling approaches should be combined with computer based M&S approaches and particularly with multi-method simulation approaches when it comes to tackling CS problems.

M&S models have become an increasingly frequent approach of representing CS. Simulation models can manage non-linearity, and successfully compute numerical functions among numerous variables and interactions that take place among various entities, stocks and agents. Furthermore, M&S allows in depth understanding and visualization of the produced simulation using 2D or 3D animations and statistical visualization (i.e. bar-charts, graphs, and pies) of a system's behavior. Finally, M&S models require less intellectual effort than analytical solutions, especially for CS problem solving, and offer flexibility in terms of adding measurements and statistical analysis whenever it is needed.

2.2 Modeling and Simulation (M&S)

Modeling and Simulation (M&S) is a highly multidisciplinary and active area across numerous scientific domains and research areas. M&S allows the experimentation of real CS problems at no risk and low cost. The modeling process is about discovering the pathways from the decomposition of CS problems to its solutions through a virtual experimentation lab, where mistakes are allowed and one can go back in time, cancel or redo things and try alternatives [6]. Modeling can exist without simulation, but a simulation cannot run without a model. During the modeling process the user maps a real world system to a virtual world and is called to select level the appropriate level of abstraction and modeling methodologies to satisfy modeling questions and well defined objectives of a particular problem.

Simulation of CS is the activity of experimenting with models of CS by reproducing data consistent with data produced by a real CS. Over the past decades simulation in general has been gaining widespread recognition as a powerful scientific tool. Nowadays, the word "simulation" has various meanings and it is used in multidisciplinary domains. In most cases, the definition of simulation is associated with a representation of a real existing system, i.e. a CS or a physical and socio-economical system of systems. Based on the field of interest, simulation has various sub-definitions [46].

M&S is widely accepted and characterized as one of the most significant aspects across several scientific fields rising new approaches in the way we learn, design, generate requirements and evaluate CS. There is a considerable amount of reported literature as it concerns the use of M&S and its impacts on decision management. Examples of reported usage includes: assisting in creative problem solving, predicting outcomes, accounting for system variances, promoting cost-effective total solutions, helping us quantify performance metrics and serving as a means of communication [47] [29], [48]. M&S together allows experimentation with a model of a real system in order to better understand and determine the behavior of a system, the processes and how the system responds to changes in its structure, environment or underlying assumptions [49].

M&S system models can be categorized as deterministic or stochastic. A deterministic model produces the same output in each run considering no randomness (stochastic), while in a stochastic model the outputs differ from run to run. In addition, a system can be either static or dynamic. In a dynamic system time is considered as variable while in a static system time is not considered as variable. A static simulation model is a representation of a system at a particular time period, while a dynamic simulation model represents a system as it evolves over time. Although in the past it was widely accepted to classify a system as being either discrete or continuous based on the type of change that predominates, in this dissertation we classified system models in three different types: discrete, continuous and hybrid (continuous and discrete).

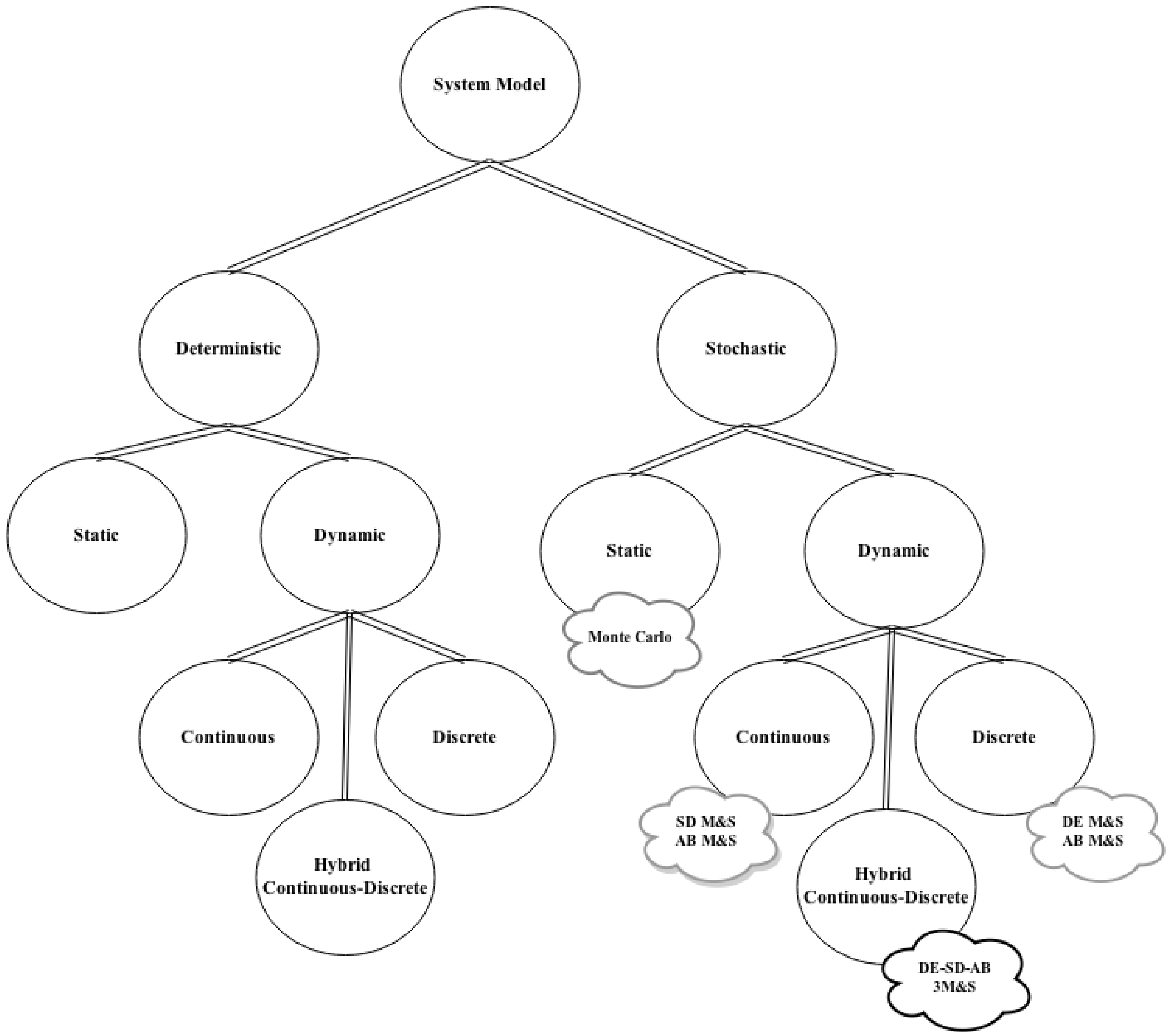


Figure 1. Deterministic and stochastic types of simulation models

If a model is discrete, the state transition mechanism is event driven. This means that the variables change instantaneously at particular discrete points in time and not continuously with respect to time as in a continuous state system [50]. In a continuous state system, the continuous variables can be assumed any real value (i.e. income, weight, and analog signals), while in a discrete state system, the discrete variables are assumed elements of a discrete set (e.g. number of cars or people. digital signals). In a time-driven system, the state can continuously change as time changes. On the other hand, in the event driven systems the occurrence of asynchronously generated discrete events force instantaneous state transitions, while the state between event occurrences remains unchanged. Finally, hybrid models consist of both discrete and continuous system state behavior.

2.3 Discrete Event (DE) Modeling and Simulation (M&S)

The first Discrete Event modeling and simulation software tool was introduced in the early 60's by an IBM engineer named Geoffrey Gordon [6]. This general purpose simulation system was called the Gordon's Programmable Simulation System (GPSS). In recent times, DE M&S is supported by various software tools, including the updated version of GPSS itself, which has been increasingly applied to assist in decision-making and evaluation in multidisciplinary domains, such as in healthcare organizations, supply chain management, manufacturing planning, and production lines.

Discrete Event (DE) Modeling and Simulation (M&S) method is a process of systematizing the behavior of a system in which its operations are described as an orderly discrete sequence of well-defined events in time. DE M&S has the capability to capture CS behavior within its interactions and/or between individuals, populations and their environments using computational and mathematical practices [51]. In this context, a DE simulation model is a computer generated experiment consisting of elements that form a model capable of representing and describing a system. Each event occurs at a specific countable number of points in time and involves a particular change in the system's state at this particular point in time. This means that between consecutive events, no change in the system's state is assumed to occur; therefore the simulation directly jumps to a specific point in time from one event to the next one.

When we observe real world processes, the majority of them consist of continuous changes. However, when we examine them from a DE M&S perspective, these continuous processes are divided into discrete parts (the variables are discrete and not continuous) and the system is being modeled as a sequence of operations being performed across entities [47], [6]. DE Modeling approach is more process-centric oriented and the randomness of the interconnected variables leads to systems behavior. DE systems are represented by sequences of discrete events in a discrete time which jumps from event to event. Some of the most common elements of DE modeling include: entities, events, queues, resources and flow charts which provide implicit feedback. An "entity" in DE is defined as the active object or object of interest within a system. Additionally, the "attribute" of an entity characterizes the property of that particular entity and the activity of that entity characterizes a time period of specified length [47]. As an "event" we describe a prompt occurrence that may alter the state of the system [47]. The "state" of a system is defined as a set of particular variables that are essential to describe a system at a specific time, in regards to the defined objective(s) of a simulation study [47].

DE models can be either deterministic or stochastic, but in this dissertation we are most interested in stochastic M&S. The data sources in DE M&S are usually historical data, numerical and/or actual data that consider informational elements such as arrival times, departure times, service times, waiting times etc. In DE stochastic models, randomness can be explicitly modeled with the appropriate statistical analysis, while the complexity increases exponentially based on the size and the requirements of the model.

DE systems focus more on modeling processes for tactical and operational organizational levels [6], [52]. The analyst seeks to understand and estimate the impact of randomness on a system with a relative precise prediction. DE models usually demonstrate High-Level of predictive ability. An understanding of the problem lies in the analysis of the randomness, which is related to interconnected processes and events. DE simulation has been widely used in a variety of domains, including manufacturing, logistics, and business process modeling, to represent how entities move through a system [55]. This M&S method is particularly useful for identifying process bottlenecks and collecting statistics on process performance measurements. The main drawback is that entities are described as passive objects with no autonomy, which results in limited ability to adapt the structure at runtime.

In order to develop a DE M&S experiment, the user (i.e. analyst, modeler) needs first to define the overall objective(s) such as the scope and purpose of the simulation study. Then, the user is called to construct a conceptual model. The conceptual model can be used as a guide to convert the collected system requirements using building blocks into a CG computational model. Some activities of the conceptual phase are: defining boundaries (input/output), level of details, Measurements of Performance (MoPs), parameters and important dynamic ad state variables that may take place.

2.4 System Dynamic (SD) Modeling and Simulation (M&S)

System dynamics (SD) is an analytical M&S method which was originally developed by Jay Forrester at MIT in the early 60's to assist managers in improving industrial processes [53], [29]. This method is based on Euler's approximation to solve a differential equation as discrete sub-sections of a continuous time interval [54].

SD method is designed to model the behavior of changing system states over time [54]. In SD, instead of independent and identically distributed (IID) entities, the user deals with homogenized entities, stocks (accumulations) and flows, which continually interact over time to form a unified whole [6]. SD is a toolset of learning and understanding how a system's behavior, policy or strategy changes over time. The system's behavior is affected by internal feedback loops and time delays. The main advantage of this method is its ability to focus on the aggregate effect, rather than the individual effect of individual entities. It allows for modeling the mathematics, the relationships, and each of the causal dependencies in a dynamic system. Thus, the impact of various policies on the system can be examined [29].

SD M&S method focuses more on modeling processes for strategic organizational levels [6], [52]. In addition, SD method deals effectively with parallel synchronization challenges by updating all variables and increments with positive and negative feedbacks, and time delays that compose the interactions in short amount of time. These key elements illustrate a nonlinear relationship, which aid the user in detecting the elements that considered important to the system and those that are expected to generate an impact to a specific problem situation [29].

In addition, SD method combines qualitative and quantitative information in order to enhance the comprehension of a recognized problem, as well as to improve the understanding of the structure of the problem and the relationships present among relevant variables. It is contingent on quantitative data to generate feedback models, usually deterministic, unless stochastic elements are explicitly included [29]. Often, randomness in SD is subsumed into delays or noise [29]. The modelers consider decisions and events under a continuous endogenous aspect of view, usually build on causally closed structures that can define its behavior. The analyst can determine the feedback loops within a system's circular causality to detect stocks and flows that influence the feedback loops. These stocks sometimes can be the memory of the system as well as the source of disequilibrium [29].

There is no standard way to manage and construct SD models [6]. SD M&S mehtod is characterized by a top-down systems level approach, in which a system is represented by building blocks of stocks (in which the accumulations characterize the state of the system), flows (or rates of change), causal loops (positive-negative feedback loops), delays, rates and constant or continuous parameters [6]. Stocks may represent people, money, experience, capacity etc. Flows can be rates per unit, i.e. people per day, money per second, experience per year, capacity per month. In SD, the current system's state condition is defined by a level variable that can only be affected by a rate. Additionally, a rate cannot influence directly another rate variable if a level variable doesn't exist [6]. In SD, the world can be modeled in causally closed structure capable of self revealing its behavior [6], [29].

2.4.1 Stock and Flow Diagrams. One of the most commonly used techniques for the representation of a SD models is the stock and flow diagrammatic technique which is used to describe the causal relationships of various state levels, rates, and constant parameters in a given system. Stock and flow diagrams allow us to recognize the type rate, flow and constants that are deployed. Figure 2 describes a simple stock and flow diagram, where rectangles describe "stock" and "stock1" respectively, the double arrow with the rate in the middle describes the "flow" and the cloud describes the "decision-making" rules based on differential equations of dynamic and constant parameters.

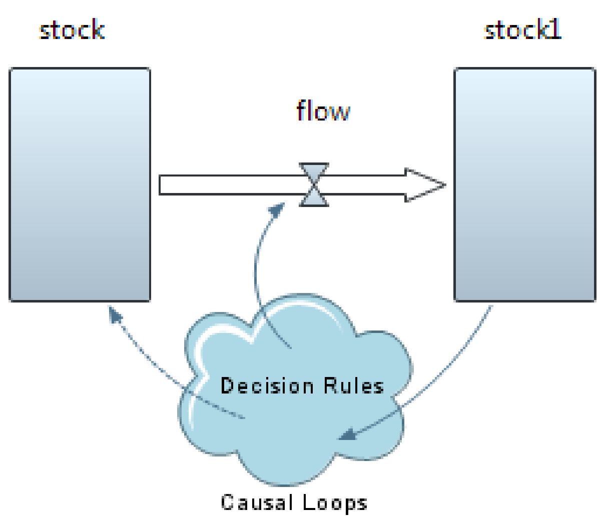


Figure 2. Simple stock and flow dynamics

2.4.2 Positive and Negative Feedback loops. Stocks and flows are both important and necessary modeling building blocks for CS. They can produce realistic dynamic behavior when components of feedback loops are regularly connected by nonlinear sets that frequently cause erratic behavior.

From a SD perspective, a system can be categorized as "open" or "closed." On one hand, open systems are characterized by outputs that respond to, but have no impact on, their inputs. On the other hand, closed systems are characterized by outputs that can do both, respond to, and impact their inputs. Closed systems perceive their own performance and are affected by their past behavior, while open systems are not. This fact brings closed systems to the center of attention. Based on the essential role of feedback in the control of closed systems, it is recommended that every feedback loop in a SD model should include at least one stock.

There are two kinds of feedback loop control: the positive and the negative feedback loop. Positive feedback loops or reinforcing feedback loops represent self-reinforcing procedures in which part of the output of a system is returned to its input in order to produce more of its input, and therefore more of its further output. Positive feedback loops have a tendency to destabilize a system from its current situation with the ability to expand or decline a system. However, they can periodically cause stabilization of the system.

On the other hand,negative feedback loops or balancing feedback loops illustrate goal-seeking procedures in which part of the output that is produced is returned to its input in order to stabilize the system to a desired situation. In general, negative feedback loops stabilize a system to a desired state, but periodically can cause destabilization of the system and oscillations.

2.4.3 Causal Loop Diagrams. In the world of SD M&S, the causal loop diagram technique is usually applied to describe positive and negative feedback procedures of cause and effect relationships between individual system variables connected in a closed loop. For example, Figure 3 illustrates two causal loop diagrams: a causal loop diagram of positive feedback loop structure and a causal loop diagram of a negative feedback structure. The arrows that connect each variable show a cause and effect relationship. The variable at the back of the arrow affects the variable at the front of the arrow in a positive or negative direction. The overall polarity of a causal loop diagram is depicted with a "+" or a "-" symbol at its center (sometimes instead of "+", or "-" symbols, are used "s" for the same direction and "o" for the opposite direction).

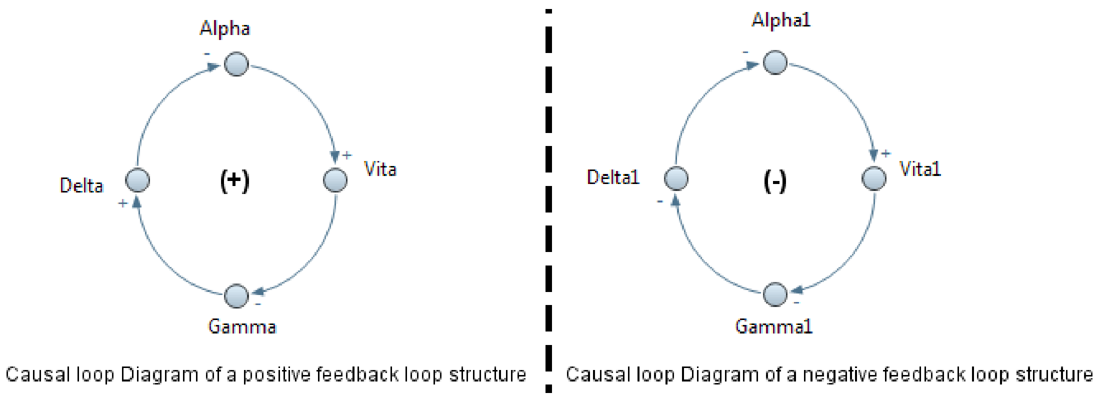


Figure 3. Positive and negative feedback loop diagrams

In the SD community, managers and decision makers classified the generic feedback loops in archetypes, applicable in various domains, in an attempt to detect precise system structures that cause particular cause–effect relationships.

However, the success of the loop diagrams and archetypes in helping decision makers solve problems in their organizations may be further supported by a 3M&S concept where micro, meso and macro perspectives are taken in consideration to gain a complete understanding of the details and dynamics of a CS.

2.5 Agent Based (AB) Modeling & Simulation (M&S)

There is no universal agreement on the exact definition of the term "agent", although definitions tend to agree on more points than they disagree on. The Agent Based (AB) simulation models, known as "multi-AB" systems are models that can execute a simulation of one heterogeneous population or more (multi-AB), clusters or networks of agents, and their interactions among them and their environments. The agent's heterogeneity may be initiated in terms of a different agent: location, level of experience, level of knowledge, and other identified attributes within an interactive environment. The global behavior of a system emerges out of many concurrent individual behaviors and/or clusters of agent behaviors (multi-AB). The simulated outcome of micro-level interactions among the agents can form a global macro-level behavior. Such examples could be: the culture in an organization, understanding phenomena of emergent situation, and aid in decision-making. The agents are capable of representing various aspects depending on what is the interest of the M&S study such as: individuals, (human task operators, machines, customers, pedestrians, biological organisms etc), clusters, networks, organizations, companies etc.

Initially, AB history started by two friends, Von Neumann and Stanislaw Ulam, who created a machine capable of replicating itself as a collection of cells on a grid [154]. Later, this theory which was termed cellular automata advanced to AB by introducing rules such as the "Game of Life" by the mathematician John Conway [154]. In 70's and 80's AB M&S adapted mostly in academia when in 90's the interest exploded as more software's released and more practitioners start adopting this method [6], [55]. The adoption of AB M&S method increased due to the desire of the modelers community for more information and details into systems that were not well-captured by the other two M&S methods (DE and SD) [6]. In addition, AB M&S attracted more attention because of the continuous progress of computer science (CPU power and memory, software availability), and modeling advancements such as the Unified Modeling Language (UML), and the state charts were introduced. Nowadays there are a lot of software tools that not only can create AB models, but they can also combine them with SD and DE models.

Agent Based (AB) is a more recent M&S method than DE or SD and can be applied for strategic, tactical and operational organizational levels unless the user, analyst or modeler explicitly defines the modeling question(s). Such modeling questions could be to define the types of emergent processes or simple rules of behavior among the agents to learn and understand a global behavior. However, in some cases AB is justified as more appropriate M&S metod, because of its capability to describe a lot of details of CS, where the users may focus more on details, rather than in M&S, for understating an emerging behavior. For example, when we have randomly interconnected agents that form differential mathematical relationships, then SD models, may be a more appropriate M&S approach. AB M&S is very practical when the agents interact in non-random ways based on rules, terms, and conditions that we meet in explicitly defined networks, cluster of agents and other AB systems. Furthermore, AB M&S is often applied to assess various processes (cognitive or physical processes), in which the heterogeneity of a decision-making behavior contributes to the understanding of the overall system’s behavior.

From the viewpoint of M&S of practical applications, AB is more decentralized individual-centric level approach, or bottom-up level approach and does not assume a particular level of abstraction, neither considers standard modeling structures; it is possible to link the mathematics in order to simulate micro to macro level of perspectives [6], [55], [56], [57].

AB M&S method allows analysts to understand and present data driven efforts on patterns of symbiotic or competitive relationships [58]. The behavior and the interactions between the agents can be formalized by state-charts, UML, mathematical modeling, decision rules, and logical operators.

The system is usually modeled as a compilation of agents, where the analyst can study how the system's global behavior emerges as a result of the interactions among a lot of individual agent behaviors. The individual agent may have a nonlinear behavior characterized by state-charts, thresholds, if-then rules, or nonlinear coupling. The agents may have decision-making heuristics based on a set of predefined rules and they can exhibit various behaviors in regards to the system or state they represent. The majority of AB models in the literature consists of Agents that exhibit behavior and properties such as: adaptive ability, pro- and re-activeness, spatial awareness, learning ability, social ability, autonomy, interactive topology, anthropomorphity, continuity, and specific purpose [59], [5], [60], [61], [62], [63], [64], [65]. AB models can integrate neural networks, progressive algorithms, and other machine learning techniques to represent realistic properties such as the learning and adaption ability. Based on the software that is used, the agents may be surrounded by continuous or discrete two or three dimensional space coordinates, when some software can also integrate geographic information system space [66]. The randomness in AB is associated with variables and the dependencies of their active objects (agents). It may be synchronous with probabilistic delays or asynchronous with stochastic delays. Therefore, AB models are flexible in avoiding synchronization problems, but selecting the interpretation of their outputs is often challenging and requires statistical knowledge. AB can deal with qualitative and quantitative type of models and it can well capture more CS structures and dynamics than DE and SD M&S approaches.

2.6 Multi-Method Modeling and Simulation (3M&S)

Multi-Method Modeling and Simulation (3M&S) considers the combination and/or integration of M&S models that may consist of both discrete and continuous system state behavior. A multi-method simulation model results from the combination and/or integration of DE, AB, and SD M&S approaches. A multi-method simulation model must be able to update, change, and adapt during execution time and exchange of information. When we say "method" in M&S, we refer to a general architecture for constructing a real world system to its model. Accordingly, we call it "multi-method" due to all of the possible architectures, terms, and conditions that can be constructed among the three M&S methods (DE, SD, and AB) [6].

2.7 Meta-interpretive review of literature of comparisons, existing combinations, and/or integrations of M&S Methodologies

The scope of this section is to identify similarities and differences that characterize DE, SD, and AB M&S methodologies. The review of literature focuses more on the justification and achievement of two main objectives. The first objective is to develop in depth understanding among the different aspects and features of the three M&S methods (DE, SD, and AB), and the second objective is to obtain knowledge of meta-interpretive literature on existing frameworks that combine or integrate DE, SD, and AB models.

Problem owners deal with strategic, tactical, and operational levels; micro, meso, and macro perspectives; and detail and dynamic complexity [7], [33]. In this research, we are strongly confident that such factors can be considered and managed using the 3M&S framework.

The importance to justify the need to integrate and/or combine M&S methods to form multi-method simulation models prior to the development has been mentioned before [12], [26]. Additionally, it has been argued that before combining M&S methodologies (i.e. SD and AB), first requires to compare the methods in terms of output on similar problems in order to verify the methods and establish active and mutually influential collaboration between the models [15]. All the three M&S methodologies have strong explanatory capabilities and, although they differ in their philosophical approaches, they can be integrated and/or combined [6]. The process-centric approach of DE, the bottom-up approach of AB, and the top-down approach of aggregated feedbacks of SD may complement each other in a multi-method simulation format capable of offering realistic perspectives and useful insights of CS problems.

2.7.1 Meta-interpretive review of literature of comparisons, existing combinations, and/or integrations between AB and SD M&S. Interpretations of combination or integration between SD and AB M&S methods were detected in various domains including: Bimolecular Networks [67], supply chain systems [13], [68], [69], [70], expert systems [26], manufacturing systems [71], [72], healthcare systems [73], [74], transportation systems [75], air traffic control system [76], and web technologies [77]. Moreover, SD and AB M&S have a variety of different applications in different domains such as socio-topo-ecological simulations of regional, [78] agricultural [79], and governmental development [80]. In this section, we briefly describe a selected list of studies that helped define the list of criteria for the 3M&S framework.

The first study concerns a conceptual combination of SD and AB methods proposed by Pourdehnad et al. [81] in an attempt to explore and support group learning, in an organizational context. More specifically, Pourdehnad et al. suggest that the appropriate use of both methods can contribute to support group learning (i.e., management team) and enable the group to experiment with different actions, policies and strategies, "see" the consequences and understand the complexity of the organization. [81]. Pourdehnad et al. also detected main differences between the two approaches which are related to the behavior of the modeled system. The SD approach is applied for pre-defined model relationships in which the behavior of the system depends on the structure of the model, while the AB approach considers an "emergent" system behavior as the outcome of individual agent interactions [82], [81]. Other differences described by Pourdehnad et al. are [81] categorized in terms of:

- System scope. SD is more appropriate for business thinking and physical processes, while AB for human thinking and social processes
- Applicability. SD is recommended more for CS understanding while AB for learning a behavior
- Validity. AB model scored higher than the SD model

Besides, all the aforementioned differences in the way AB and SD approach CS problems, it was noticed that strong interactions between AB and SD can coexist and can be deployed in a synergetic way [15], [81].

Another study, which was conducted by Wakeland et al. [83] in the field of biomedical research, showed that the understanding of the aggregate behavior of a SD model and the state changes of agents are relevant and can be combined. Wakeland et al. did not conclude to a clear differentiation of when each approach over the other should be preferred. However, they recommend SD for examining systems at a high aggregation and abstraction level, and AB for studying emergent phenomena of diverse structure which can be broadly classified in individual levels (i.e receptors and molecules) [83].

Furthermore, Figueredo et al. support that both M&S approaches (SD and AB) can be helpful especially for simulating parts of the immune system. In order to achieve a clear understanding of how to acquire information from one method to the other, they compared SD and AB for different biological problems. Figueredo et al. identified differences between the two M&S methods in terms of output for similar spatial and non-spatial CS scenarios, by converting AB into SD and vice versa [84]. They concluded that both methods can capture the process of transforming the information to knowledge and understanding, but this transparency may not be so obvious [88]. Moreover, they observed that SD is more appropriate for static agents that do not involve interactions, because it is less complex approach and takes up less computational power by generating similar outputs than those acquired by AB approach. They also noticed a research gap of theoretical guidelines and frameworks to aid in selecting the most appropriate method(s) [88]. Figueredo and Aickelin [85] conducted more experiments to compare SD with AB output in regards to immune system-related problems, but this time with agents that could involve interactions (tumor growth that interacts with effector cells). They noticed that, in some simulation cases, the outputs of the models were different because of the modeling nature of each simulation approach; SD deals with continuous stocks, while AB deals with discrete number of agents [85].

In addition, Swinerd, and McNaught, suggest three architectures for combination and/or integration of simulation between SD and AB and they called them hybrid design classes. The three main different system designs detected when combining or integrating SD and AB M&S methods are: the integrated, the interfaced and the sequential system design [16]. These different system architectures are described in regards to the combination or integration between SD and AB methods and the output of the composed hybrid model.

According to Swinerd et al. [16], in the integrated hybrid design of AB and SD, models can interact and provide separate outputs in three different ways:

- a SD model is integrated within Agents (Agents with internal SD structure)
- a SD model is applied to bound aggregate measures of an AB model (i.e stocked agents) and
- SD aggregate measures, observations, and statistics of an AB model can be applied to impact parameters that are evolved within this particular SD model which can exhibit emerging behavior

The constraints of the feedback process when combining and/or integrating SD and AB models are not limited to these interpretations [16].

More simulation studies that compare SD and AB approaches reached similar conclusions for a bass diffusion model, a susceptible infected recovered (SIR) model and a predator-prey model [6], [55]. These studies also conclude that AB models are harder to develop, verify, validate and document [6], [55]. In addition, AB models require more computational resources for M&S and the produced outputs are more difficult to be understood and explained [6], [55].

However, the appropriateness of selecting between M&S methods depends more on the objectives of the study, the modeling questions, and the level of abstraction, rather than in the application that is being modeled [55], [86]. For example, when the objective is to capture and illustrate the behavior and the interactions that take place among living organisms, then AB is recommended, while SD would be better, if the quantification of whole populations is required.

Schieritz and Milling conducted another useful comparison between AB and SD methods for non-linear socio-economical systems [60]. This study describes how an analyst would model the forest and how the tree, by approaching the modeling problem either with SD, or with AB modeling. In this comparison study between SD and AB [60], it is recommended that SD would be more appropriate for macroscopic modeling levels, while AB would fit better in microscopic modeling levels, because the behavior of the system is analyzed differently. With this astonishing example, Schieritz and Milling illustrate the differences between top-down (SD) and bottom-up (AB) approach and alternative ways to analyze the behavior of a system [60]. Schieritz, and Milling conclude that in a SD model the system is analyzed based on the structure, while in an AB model based on rules [60]. When both objectives become important for a particular study, the integration or combination between SD and AB could provide potential aid to decision makers to expand their thinking considering both, macro and micro perspectives (the forest and the tree). A summary of the studies described above is depicted in Table 1.

Table 1. Summary of findings from meta-interpretive review for AB and SD comparisons

Criteria	SD	AB	Reference
Modeling Philosophy (Methodology Perspective)	Overall behavior of the system depends on the structure of the model and pre-defined model relationships	Overall “emergent” system behavior of interdependencies among individual agents	Pourdehnad et al. [81] [82], Wakeland et al., Figueredo et al. [84]., Borshchev [6], [86]
Problem Resolution (Problem Perspective)	Aggregated level, Quantification of whole populations	More detailed Level, individual levels, Interactions that take place among individuals	Pourdehnad et al. [81] [82], Wakeland et al. [83], Figueredo et al. [84]. Borshchev [6], Siebers et al. [86]
System Representation (System Perspective)	Stocks and Flows	Individual agents	Pourdehnad et al. [81] [82], Wakeland et al. [83], Figueredo et al. [84]. Borshchev [6], Siebers et al. [86]
Abstraction Level (System Perspective)	High-Level of abstraction	Any Level of abstraction	Pourdehnad et al. [81], Wakeland et al. [83], Figueredo

Criteria	SD	AB	Reference
			et al. [84], Borshchev [6], Siebers et al. [86]
Time, (Methodology Perspective)	Continuous	Discrete,	Schieritz and Milling [60], Figueredo and Aickelin [82]
Object (Methodology Perspective)	Stocks and Flows, Feedback	Number of agents	Schieritz and Milling [60], Figueredo and Aickelin [82]
Situation (Problem Perspective),	Analysis based on structure and flows	Analysis based on rules	Schieritz and Milling [60], Figueredo and Aickelin [82]
Modeling Approach	Top-down	Bottom-up	Schieritz and Milling [60]

2.7.2 Meta-interpretive review of literature of comparisons, existing combinations, and/or integrations between DE and SD M&S. The combination and/or integration between SD and DE M&S has been used to answer questions in various domains of CS that neither SD nor DE could support in a stand-alone M&S format. Different M&S combinations have been applied based on the different technical and philosophical aspects of each method. Each M&S method acts differently in capturing and interpreting CS problems and systems perspectives [87]. In this section, we describe a selected list of existing hybrid SD and DE studies and comparisons that helped in defining the list of criteria for the 3M&S framework.

Coyle approached the integration of DE and SD M&S methods in his attempt to find alternative ways to integrate DE M&S in a SD environment [88]. Coyle identified two main points in the comparison between DE and SD M&S: (1) both M&S approaches can be applied in the modeling structure of open and closed loop systems and (2) the majority of DE models are stochastic using more random variables and statistical distributions, while the SD models are usually deterministic; analysts focus more on training and understanding rather than on randomness.

In the context of business processes, Sweetser provides an interesting comparison between DE and SD approaches. Sweetser [89] concludes that both approaches can model and generate similar outputs for some particular problems. However, the appropriateness of each method is characterized by different perspectives in the conceptualization process based on the objectives and the system that is taken under consideration. Sweetser recommends SD for problems related to continuous processes, where feedback considerably influences the behavior of a system by generating dynamic changes in its behavior [89]. On the other hand, DE is recommended when detailed examination of a system exhibits' linear processes and discrete changes in its behavior [89]. Moreover, DE is recommended when the user is more interested in accurate and statistically valid assessments of a system's MoPs, while SD as a decision support tool for learning and training [89].

Another comparison between DE and SD worth noting is presented by Brailsford and Hilton in the context of health care organizations [87]. Brailsford and Hilton [87] establish the first technical criteria that suggest when each M&S method is more appropriate than the other. Some of the selection criteria between DE and SD were also adapted by Morecroft and Robinson [90]. More specifically, DE is recommended as a more suitable approach for systems that operate like networks of queues and activities. In this case, independent and identically distributed (IID) objects (entities) exhibit changes to their state when an event occurs at discrete points of time. On the other hand, SD is mostly recommended for deterministic systems that operate as groups of stocks and flows. In this case, all objects are considered as a continuous quantity, in which the time is modeled as a delay in equal duration time steps and the state changes occur continuously [87], [90].

Additionally, DE and SD approaches have been compared in terms of organizational level of abstraction, in which SD applies at a strategic organizational level, while DE applies at the tactical and operational organizational level of abstraction [89], [91], [55]. In terms of feedback impact on a system, SD uses closed loop structures in which causal interactions and feedback effects are very important, while DE models are usually open loop structures that are less interested in feedback effects [88], [89], [87]. In terms of system's modeling representation and complexity, DE M&S adapts more analytic perspectives (meso to micro aspect of view) with a narrow focus (more details), while SD adapts a holistic system's perspective by applying a wider focus approach (macro aspect of view) [91], [92].

Furthermore, Tako and Robinson conducted a quantitative verbal protocol analysis (VPA) to compare DE and SD methodologies based on the user perception, using Subject Matter Experts (SMEs) from both M&S communities [93]. Tako and Robinson asked modelers to think out loud during the modeling and development process of simulation models for particular problem scenarios [94]. They compared DE and SD methodologies using VPA in terms of: problem structure, conceptual modeling, data inputs, model coding, V&V, output, and experimentation. The conclusions from this comparison study describe that all SME's switch between modeling topics, although the DE SMEs follow a further linear progression compared to SD SMEs. In addition, Tako and Robinson noticed that DE SMEs paid more attention on model coding and the process of V&V, while SD SMEs focused more on the conceptualization of the modeling process [94].

Additionally, Lane's comparison between SD and DE describes three modes of discourse [91]. The first mode focuses on the differences between the two M&S methods, the second implies that both methods are similar, and the third mode presents how to link the two methods while acknowledging and respecting the differences between them [91]. Lane strongly supports the third mode as it involves a wide area of applications for which he proposed a three dimensional model that includes various parameters for organizational, dynamic, and detail complexity [91]. According to Lane, organizational complexity occurs because of the numerous perspectives and the antagonistic attitudes between the different groups of interest. Detail complexity occurs from the various variables and attributes and dynamic complexity is related to the interaction variables producing non–linear behavior [91]. Lane concludes that DE and SD M&S methods work better for different types of complexity, where SD is better applied to capture dynamic complexity for homogenized entities, continuous policies, and emergent behaviors, while DE captures better detail complexity, IID entities, individual attributes, decisions, and events [91]. In addition, DE is recommended for operational problems while SD for strategic problems [91]. Most of the criteria recommended by Lane's [91] DE-SD comparison agree with the conclusions made by Brailsford and Hilton [87] and Morecroft and Robinson [90].

Morecroft and Robinson [90], similarly to Schiertz and Milling [60], focused on similar problem scenarios considering both DE and SD M&S methodologies. Morecroft and Robinson conducted a comparison study [90] which focuses more on the system representation and interpretation. Some of the most important differences that they pointed out, regarding the fishery model example, are similar to the conclusions of the comparison conducted by Brailsford and Hilton [87]. They noticed that SD is more suitable for capturing and understanding the performance of interconnected system components over long time scale based on the internal system feedback structure. Morecroft and Robinson underline that SD modeling feedback structure is mostly described explicitly by a set of non-linear equations, where randomness is rarely considered, or assumed as noise. On the other hand, for the DE approach, they noticed that the modeling feedback is mostly described implicitly by a linear relationship [90]. Finally, Morecroft and Robinson [90] similarly to Brailsford and Hilton [87], recommend that DE satisfies better objectives related to decision support in terms of optimization, prediction, and comparison of alternative scenarios, while SD is more appropriate for objectives of policy making and assessment, training, and understanding.

Furthermore, in the concept of combining M&S methods, it was pointed out that, when combining more methodologies, it is possible to represent a more inclusive way of dealing with the complexity of a real world system, but this may present challenges due to the diverse philosophical aspects of each M&S methods [55], [19]. Although combining or integrating DE and SD present challenges due to the different characteristics that each method exhibits, several studies that combine, and/or integrate discrete and continuous aspects have been proposed.

The works of Petroulakis [95], Lee et al. [96], and Helal [10] focus on combining continuous and discrete aspects into supply-chain systems, while Rabelo et al. [97] propose a theoretical framework for integrated deployment of SD and DE to study local production decisions in regards to the global market. In these studies, SD is applied to assist decision-making for strategic levels, while DE to assist in operational levels.

Venkateswaran and Son applied SD to model the management of a facility inventory and DE for the shop-floor operations [98]. This discrete-continuous framework captures the necessity of using two-level Hierarchical Production Planning (HPP) architecture to simulate alternative types of decision-making by applying SD for high-level aggregate functions and DE for lower-level individualized functions [98]. Venkateswaran and Son suggested that High-Level Architecture (HLA) for modeling multiple hybrid and complex environments [9] allows to coordinate and interface with multiple simulations, model types, protocols, algorithms, and communication requirements into a hybrid framework.

Martin and Raffo applied hybrid DE-SD M&S to evaluate concurrent changes to the process and project environment of a software development company [99]. This hybrid M&S approach improved software development process in terms of time, quality, and project performance [99]. Martin and Raffo suggest that more inclusive process modeling enables problem owners and especially managers to explain hypothetical process changes, as well as to build up financial analyses of the impact of particular changes that need to be tacked in business [99]. Therefore, Martin and Raffo used SD for project environment, as a set of differential equations, and DE for the process activities [99]. By combining discrete processes and differential equations over time they were able to depict the performance of project variables such as motivation, staff levels, and quantity of detected errors. Martin and Raffo noticed that these models capture the effects of feedback loops that may be present in the project environment but are restricted in their ability to correspond to a discrete event process.

Moreno-Lizaranzu et al. conducted another research study that combines discrete and continuous aspects in the control of manufacturing systems [100]. Moreno-Lizaranzu et al. developed on RapidCIM a message-based process control system, which was extended to support real time communication by accessing databases remotely and sending messages. These messages were used to manage hardware equipment which performs both continuous and discrete processing activities. This hybrid control system prototype integrates unit processes and operational decisions by combining continuous and discrete event simulation into a message-based process control system. One of the main problems in the area of computer control of manufacturing systems, which was pointed out by Moreno-Lizaranzu, is that existing software and hardware needs to be compatible in order to plug in and run. One way to deal with this challenge is to equip the shop floor control system developers with software that automatically generates code. The ability to automatically generate code can significantly decrease the cost of developing and integrating manufacturing systems, while it allows a more detail simulation to be used for analyses and control. Thus, Moreno-Lizaranzu et al. developed a DE queuing network at a higher abstraction level capable to capture and correspond to component activities, their interactions, and the exchanged artifacts. At the lower abstraction level, they applied continuous modeling and analytical techniques in order to explain the behavior of the introduced activities [100]. This hybrid DE-SD modeling approach applied in a waterfall-based software process to examine and learn the effects of the requirements when the lack of stability causes various process quality attributes in time of delivery, effort of productivity, percentage of revision, and quality of product [100]. Moreno-Lizaranzu et al., demonstrated that the simulation outcomes of this hybrid model can present both quantitative and qualitative recommendations according to what software process improvement needs to be done to meet organizational requirements [100].

Furthermore, Brailsford, and Hilton support that the answer to the question of when to select between DE and SD M&S methods is based more on the rationale of the model instead of the system that is being modeled [87]. On the other hand, it is argued that there is a strong fit among M&S approaches based on the system, problem, and methodology perspectives that should be considered prior to the M&S process when it comes to deciding for integration and/or combination between SD and DE methods [101], [102], [51], [11].

In the literature, Brailsford and Hilton presented guidance as it concerns the selection criteria for combination and/or integration between SD and DE based on the problem and methodology perspectives [87], but not including system perspectives. On the other hand, Chahal et al. [11] modified and expanded the selection criteria to also incorporate system perspective criteria [102], but not considering the AB approach [24]. The methodology perspective describes philosophical assumptions, technical characteristics, capabilities, and limitations of each M&S method [102]. The system perspective corresponds to potential features and naturalness of the system that is being modeled and simulated. The problem perspective refers to different aspects of the problem [102].

In situations where more M&S models get involved, M&S criteria consider that the problem objective is influenced by both detail and dynamic complexity [7], [33]. However, it is necessary to prioritize which methodology tackles the most significant issues based on the higher importance [24], [87].

Table 2 summarizes the findings from the meta-interpretive review for SD and DE comparisons.

Table 2. Summary of findings from meta-interpretive review for SD and DE comparisons

Criteria	**SD**	**DE**	**Reference**
Randomness ***(Methodology Perspective)***	SD are usually deterministic	The majority of DE models are stochastic	Coyle [88]
System Focus, System Process; System Representation; ***(System***	SD is recommended for systems related to continuous processes; Holistic system view; Stocks, and flows	DE is recommended for detailed examination of a system; Queues and activities; Analytic perspective	Sweetser [89]; Brailsford and Hilton [87]; Morecroft and Robinson [90]; [91], [92]

Criteria	SD	DE	Reference
Perspective)			
Problem Scope Level *(Problem Perspective)*	SD applies at a strategic organizational level	DE applies at the tactical and operational organizational	[89], [91], [55]. Petroulakis [95], Lee et al. [96], and Helal [10]
Modeling Philosophy *(Methodology Perspective)*	SD uses closed loop structures in which causal interactions and feedback effects are very important	DE models are usually open loop structures that are less interested in feedback effects	[88], [89], [87].
Complexity (System Perspective)	SD is better applied to capture dynamic complexity	DE captures better detail complexity	Lane [91]
Organizational Decision Support *(Problem Perspective)*	SD is more appropriate for objectives of policy making and assessment, training and understanding	DE satisfies better objectives related to decision support in terms of optimization, prediction and comparison of alternative scenarios	Morecroft and Robinson [90], Lane [91], Brailsford and Hilton [87];

Criteria	SD	DE	Reference
Problem Resolution (Problem Perspective)	SD for high-level aggregate functions	DE for lower-level individualized functions	[98]

2.7.3 Meta-interpretive review of literature of comparisons, existing combinations, and/or integrations between DE and AB M&S. Each M&S approach has its own academic community and its supporters. Analysts or modelers who have a strong background in a particular M&S method, sometimes show little appreciation for the other methods by allowing intellectual and institutional divisions [89], [91]. An example of this contradiction is detected in panel discussions presented between Siebers et al. [86] and Tjahjono [103]. In the literature it has been observed that some modelers or analysts may favor to select a particular M&S method due to the directed expertise of having a strong background, or because they feel more confident and familiar with a particular approach [87] [90].

In spite of this antagonistic attitude [17], [86], [103], other studies support the collaboration of the approaches and show more appreciation and respect for different M&S approaches, by seeking common ground for their combination and/or integration. In the literature we identify existing frameworks that combine or integrate DE-AB M&S across multidisciplinary research domains such as: in the healthcare domain [104], [105], in urban dynamics and logistics [106], [107], [108] in management, information and simulation systems [18], [109], in robotics in CIM production [110], as well as in militarily research [111], [112], and real time applications [113].

Some examples between DE and AB combination and/or integration in supply chain and health care systems are presented by Borschev [6]. In the first case, Borschev shows how a user can integrate a DE business process inside agents that represent supply chain elements [6]. In the second case, Borschev demonstrates how a user can model agents who temporally transformed to entities in order to request treatment from a health care center, captured by a DE method [6].

Furthermore, Majid et al. conducted a comparison study between AB and DE to examine which approach is more appropriate to capture and represent a human centric system considering human reactive behavior by developing two separate models [17]. The authors concluded that both M&S methods could provide very similar results for one MoP ("waiting time") with minor differences (AB scores slightly better). Analyzing the measures of central tendency of these human reactive behavior experiments revealed some advantages and disadvantages between AB and DE approaches. For example, by observing the variability between the two methods, the DE model could not reproduce the actual variability exhibited in the observed system as the AB model could. Although, AB approach could score slightly more accurate results, DE is more frequently used approach especially in this particular industry. In addition, Majid et al. noticed that the design, the development and the V&V of such models seems to require less effort and time with DE approach rather than with AB. On the other hand, Majid et al. underlined that DE may face limitations (i.e. it cannot capture proactive human centric behavior that AB can) that usually are considered as constraints or assumptions during the design, development and V&V phase. In contrast, AB M&S requires more attention during the design and development phases

[17]. The users that apply AB M&S must pay attention to both micro and macro levels of a system. This is important because if one focuses only in modeling individual entities and ignores the macro behavior of a system, a macro level validation may be impossible to achieve [17].

Dubiel, and Tsimhoni proposed another type of hybrid simulation that deploys AB and DE M&S in order to capture realistic human traveling in a theme park [18]. The visitors of the theme park were modeled as intelligent agents with "human-like" behavior and abilities such as: visual memory, perception of the environment (visual ability), navigation to objectives (ie, I want to go to rollercoaster X) and meta-knowledge ability (meaning that agents know when to ask information or use maps to follow directions) [18]. The AB model was integrated into a DE queuing theory model. This AB-DE deployment process allows agents to make real time decisions such as to avoid obstacles, or change route direction because of their hybrid modeling mobility and existence as "entity/agents".

Finally, Uhrmacher and Gugler developed JAMES, which allows deployment of DE-AB M&S in a java based environment [114]. The authors presented how JAMES can execute a moderately optimistic strategy which separates simulation and external deliberation into different threads, by allowing simulation and deliberation to proceed in parallel, by utilizing DE simulation events as points of synchronization.

2.7.4 Meta-interpretive review of literature of comparisons, existing combinations, and/or integrations among DE, SD, and AB M&S. Existing frameworks that combine or integrate DE, SD, and AB M&S approaches have been applied across multidisciplinary research domains such as: task analysis [115], energy systems [116], supply chain management and logistics [117], healthcare organizations [21] and System of Systems (SoS) [20]. In this section, we review a selected list of multi-method studies that helped in the identification of criteria for the M&S framework.

Lynch et al. proposed a Multi Paradigm Modeling Framework (MPMF) for M&S of problems whose specification are constituted by stipulatory obligations that allow for a set of alternative questions to be handled from a problem situation apart from the use of only one modeling approach [22]. The MPMF framework recognizes macro, meso, and micro levels of resolution from what is noted and assumed in regards to the problem situation [22]. Lynch et al. mapped the different levels of granularity separately from different modeling approaches and combined them to provide an inclusive model for the spread of obesity and equivalent simulation of the problem situation [22]**.** Lynch et al. conclude that the MPMF framework could manage interactions of elements at different resolution levels while only one modeling approach could not. However, they recommend applying the minimum number of possible M&S approaches in order to best answer the desired modeling questions. Lynch et al. mention that when only one modeling approach is adequate to answer the question, then the framework must be skipped [22]. In Table 3 we summarize the recommendations of Lynch et al. in regards to the appropriateness of each method.

Table 3. Criteria for appropriate M&S selection obtained by Lynch et al. [22]

Criteria	**SD**	**DE**	**AB**
Level of Resolution	High-Level focus on system level changes	Low resolution and sometimes also high resolution	In depth at any level (Low to High-Level)

Answering Modeling questions and problem objectives that need	continuous time	Time is evolved based on important events	Agent based can contain both continuous and discrete elements
Interactions that focus on	cause and effect relationships	Event driven changes	Object to object or object to environment
Type of entities	homogenized at the level of the entire population	Independent and identical entities or groups (batches)	Individual level
Type of Data	Equation based	empirical data	Represent theory or rules and empirical data

Prukner and German [118] deploy the three M&S approaches together in order to explore alternative scenarios of electricity generation systems and detect risks and miscalculations under politico-economic constraints. Prukner and German [118] applied DE and AB for discrete events and state changes of a gas power plant and SD to capture continuously changing processes such as the electricity demand, the charging or discharging of electricity storages, and other dynamic variables [118].

Djanatliev and German [21] deployed the three M&S methods together, in order to provide decision-support of health technology assessments. Djanatliev and German recommend SD for macroscopic level of abstraction to capture population and disease dynamics following top-down modeling approach, and AB with DE in a common hospital environment. DE applied for meso levels of abstraction, to capture workflow aspects by following a process-oriented modeling approach, and AB applied for micro levels of abstraction to capture more details of interactions on individual level by following a bottom-up approach [21].

Kremers et al. also combined the three M&S methods to create a flexible multi-method simulation model for the output of a wind power system [119]. This multi-method simulation model deploys continuous models for the wind speed generation and the power of the turbines, DE for capturing the changing mean speeds per hour and the states of the turbines, and AB for capturing the failure behavior of a heterogeneous set of turbines [119]. The combination of multiple M&S methods allowed Kremers et al. to develop a more realistic and flexible model that can benefit from the different advantages of each approach [119].

Borshchev and Filippov present differences and similarities of the three M&S methods [55]. For in-depth understanding they place the three M&S approaches based on the level of abstraction and based on the different applications that each M&S method would be more appropriate [55], [6]. DE is placed on meso to micro level (more details) of abstraction, SD on meso to macro level (less details) of abstraction and AB on any level of abstraction. In general, the three M&S methods have fundamental similarities in their main involved stages of implementing a simulation study such as problem definition and objectives, conceptual modeling, CG development, V&V, learning, and understanding of the results [6], [93].

Borshchev and Filippov also discuss the correspondence between DE, SD, and AB models and presented in detail how an AB model can be developed from an existing SD or DE model and how it can be advanced to represent and capture CS behavior, dependencies, and interactions [55]. Furthermore, in the literature, Borshchev mentions that the number of 3M&S architectures is endless. Therefore, he describes some of the most commonly used architectures for combination and/or integration among DE, SD, and AB models [6] as follows:

- Agents within a SD environment
- Agents interact with DE process model
- Agents that for a short time period behave as entities in a DE process model
- A DE process model connected to a SD model
- A DE process model within Agents
- SD within agents

Borschev recommends that one can deploy 3M&S to develop a simple, complex, flat, hierarchical, replicated, static or dynamically changing architecture, but the appropriate structure selection should be based on the fundamental criterion of the "naturalness" of the model [6]. Subsequently, when a user combines and/or integrates M&S approaches, the produced model must be clear and easy to interpret and explain [6].

Furthermore, Lonz and Jost conducted a comparison study among all the M&S approaches [120]. This study reveals differences and similarities among the three M&S methods in regards to the purpose, the object, and the methodology of a 3M&S study, considering also other system's perspectives, important assumptions, and technical differences [120]. The study concludes with some criteria for selecting adequate M&S methods. AB approach is recommended as more suitable for strategic CS problems and in situations that involve interacting entities, spatial distributions, and heterogeneity. SD is recommended for strategic CS problems, macroscopic policy development, and aggregated perspectives, as well as in situations where feedbacks and nonlinearities take place. Finally, DE M&S is suggested as more appropriate for solving Logistic problems and quantitative optimization. DE is better applied in situations where stochastic variations and linear relationships take place within a CS.

Furthermore, Sumari et al. compared the three M&S approaches using taxonomy to detect features, advantages, and disadvantages [121]. As it concerns SD, Sumari et al. conclude that it is better applied to gain in-depth understanding and learning of CS behavior in long term aspects. Additionally, they conclude that SD focuses more on the flow and dynamic feedback behavior of a specific CS scenario and it is usually applied in policy making at strategic levels [121]. An advantage of SD compared to DE and AB is the ability to reveal relevant factors that cause impacts within a CS. SD as well as AB and DE models can be used to test and adjust alternative scenarios to gain different results and knowledge. One of the weak points of SD is that complexity increases linearly with the size of the CS model. Similarly, in DE M&S the complexity increases exponentially based on the size of the CS model and in AB complexity increases as more details are added in the model. Sumari et al. [121] conclude that DE is more suitable for queuing systems or to assess and compare alternative scenarios and is described as a process-centric approach, usually applied to assist in decision and prediction making in operational and tactical organizational levels. As far as the AB approach is concerned, the authors recommended that it is more suitable for capturing emergent phenomena and identifying interactions and operations of agents capable of adding more details and realism. A strong point of AB is its flexibility and appropriateness to study emergency and behavioral models, but it requires strong programming and computational skills.

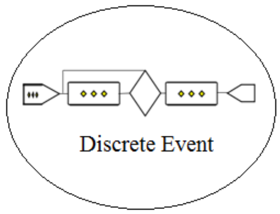
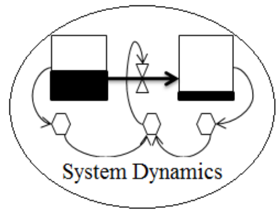
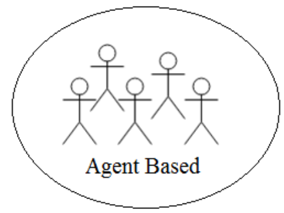
In the field of supply chain modeling, Owen et al. [122] proposed another framework for selecting among DE, SD, and AB based on matching characteristics of each technique to capture specific simulation aspects based on the problem perspective such as: modeling elements, individual entities, time treatment, structure of system, spatial relationships, delays, feedback, decision-making, randomness and uncertainty, state changes, human agents, adaptation, and mathematical formulation.

In the same context of supply chain, another comparison among DE, SD, and AB is conducted by Behadani [123], who evaluated the three methodologies for modeling supply chains as complex socio-technical systems.

A meta-interpretative review between differences and similarities among the three M&S methods has been conducted. Different technical and philosophical aspects of each method has been discussed in the way they illustrate and capture CS problems and systems perspectives, as well as the difference in the way they have been combined, integrated, and applied.

In Table 4, Table 5, and Table 6, we attempt to summarize the most important features and differences among the three main M&S methods (DE, SD, and AB), by establishing criteria based on three perspectives: methodology (Table 4), problem (Table 6), and system (Table 5).

Table 4. Methodology Perspective Criteria for DE, SD, and AB M&S

Methodology Perspective			
Criteria			
Modeling Approach	Process-Centric	Top-Down	Bottom-Up
Modeling Philosophy	Randomness related to interconnected variables leads to system behavior	Causal closed structures causes and defines system's behavior	Global behavior emerges out of concurrent agent behaviors
Object	Entity	Feedback	Agent
Object characteristic	Passive	Indistinct	Active
Time	Discrete	Continuous	Discrete
Space	Discrete 2D/3D	Continuous 2D/3D	Discrete/Continuous 2D/3D
Relationships	Non-Linear/Linear Focus more on Linear	Non-Linear/Linear Focus more on non-linear	Non-Linear/Linear Focus more on non-linear
Feedback	Mostly Implicit Flow-Charts	Mostly Explicit Causal Loops	Mostly Implicit State-Charts

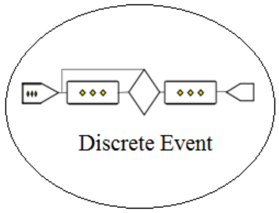
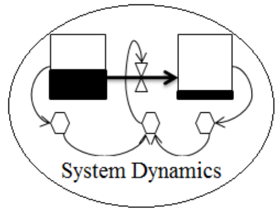
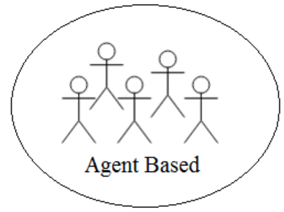
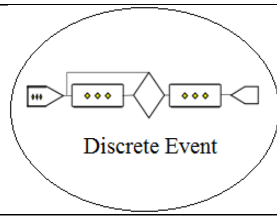
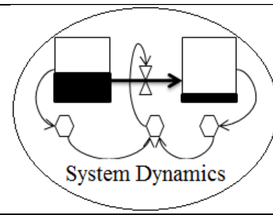
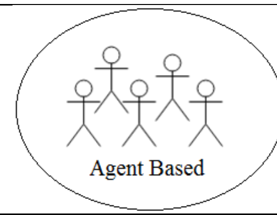
Methodology Perspective			
Criteria			
Randomness	Mostly stochastic High Importance	Mostly deterministic Low Importance	Mostly Stochastic High-Low Importance
Predictive Level	Scores High	Scores Lower	Scores Higher
Numerical Data	Highly dependent	Not-Highly dependent	Highly dependent
Input Data Sources	Historical, Empirical, Numerical Data	Historical, Subjective Judgmental data	Historical, Empirical, Numerical data
Output Data Analysis	Strong Statistical Knowledge Required	No Strong Statistical Knowledge Required (Easier Interpretation)	Strong Statistical Knowledge Required (Challenging)

Table 5. System Perspective Criteria of DE, SD, and AB M&S

System Perspective			
Criteria			
System Focus	Narrow, Analytic View	Broad, Holistic View Analysis of structure	Narrow/Broad View Analysis of Rules
Abstraction Level	Meso -Micro Level	Meso-Macro Level	Any Level of Abstraction (Micro-Meso-Macro)
System Process	Discrete	Continuous	Discrete/Continuous
Control of the system process flow	Holding	Rates	Transaction Mechanisms
System Representation	Sequence of Discrete Events, Activities, dynamic events	Continuous flows and Stocks, Environmental dynamic parameters	Individual agents, clusters or networks of Agents, state
Complexity	Detail	Dynamic	Detail/Dynamic
Complex System Understanding	Based on Randomness of interconnected events	Based on parameter estimation of dynamic causal-effects relationships	Based on overall behavior of interdependencies
Visualization	Advanced	Limited	Advanced

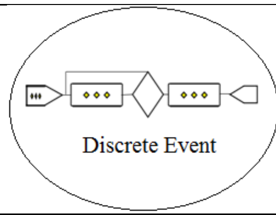
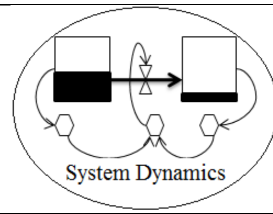
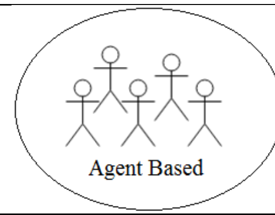
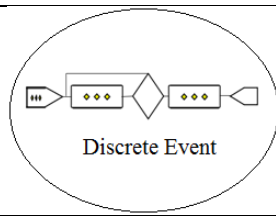
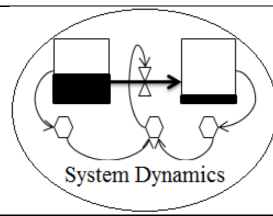
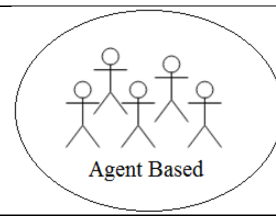
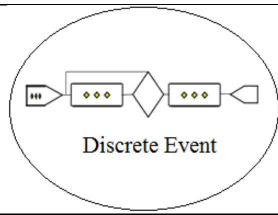
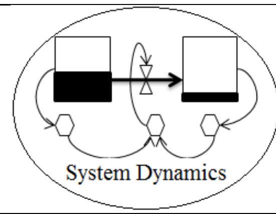
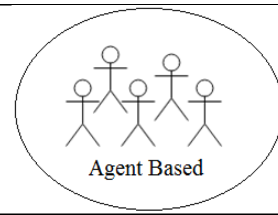
System Perspective			
Criteria			
Interaction with External Environment	Mostly Isolated No interactions	Mostly Accessible cross boundary interactions	Mostly Accessible Periodic boundary interactions

Table 6. Problem Perspective Criteria of DE, SD, and AB M&S

Problem Perspective			
Criteria			
Problem Scope Level	Operational –Tactical	Strategic	Any Level
Situation	Queues	Flows	Rules
Problem Resolution	Detailed Level	Aggregated Level	More detailed Level/Aggregated Level
Level of Randomness	High	Low	Low-High
Level of Accuracy	Precise Prediction Meso-Micro	Not restricted to prediction Meso-Macro	Precise Prediction Micro (with more details)-Meso-Macro

Problem Perspective			
Criteria			
Data Type	Quantitative Data	Qualitative Data	Quantitative/Qualitative
Organizational Decision Support	Mostly used for: Optimization, Prediction, Bottlenecks, Comparison of Alternatives	Mostly used for: Policy-Making, Learning & Understanding Reveal of dynamically factors and cause and effect relationships	Mostly used for: Optimization, Understanding of emergent phenomena/situations, Learning and adapting mechanisms, Reactive and proactive behaviors.

To summarize, in this section, we provided a review of literature of existing frameworks and studies that compare, combine, and/or integrate the three M&S approaches. We summarized the most important features, similarities and differences among the three M&S approaches based on system, problem and methodology perspectives. In the next sections, we summarize limitations of existing hybrid frameworks and research gaps that we identified in the review of the literature.

2.8 Limitations of existing frameworks

Several hybrid M&S approaches, frameworks, and studies that compare, combine, and/or integrate DE, SD, and AB models have been described. The author of this dissertation noticed that there is limited guidance on when, why, and how to combine, and/or integrate DE, SD, and AB approaches, as well as in the way the models interact and formulate relationships to exchange information. The existing hybrid frameworks focus more on how to deal with specific problems rather than on how to provide a broader way of applicability to various problem situations. For example, Venkateswaran et al. [9] mentions that aggregate production released orders from SD can be passed down to DE as operational performance indicators such as work in process, lead time, throughput etc which can pass from DE to SD. As it can be observed, the language used by Venkateswaran et al. is very domain specific to hierarchical production planning and it cannot be applied to describe other CS or different problem scenarios.

Furthermore, in the review of the literature, authors have applied various hybrid simulation studies with respect to interaction and information exchange; however, they do not provide guidelines with regards to the relationships that can be formed between the interaction points. For instance, Chachal et al. [11] proposed a generic conceptual framework for hybrid simulation in healthcare, but is limited to only a combination between DE and SD and does not include AB. In this dissertation we argue with frameworks [24] that suggest starting the development and implementation of the models before the identification of the interaction points and then to map and formulate their interaction relationships. In contrast, the 3M&S framework suggests first to conceptualize the identification of interaction points, justify and define the types of relationships for information exchange of the proposed models and then to develop and implement the actual models. The reason for following this order is that the author of this dissertation found more practical to justify and conceptualize first how and for what objective the models will be connected and then to start the implementation of them.

In addition, existing hybrid frameworks such as those provided by Venkateswaran et al. [9] and Helal et al. [124] are forced by the author‘s particular problem solution assuming a problem-centric approach. Their approach starts by defining a problem which is assumed to require a hybrid solution and then they analyze technical aspects of interactions between SD and DE, rather than providing instructions to identify when and why this particular problem indeed requires multi-method modeling and simulation, as well as what and how is the information exchanged among SD, DE and AB models. On the other hand, Mingers and Brocklesby [19] argues that theoretical framework should be established prior to the investigation of the logical possibilities to technically combine M&S approaches.

Existing hybrid simulation studies such as Venkateswaran et al. [9], Helal et al. [124], Martin and Raffo [99], Alvanchi et al. [125], Matsopoulos [111], Lektauers [107], Shengnan [126], Schieritz [68], Größler et al. [70], focus more on addressing the technical interoperability and synchronization mechanisms between the models rather than in a generic guidance that could aid in different problem situation of CS. None of the existing frameworks have attempted to provide a generic guideline and methodology on CS aspects including all three M&S methods (DE.SD.AB). Therefore, another limitation that was detected compared to other existing frameworks [9], [124] is that they have been developed based on the assumption that their problem requires combination/integration of DE, SD, and AB deployment.

There is no methodology or guidance to identify selection criteria based on problem, system and methodology perspectives, as well as to justify whether, or not, a problem requires multi-method modeling and simulation among DE, SD, and AB. Moreover, the literature of the multi-method modeling and simulation architectures and approaches does not clearly illustrate the context of how information is exchanged among DE, SD, and AB models and what are the relationships between the interaction points. Therefore, there is a need for a generic 3M&S (DE.SD.AB) framework for CS capable of providing generic guideline on the following aspects:

- Identify criteria for aiding in selection among DE, SD, and AB approaches
- Identify and justify why and when a problem requires multi-method modeling and simulation (3M&S)
- Identify how the DE, SD, and AB models interact with each other in order to exchange information (generic types of relationships for the information exchange)

2.9 Research Gap Identified

It has been argued that the assignment to research the rational possibilities for combining and/or integrating approaches first requires the establishment of a relevant conceptual framework and then perform results [19]. However, from the reported literature it has been observed that this has followed an alternative order.

Conceptual frameworks are necessary to offer useful guidance for combining and/or integrating M&S methods [36], [37]. The existing conceptual frameworks have been limited between the combination and/or integration of two methods without providing guidance on when, why, and how to deploy DE, SD, and AB M&S to form 3M&S models to solve CS problems. More specifically:

- In the literature, it has been argued that the use of hybrid simulation can be justified if there are strong interactions between elements represented between these two M&S methods (DE, SD), but not including AB.
- The literature did not provide multi-method modeling and simulation framework or guideline for integration or combination of the three M&S methods (DE, SD, and AB).
- In this research we investigated the interactions among elements represented by the three M&S approaches by developing a list of generic criteria based on the different perspectives of each method (system, problem and methodology).

The 3M&S Framework is an attempt to fill these gaps and the proposed methodology (Chapter 3) provides a guideline to achieve this. The 3M&S framework aims to offer a guideline to combine, and/or integrate the three main M&S approaches (DE, SD, and AB), along with the capability to provide instructions for integrated deployment or combination of DE, SD, and AB M&S to form 3M&S models.

The 3M&S framework should also be able to provide guidelines on identifying that the problem actually requires 3M&S. The 3M&S framework is not restricted to the M&S process of AB, SD, and DE approaches neither suggests that all three of these approaches must always be deployed simultaneously for a simulation implementation.

CHAPTER 3: OVERVIEW OF 3M&S FRAMEWORK

The purpose of this chapter is to provide an overview of a generic conceptual framework, termed 3M&S framework [27], for applying Multi-Method Modeling and Simulation (3M&S). The framework offers useful guidance for combining and/or integrating different M&S methods. The term "multi-method" is used to refer to all the possible architectures that can be constructed with more than two M&S methods [6], [17], [25]. Furthermore, we use the term 3M&S to refer to a model implemented following the 3M&S framework.

The two major contributions of this section include: (1) a methodology and a framework that guide the user through the development of 3M&S model(s) to solve CS problems and (2) an algorithm that recommends appropriate M&S method(s) based on the user selected criteria for user defined objective(s).

3.1 Overview of 3M&S Framework

This section provides a brief overview of the conceptual 3M&S framework. The Unified Modeling Language (UML) was used to describe different levels of abstraction of the framework, modeling concepts and constructs to illustrate the actions that a user performs in order to implement a goal, while interacting with a CS [127]. The framework is examined from both a high-level view as well as from an internal view. The latter approach offers a guideline of the 3M&S architecture, an understanding of different model components and how they interact. Figure 4 depicts a high-level activity diagram of the 3M&S framework divided in four main phases.

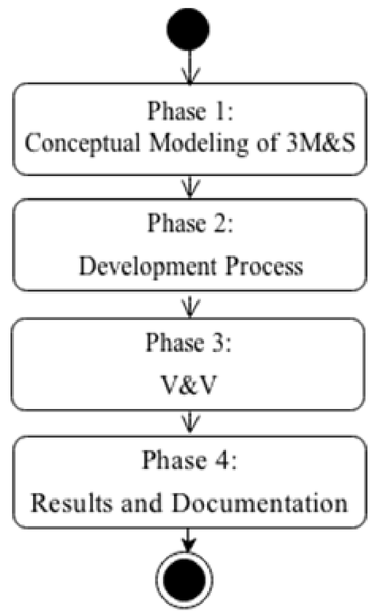


Figure 4. High-Level view of 3M&S Framework**.**

Phase 1 includes the conceptual modeling, where the user has to define the problem, decompose objectives to sub-objectives, define the scope, the constraints and select M&S method(s). Additionally, we examine Q1, Q2 and Q3. Phase 2 describes the development process of the actual model construction. This phase includes the development activities of the produced algorithms from Phase 1, as well as calibration of the Computer Generated (CG) model(s). Phase 3 consists of the Verification and Validation (V&V) process. This phase takes place after the execution of the simulation and before the documentation of results to ensure credibility of the simulation study and the produced results. The relationship between Phase 2 and 3 is iterative and frequent updates to the model may occur. Finally, Phase 4 includes the preparation of the simulation report, the documentation of the results as well as examination of future improvements.

This chapter describes Phase 1 in detail, while Chapter 4 provides a further description of phases 2, 3 and 4 and evaluates the 3M&S framework with real case studies.

3.2 Phase 1: Conceptual Modeling of 3M&S

This section describes the conceptual modeling steps of the 3M&S framework, which is composed of the activities illustrated in Figure 5. The framework incorporates steps from typical M&S methodologies followed for the implementation of a single type M&S method [1], [49] as well as for combining DE and SD models [24]. The 3M&S framework also includes the following unique elements: steps for integration of AB models, an algorithm that helps the user select appropriate M&S methods, steps for the identification of interaction points and types of relationships among interaction points for all three methods.

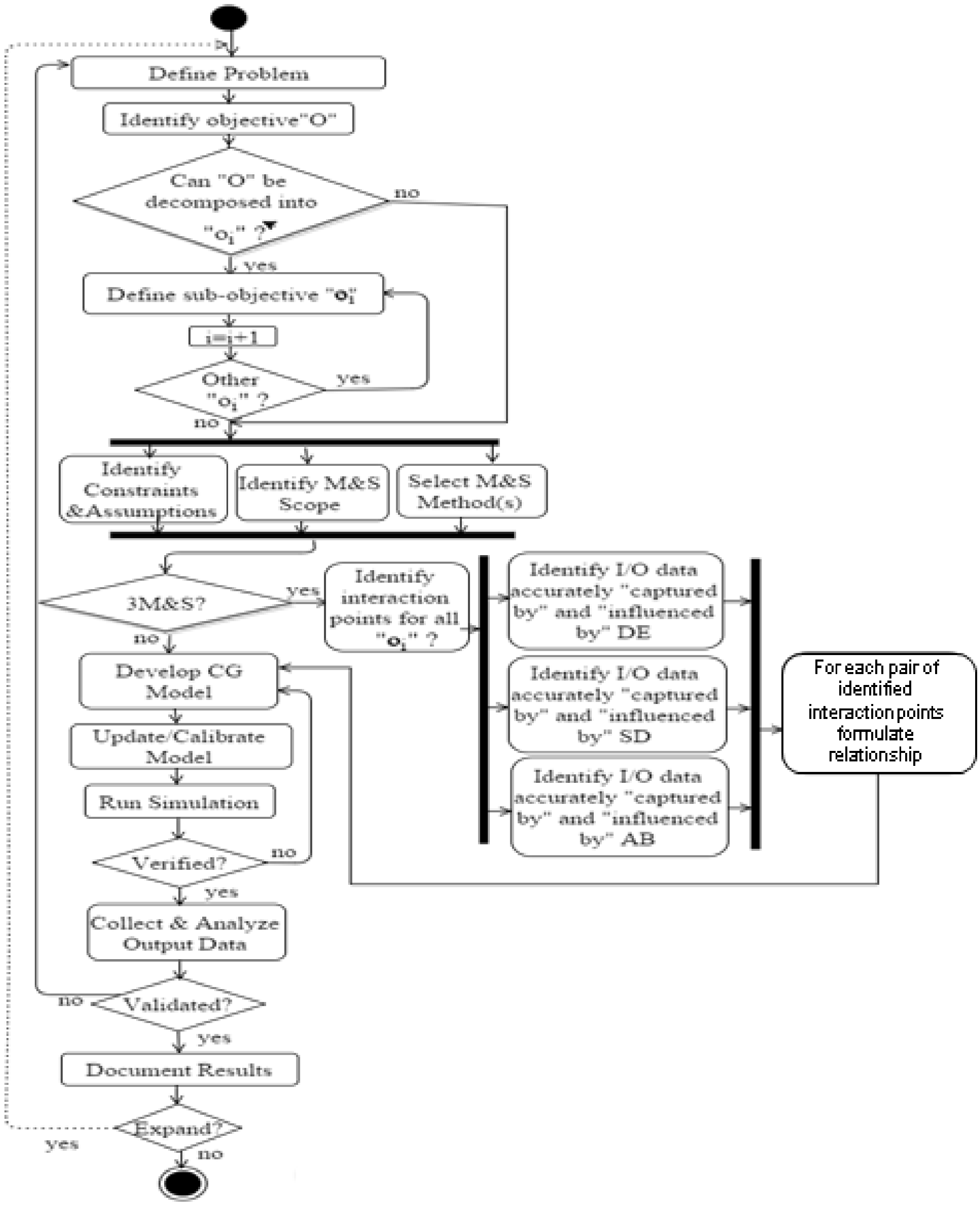


Figure 5. Activity diagram of internal view of 3M&S Framework

3.2.1 Define Problem. The first step the user needs to perform is to explicitly define the main problem and its surrounding environment. Appropriate time and effort must be invested on the understanding of the problem and on clearly defining the problem's objectives and sub-objectives before starting to seek solutions.

3.2.2 Identify objective(s) "O" and decompose them into sub-objectives "o_i". The next step is to identify the objectives of the simulation study. This is a critical stage, where the user is called to follow the third principle of modeling, known as "Divide and conquer" [128] or as decomposition of the main purpose [129]. According to Pidd's modeling principle [128], [130] the user has to decompose the overall objective of the study into sub-objectives. The decomposition of the overall objective into smaller objectives reduces the complexity of the modeling process, as well as the V&V process [131], [132], [49]. In addition, it assists in selecting the appropriate M&S method within a CS context that may require 3M&S approach to analysis.

The main concept of decomposition to sub-objectives is to examine the existence of possible fluctuating variables that have a significant impact on the overall objective [131], [12]. Then the user follows three parallel activities (Figure 6): "Identify Assumptions & Constraints", "Identify M&S Scope", and "Select M&S Method(s)". If the overall objective "O" cannot be decomposed to smaller sub-objectives "o_i", the user continues with the three parallel activities. Otherwise, the user decomposes "O" into "o_i" sub-objectives and conducts the three parallel activities for each "o_i". The objectives and sub-objective are defined prior to the selection of M&S method or prior to possible revisions of current deployed simulations [131], [132].

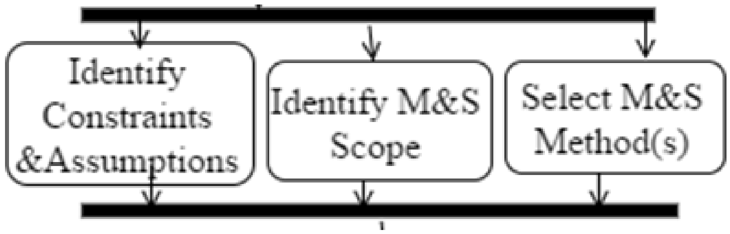


Figure 6. High-Level view of Phase 1 of 3M&S framework.

As we mentioned earlier, identification of constraints and assumptions, M&S scope and M&S method should be conducted concurrently.

3.2.2.1 Identify constraints and assumptions. Once the user finishes with the decomposition of the main objective into sub- objectives, he/she is directed to the identification of the assumptions and constraints under which the 3M&S study is performed. The defined assumptions and constraints play an essential role for the successful V&V of the simulation model.

Constraints may include environmental conditions that can restrict the possibilities of particular actions occurrence, or specific attributes that may need to be satisfied for the execution of specific actions [49]. If some of the objectives cannot be adequately achieved and/or constraints are violated while developing the scope, then the expectations of the study can be reduced and/or constraints may need to be turned off. Therefore, we strongly recommend that the user considers frequent feedback from the problem owners in regards to the modeling assumptions and rational of the model, timeline of the 3M&S study, access to applicable data, cost constraints and other constrains associated with activities that depend on time, available resources and/or conditions.

3.2.2.2 Identify M&S scope. The identification of the M&S scope is very significant as it builds a strong bridge of communication between the problem owner and the solver (user/modeler/simulationist/ analyst) and it provides all the necessary information, clarifications and expectations of both parties.

In addition, the M&S scope is what helps achieve the individual objectives without violating the given constrains and assumptions. Therefore, we need to clearly define the aspects that will be considered in the simulation for each sub-objective. Those aspects are detailed described in the following sub-sections (3.2.2.1-3.2.2.5). Figure 7 presents the activity "Identify Scope", which is composed of five parallel activities that the user has to define for each of the DE, SD, and AB model(s).

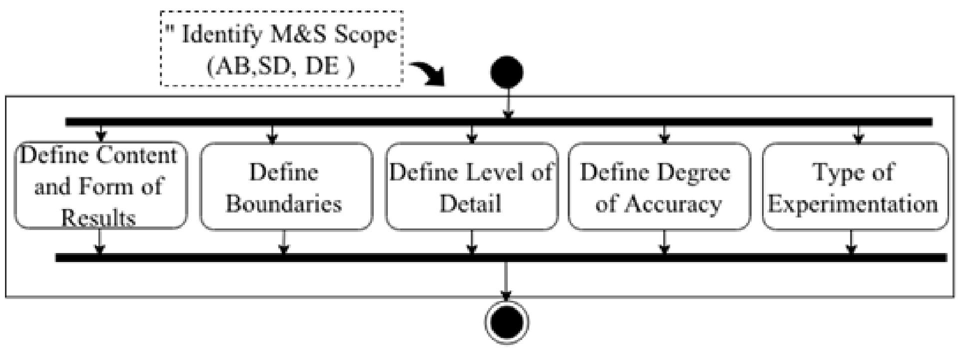


Figure 7. Identify scope activity

3.2.2.2.1 Define content and form of results. The activity of defining the content and form of results may vary from low (basic statistics) to high detail. For example, if an inclusive animation or very detailed statistics are expected for the simulation study, the time and effort engaged to implement a project may be considerably affected [49].

3.2.2.2.2 Define boundaries. The activity of defining the beginning, ending, upper, and lower boundaries is depicted in Figure 8. The beginning boundary specifies where the simulated model starts and it is associated with the inputs which activate the model to begin. The ending boundary specifies where the simulation terminates and it is associated with the outputs of the simulated model. The upper boundary specifies where and when other inputs enter the model during the simulation execution time. The lower boundary specifies what outputs leave the model during the simulation run time.

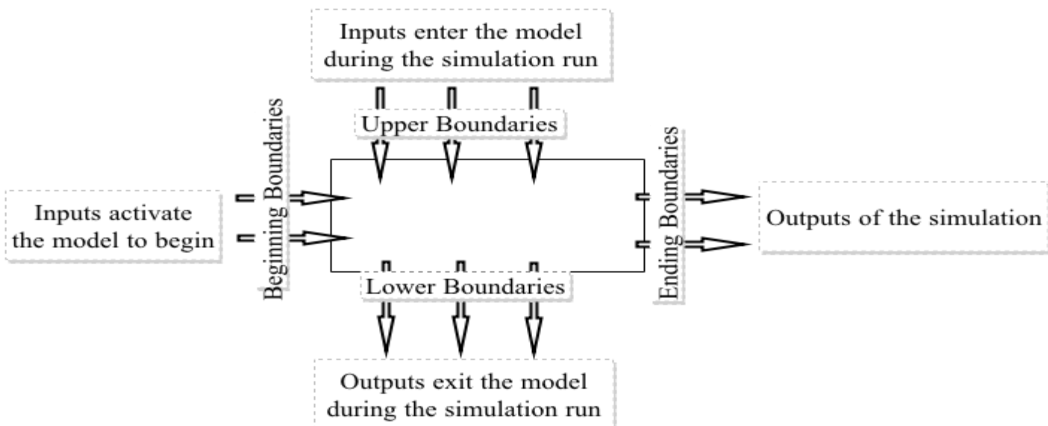


Figure 8. The four boundaries (Beginning, Ending, Upper and Lower)

3.2.2.2.3 Define level of details. The level of detail is defined by the level of precision that is needed in the output and it is associated with factors such as: detail and dynamic complexity, size of the model, as well as time to develop and validate the model [7], [33], [49]. Finding the appropriate level of detail is also significant in order to meet the objectives of the simulation study. If the user considers too many details, the M&S development as well as the V&V of the model requires more effort and time. On the other hand, by considering few details and excluding important factors may result in an unrealistic and insufficient model. Therefore, the user needs to define appropriate level of detail by considering an adequate amount of detail in order to meet the given objectives of a simulation study. Figure 9 depicts how the level of detail affects the M&S development time. The more detail one adds, the more the M&S development time increases.

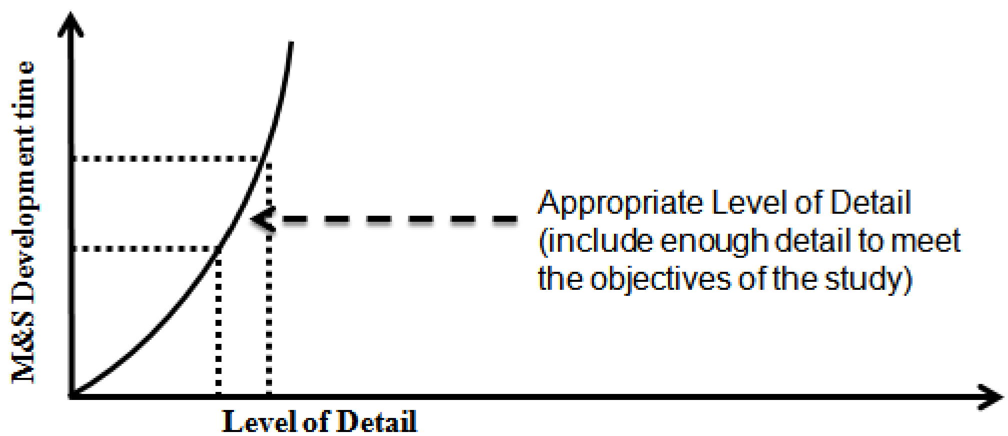


Figure 9. Impact of level of detail on M&S development time

3.2.2.2.4 Define degree of accuracy. The degree of accuracy corresponds to the validity of data being employed. At this point, the user collects, prepares and validates the input data before starts development (input data analysis). Data collected for M&S consist of two types: numeric and logic [49]. Numeric data define quantitative information according to the elements being modeled such as costs, batch sizes, inter-arrival times, waiting times, and service times. Logic data describe the work-flow of a model, and capture information such as: model objects and their behaviors, policy rules, prioritization of processes, assignment of resources.

3.2.2.2.5 Define type of experimentation. Finally, type of experimentation specifies the type of analysis that will be conducted [49]. For example, the user may conduct the analysis of: capacity, sensitivity, decision response, comparison, optimization, visualization.

3.2.2.3 Selection of M&S method(s). In this activity, the user is prompted to select the M&S method(s) that best satisfy the decomposed objectives o_i. At this point, the framework aims to guide the user to select among the j most appropriate M&S method(s) based on the provided user input, where j = 1, 2, 3. This activity consists of a set of criteria $\mathbb{C}$ for each M&S method.

Definition 1: A criterion $c_i \in \mathbb{C}$ is a reference point for the selection among the three M&S methods. Each criterion may be satisfied by up to three relevant Variables of Interest (VoI_{ij}). Each criterion is defined as in (1).

$$c_i \in \mathbb{C} \text{ where } c_i = \begin{cases} 1, if\ selected \\ 0, otherwise \end{cases} \tag{1}$$

Definition 2: A Variable of Interest (VoI_{ij}) represents the value associated with a criterion ci and a j M&S method. Each VoI is defined as in (2).

$$\forall\ o_i \in \mathbb{O} \Leftrightarrow \mathrm{VoI_{ij}} \in c_i \vdash j \text{ M\&S method (DE, SD or AB)}$$

$$\mathrm{VoI_{ij}} = \{\ c_i, \qquad if\ selected \tag{2}$$

Definition 3: A weight w_{ij} is a numerical value assigned to a VoI_{ij} for a selected criterion c_i and a j M&S method. The value of a weight can range from 0 to 10.

$$w_{ij} = 0, .., 10.$$

In particular, the method selection is based on (3), where:

$$Score_{Method} = \max \sum_{j=1}^{3} \sum_{i=1}^{k} (w_{ij} * VoI_{ij}) \tag{3}$$

1. The user selects k number of criteria $c_i \in \mathbb{C}$ that best fit the problem, system and methodology perspectives of a particular objective o_i. The list of criteria can be found in Tables 4, 5, and 6 in Chapter 2.
2. The user is called to assign numerical weights w_{ij} for each VoI_{ij} of k selected criteria c_i. This needs to be done in order to quantify the relative importance of each VoI_{ij} and provide a rational basis for the decisions being made.
3. The additive functions are ranked from best to worst.
4. The framework returns the higher-scored method for each sub-objective o_i based on (3).

An example of how the user interacts with a 3M&S framework for the selected criteria c_i of an individual objective "o_i" is described by the UML sequence diagram of Figure 10.

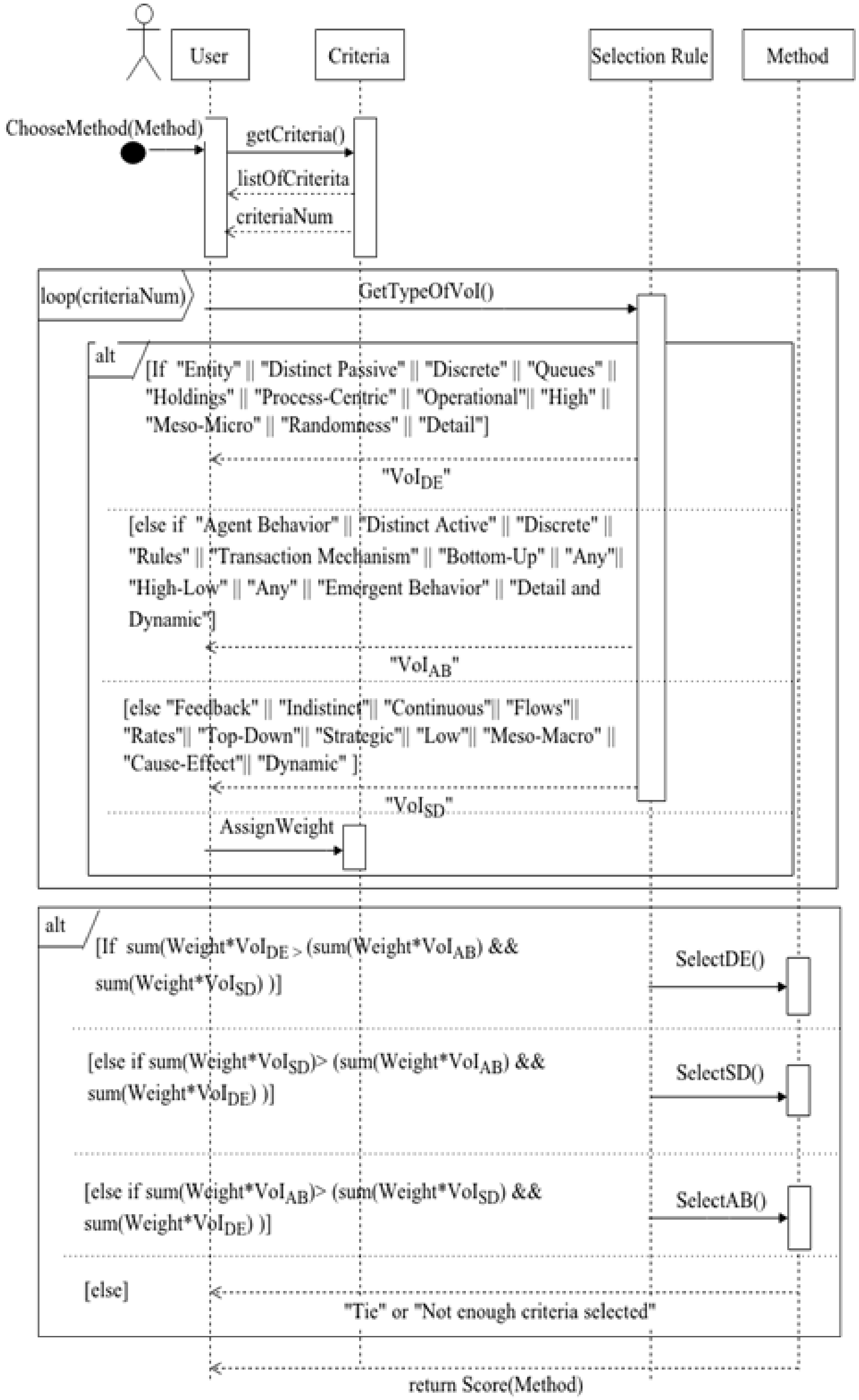


Figure 10. Selection of M&S Method

Once the M&S methods are selected for each sub-objective, if all “o_i” are described by a single type M&S method, then there is no need to apply multi-method modeling and simulation (3M&S is not required) and the framework continues with Phases 2, 3 and 4. On the other hand, if the sub-objectives are satisfied by different M&S methods, then 3M&S is required and the user is called to identify the interaction points for all “o_i”. In this case, investigation of Q.1 (”When and Why 3M&S is required?”) takes place, while Q.2 (“What are the interaction points?”) and Q.3 (“How AB, DE and SD formulate relationships between interaction points to exchange information?”) will be investigated following the activities of sections 3.3 and 3.4. In contrast to Chahal’s hybrid framework [24], which suggests starting the development of the models before the identification of the interaction points and the mapping of their relationships, we first conceptualize the identification of interaction points and the type of information exchange between inputs/outputs of the proposed models and then we start developing the actual models. The reason for altering this order is that we found more useful to justify and conceptualize first how the models are connected and then implement them.

3.2.3 Identify Interaction Points. We define the data of I/O information exchange among the different models as "interaction points". The mapping among DE, SD, and AB takes place prior to the development of a 3M&S model (answering Q.2). The user is called to identify the interaction points, which consist of input and output data of DE, SD, and AB M&S models and their corresponding variables which are properly “captured by” or “influenced by” M&S models (Figure 11). The same process applies to models that are either hybrid (combination of two methods) or deployment of three methods.

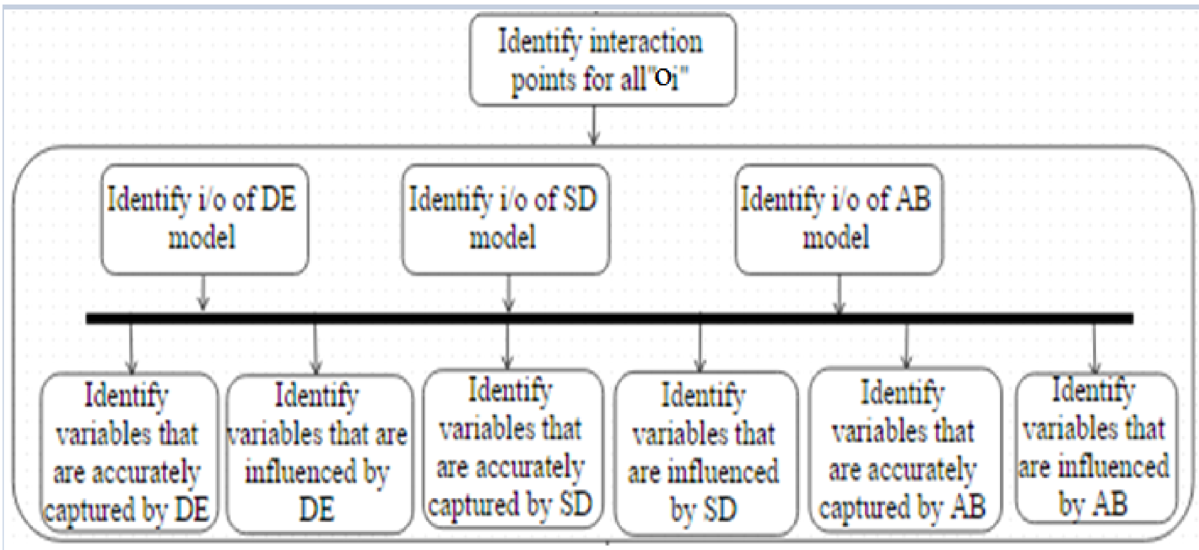


Figure 11. Identification of interaction points among DE, SD, and AB models

3.2.4 Formulate Relationships among DE, SD, and AB interaction points. In this activity, the user has to identify the type of interaction for each pair of mapped interaction points (answering Q.3). In order to identify how AB, DE and SD objectives-models interact with each other to exchange information, all the relationships among pair of interaction points need be well defined. Table 7 summarizes the different types of interactive relationships that can be formed between DE, SD, and AB models.

We conducted a review of related literature and an evaluation (theoretical and empirical) of a hybrid framework that is presented by Chahal for combining DE with SD [24]. Our review showed that frameworks must provide a guideline to potential users in regards to the relationships between the interaction points that exchange information.

Chahal identified and proposed three generic types of relationships that can be formed between DE and SD interaction points: "direct replacement of variables", “aggregation/disaggregation” and “causal” relationships [24]. We further expanded the relationships between the interaction points of information exchange to include AB because the number of relationships increases as the AB is included.

More specifically, AB interactions can involve state changes, inject, adding or removing objects or entities, transfer entities, control flow statements, trigger event and state chart control relationships. Therefore we define two main categories and their subcategories to describe relationships of interaction points that involve exchange of information among DE, SD, and AB. These two categories consist of the ***value assignment*** relationships and ***impact statements*** relationships.

- As ***Value Assignment Relationships*** we define the relationships which include mathematical formulations and replacement of values between equivalent variables. This category consists of the tree subcategories adapted by Chahal [24].
  - The “*direct replacement of values of variables*” corresponds to interaction points that represent equivalent variables of information exchange in both models.
  - The “*aggregation/disaggregation*” corresponds to interaction points that seize values of information exchange that need to be aggregated (accumulated) or disaggregated from the one model to equivalent values of the other model.
  - “*Causal relationships*” corresponds to interaction points that are described by explicitly mathematical relationships.
- As ***Impact Statements relationships*** we define relationships that cannot be expressed using value assignment relationships, but they are related to more abstract concepts. Each

of the impact statements relationships may contain one or more, or combination of value assignment relationships. Such impact statements relationships can be:

- "Add/Remove/Inject/Transfer agents or entities"
- "Control Flow relationships" which corresponds to "if", "for", "while" statements and define the flow of a particular logic.
- "Trigger Event relationships" which can be of different type such as: timeout, message, condition, rate, and arrival.
- "State chart control" corresponds to the state that may control the flow among two models, update variables from other models or trigger any other type of relationship.

Table 7 describes the two main relationship categories, the different types of relationships as well as an expression example for each type.

Table 7. Types of relationships for interaction points

Category	**Types of relationship**	**Expressions**	**Examples**
A. Value Assignment	*A.1 Direct replacement*	Value of AB variable = Value of SD or DE variable and vice versa of or all possible combinations.	value of SD variable "number_of_not_treated_patients_per_day"= value of DE variable "number_of_not_treated_patients" (Figure 13)
	A.2 Aggregation/ disaggregation	1. Var_{AB} = Aggregated (equivalent variables or	the SD rate of "arrivals_per_day" is disaggregated and passed to the DE entry point variable

Category	Types of relationship	Expressions	Examples
		vectors in SD or DE) 2. Var_{AB} = Diseggregated (equivalent variables or vectors in SD or DE) *The same expressions apply for all pair combinations*	in the form of inter-arrival time (Figure 14)
	A.3 Causal relationships	1. Var_{AB}= Math_ Function($Var_{DE\ or\ SD}$) *The same expressions apply for all pair combinations*	LossDueToLongWaitingTime" ="number_of_not_treated_patents_per_day" * "lost_profit_per_patient_not_treated" (Figure 17)
B. Impact Statements	*B.1 Add/Remove/ inject agents or entities*	1. $object_{DE}$.inject($object_{AB}$); 2. $object_{AB}$.remove_ objects($object_{DE/SD}$); 3. $object_{AB}$.add_objects($object_{DE/SD}$); *The same expressions apply for all pair combinations*	• the DE model adds entities to the AB population (patients) (Figure 15) • the AB model removes entities from the DE process (Figure 16)
	B.2 Control Flow	If, for, while statements	the interaction between AB and DE is controlled by an if statement (Figure 16)
	B.3 Trigger Event	The trigger type of the event can be: message, timeout, condition, rate,	Recurring event of timeout trigger type called "Update_not_treated_numbe

Category	Types of relationship	Expressions	Examples
		and arrival.	r “(Figure 13)
	B.4 Statechart control (combined with any of the previous types of relationship)	1. $Var_{DE\ or\ SD}$ = function (statechart.isStateActive($state_{AB}$))	the AB state-chart state “LeaveClinic” is activated and executes a function (Figure 17)

In order to provide a better understanding of how these relationships work in practice we developed a healthcare multi-method modeling and simulation example using AnyLogic [66] simulation software. In this example, we have combined the three M&S methods for a clinic in which patients arrive and wait to receive treatment. If the waiting time is greater than a specific threshold (i.e two hours) then the patient leaves the clinic and tries another healthcare provider. In this example the DE model captures the patient flow of the treatment process, where a patient enters the clinic, waits in the queue for his/her turn to receive treatment or not and then exits the clinic. The AB model captures the decision-making logic of each patient to wait for treatment or leave the clinic, and the SD model captures cost and profitability loss for those patients that abandoned the clinic due to long waiting times. Figure 12 illustrates the deployment of all the three M&S methods together.

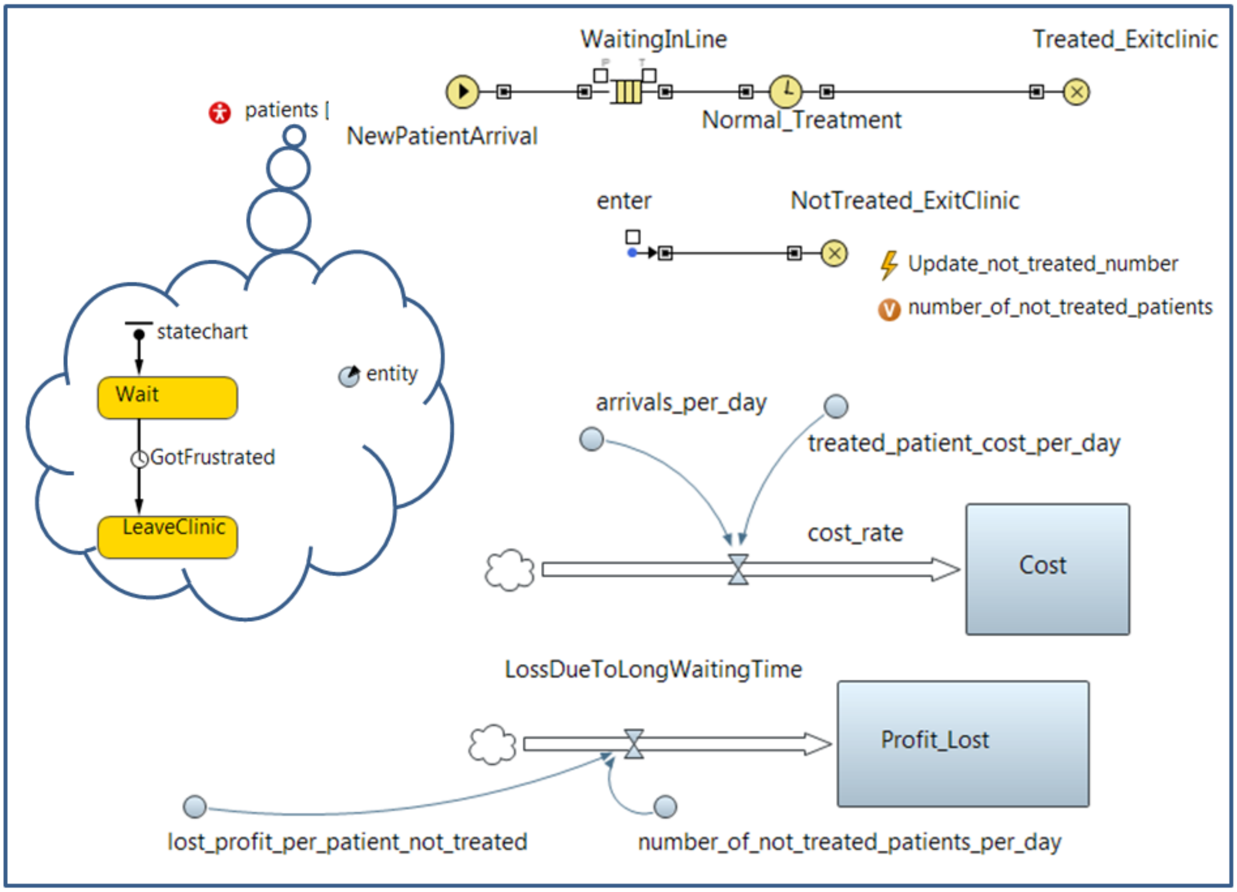


Figure 12. Example that combines different types of relationships

In Figure 13 we illustrate two types of relationship for interaction between DE and SD models. During the simulation run time the DE model triggers an event of a timeout trigger type (B.3 relationship type), which, in turn, directly replaces (A.1 relationship type) the value of SD variable "number_of_not_treated_patients_per_day" with its equivalent variable that is calculated by the DE model ("number_of_not_treated_patients"). In both DE and SD models the related interaction points represent variables whose values are equivalent to each other.

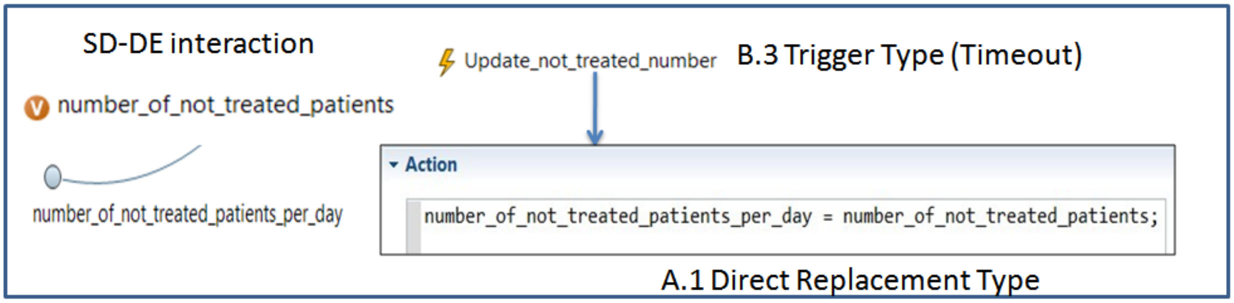


Figure 13. Combination of A.1 and B.3 type of relationships during SD-DE interaction

In Figure 14 we illustrate a disaggregated type of relationship (A.2 type) for interaction between SD and DE models. During the simulation run time the SD rate of "arrivals_per_day" is disaggregated and passed to the DE entry point variable in the form of inter-arrival time. This type of relationship is type of disaggregation because the arrivals per day break down to smaller time intervals between each arrival.

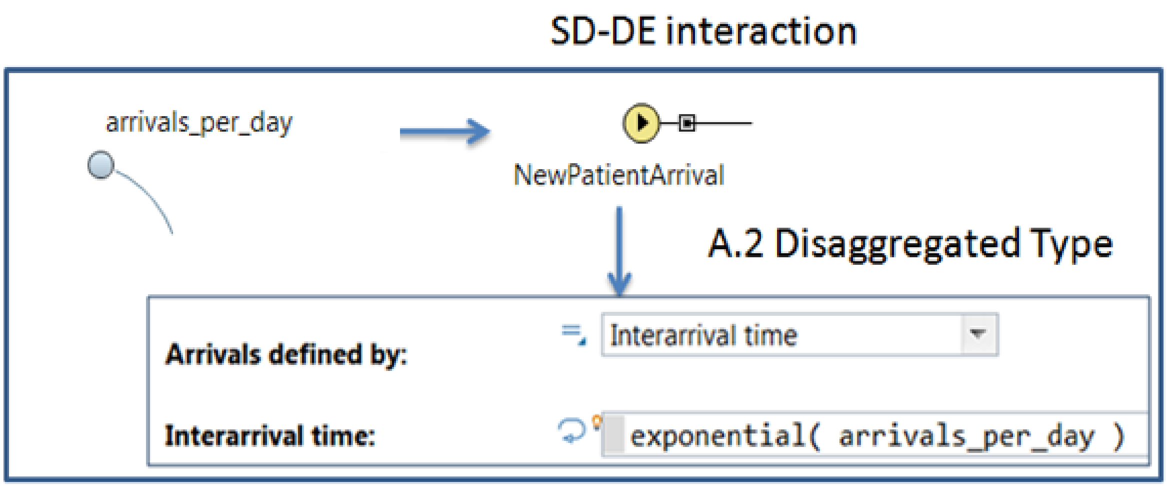


Figure 14. A.2 Type of relationship during SD-DE interaction

In Figure 15 we illustrate an "add entity type" (B.1 type) of relationship for interaction between AB and DE models. During the simulation run time the DE model adds entities to the AB population (patients).

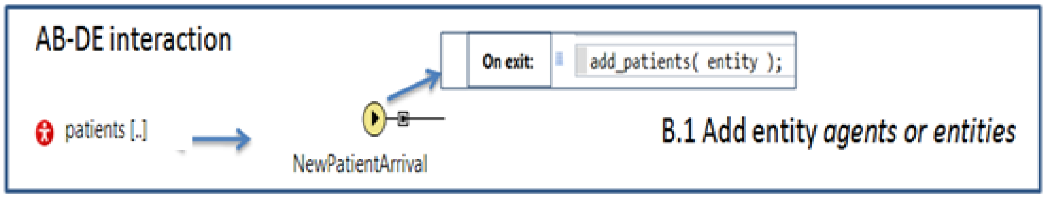


Figure 15. B.1 Type of relationship during AB-DE interaction

In figure 16 we illustrate two types of relationship for interaction between AB and DE models. During the simulation run time the AB Control flow (B.2 type) changes the process flow for the corresponding entity. More specifically the AB transition removes (B.1 type) the corresponding entities which can be either in the "WaitingInLine" or in the "Normal__Treatment" stage of the DE process and then transfers it into the "enter" object to exit the clinic.

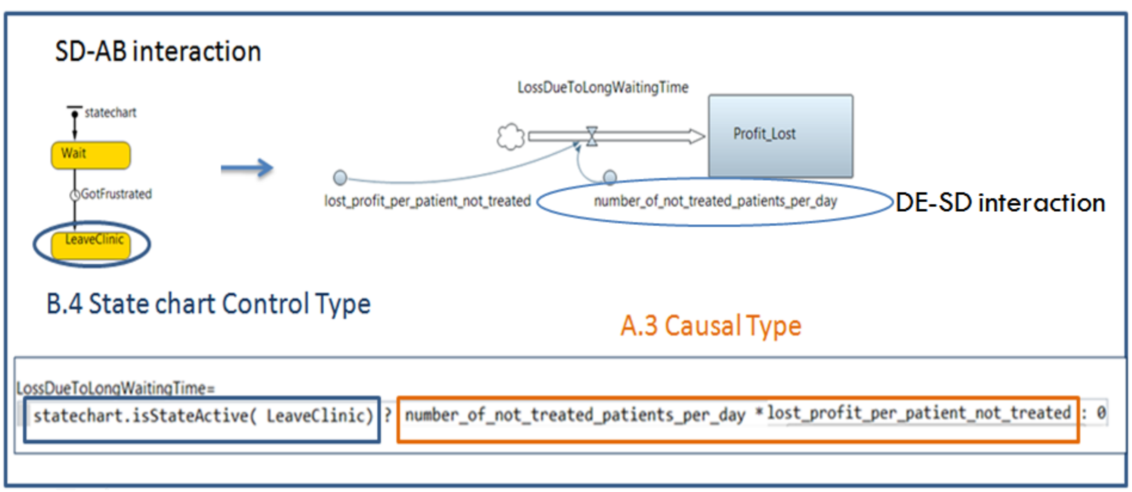


Figure 16. Combination of B.1 and B.2 type of relationships during AB-DE interaction

In Figure 17 we illustrate two types of relationship for interaction between AB and SD models. During the simulation run time the SD variable “LossDueToLongWaitingTime” is controlled (B.4 type) by the AB state of “LeaveClinic”. When the AB state-chart state “LeaveClinic” is activated, the SD variable “LossDueToLongWaitingTime” is explicitly described by the mathematical expression (A.3 type) “number_of_not_treated_patents_per_day” multiplied by “lost_profit_per_patient_not_treated”.

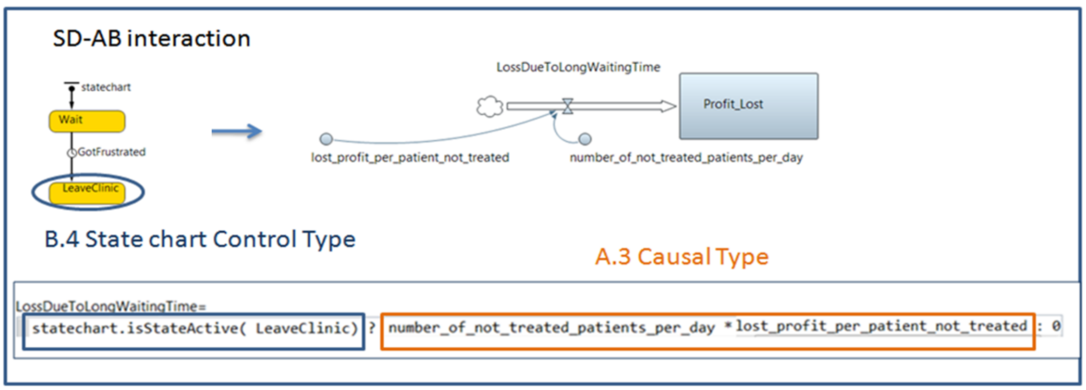


Figure 17. Combination of A.3 and B.4 type of relationship during SD-AB interaction

Phases 2, 3 and 4 are related to the actual model implementation. The next Chapter describes examples that evaluate all four phases of the 3M&S framework.

CHAPTER 4: EVALUATION OF 3M&S FRAMEWORK

In this chapter, we present examples that show how the 3M&S Framework can be applied to form 3M&S models capable of dealing with CS problems in multiple domains. The first case study concerns the application of the 3M&S framework for optimizing the waiting times in concession queues for a movie theater. The second case study applies the framework to assist in the development of a multi-method simulation application for task analysis tool. Finally, the framework is also applied to design a robotic simulation application to run experiments prior to actual robot implementation.

In all three cases, the following phases and steps have been followed:

- In Phase 1, we conduct the conceptual modeling steps: define the overall problem, decompose objectives to sub-objectives, define scope, constraints and select M&S method(s). Additionally, the user investigates and answers the research questions Q1, Q2 and Q3.
- In Phase 2, we describe the development process of the actual multi-method simulation model construction. This phase includes the development activities of multi-method simulation study, programming, implementation of the produced algorithms from Phase 1. The user continues with calibration of the Computer Generated (CG) model(s) and V&V of Phase.
- Phase 3 consists of the Verification and Validation (V&V) process of the multi-method simulation model. This phase takes place after the execution of the simulation and before the documentation of results to ensure credibility of the simulation study

and the produced results. The relationship between Phase 2 and 3 is iterative and frequent updates to the 3M&S model may occur.

- Finally, Phase 4 includes the preparation of the simulation report, the documentation of the results as well as examination of future improvements.

4.1 Case 1: 3M&S study in Entertainment Industry - Multi-Theater Unit (MTU)

In this section, we present a case study for a Multi-Theater Movie Complex Unit (MMCU) showing how the 3M&S Framework can be applied to provide a solution for a problem within the entertainment industry. Based on the user-defined objectives, assumptions and selection of criteria, the framework suggested the development of a model consisting of three M&S methods. We will refer to the model implemented using the framework as 3M&S model. The developed 3M&S model combines and integrates the three M&S approaches (DE, SD, and AB), and defines terms and conditions to fit each problem objective using M&S method(s).

<u>Define Problem</u>

The movie theater industry has a tendency to build large complexes that project several movies simultaneously [133]. Consider a particular Multi-Theater Movie Complex Unit, which is referred to as MMCU system. This MMCU currently occupies 4 ticket sellers, 6 concessions and 1 ticket collector. Figure 18 illustrates the MMCU General System given the six concession stand lines, the ticket selling queue, the ticket sellers (TS), the ticket collection queue and the ticket collector.

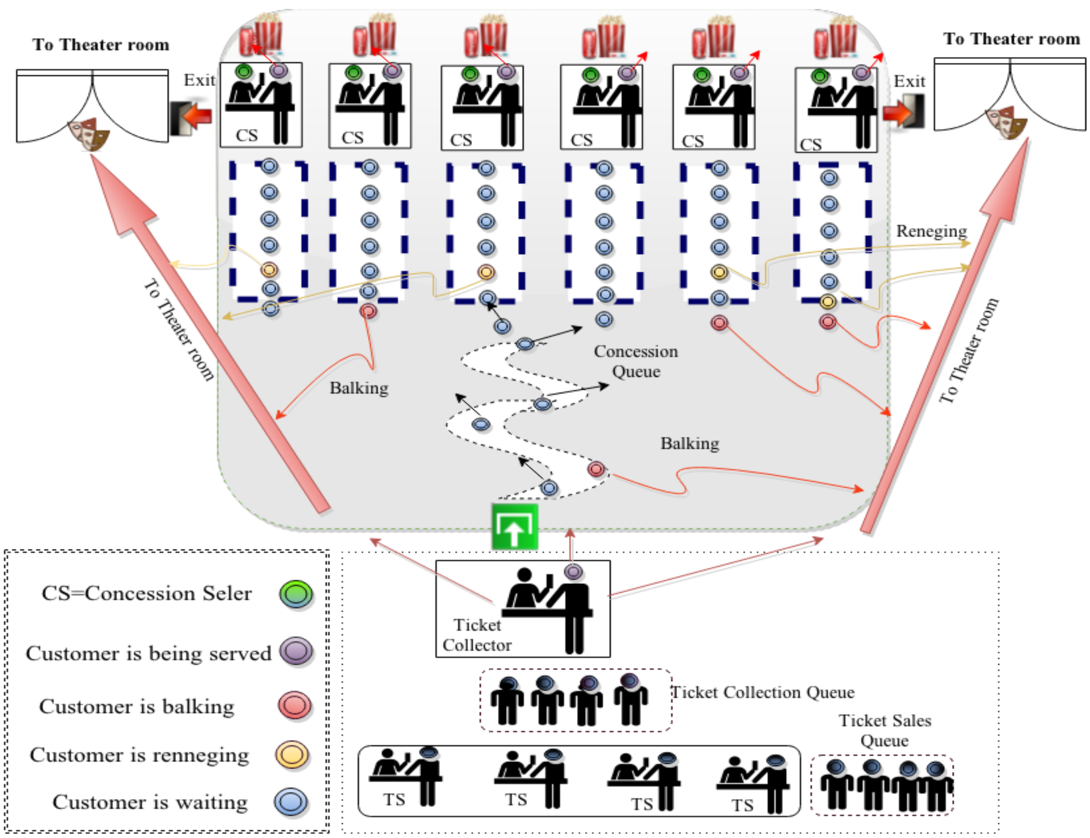


Figure 18. MMCU General System

After several informal visits and interviews with the management, we observed a process performance gap during the MMCU operational hours. More specifically, the specific MMCU can become very crowded during specific peak times of the day and of the week, while being nearly empty at others. The problem was detected on the system processes involving the concessions. The ordinary high activity times were detected on Friday and Saturday nights between 7 PM and 10 PM causing bottlenecks in the concession stands due to long waiting lines.

At this time, the MMCU has been losing concession stand sales due to customers either reneging while waiting too long in line, or balking by walking away from the concession stand, resulting in profitability loss for the company.

Identify Overall Objective “O” and decompose it into sub-objectives "o_i"

The overall Objective “O” is to improve the movie theater product consumption and customer service and lead to increased customer satisfaction and MMCU profits. In other words, we need to simulate different system designs and compare them to identify the best alternative design among the simulated ones to reduce total waiting time, reneging and balking.

Then, we decompose “O” to the following objectives “o_i”:

- o_1: Investigate alternative configurations of MMCU to reduce waiting time and total time in system
- o_2: Investigate balking behavior
- o_3: Investigate reneging behavior

Identify Constraints and Assumptions

As we mentioned earlier, assumptions are essential when creating a simulation model as it is not feasible to include all the possible events that will occur in reality. Therefore, during this system analysis, the following modeling constraints and assumptions are taken into consideration:

- There are only six concessions to fulfill all the orders
- The period of the study is between 7pm to 10pm
- Customers do not leave the MMCU immediately after entering
- Employees do not take breaks during the high-activity periods of interest
- Customers can visit the concession as many times as they want
- All cashiers were considered to work at the same speed and perform identical tasks. (Therefore, the same Service Times distribution was used for all the cashiers)
- Customers do not jockey to another line due to actual queue boundaries and fair queuing system.
- The Customers' travel time to be served is 0
- Each waiting queue has initial capacity up to ten customers. The line is determined to be long if the queue capacity is exceeded
- Customers arrive as batches/groups of one, two, three, four or more customers, who processed individually and leave the concessions again as batches/groups, when all the members of the batch have been processed

Identify M&S Scope for all sub-objectives

The M&S scope is what helps achieve the objectives without violating the given constrains. Therefore, we need to clearly define the aspects that will be included in the simulation for each sub-objective. Those aspects are described in the following sections.

Define content and form of results

The content and form of results of this study requires High-Level of detail including statistical input and output (I/O) data analysis, as well as visualization of the process through animation. For sub-objective o_1, the content and form of results require detailed statistics for waiting times, total time in system and queue size, as well as animation of the process. For sub-objectives o_2 and o_3, the content and form of results require detailed statistics regarding the number of balkers and renegers, respectively.

Define boundaries

The next step is to define the boundaries and, more specifically, the beginning, ending, upper and lower boundaries that involve I/O data of information exchange, as well as the performance measures that considered for V&V of alternative MMCU system designs. Table 8 illustrates the beginning boundary data, and the ending boundary data (outputs) as the performance measures. The beginning boundary data were used as input to calculate the defined measurements of performance (outputs). The performance measures were used for evaluation of the MMCU alternative designs.

Table 8. Boundaries

Type	Name	Description
Input Data [a]	Customer Number	Number of customers entering the system
	Current Queue Size	Number of customers in concession queue after a new arrival at a particular time.
	Interarrival Batch Time	Time between the arrivals of batches of customers to the concession stand
	Batch size	Number of individual customers who arrive together as a batch.
	Concession Seller Service Time	Time required for the concession seller to serve the customer.
	Renege Time	Time a customer is willing to wait for the concession seller to service him before he leaves the queue.
Output Data	Average Customer Waiting Time at Concession Stand	Average time a customer may spend in concession stand queue waiting to be served.
	Reneging Counter	Number of people that abandon the queue because it is too long.
	Balking Counter	Number of people that never commit to the queue because it is too long.
	Total Time in System	Interval of time beginning when the customer

Type	Name	Description
		arrives at Concession Stand queue and ending when the customer exits the system and proceeds to the theater room.
	Average Queue Length	Average queue length in concession while waiting to be served

Units for all times are in minutes.

[a]Input data collection was based on observation and interviews with the manager of the MMCU.

Table 9 illustrates the upper and lower I/O data information exchange among the three sub-objectives.

Table 9. Upper and Lower Boundaries I/O Data

	Sub-objective o_1	**Sub-objective o_2**	**Sub-objective o_3**
Upper Boundary Data Inputs	Customer ID, Server ID	Customer ID, Server ID queue size	Customer ID, Server ID “Patience[a] Starts”
Lower Boundary Data Outputs	Update queue size, Served state	Balk state, Update queue size	“Patience[a] Ends”, Renege State, Update queue size

[a]Patience is used to define the average time a customer is willing to wait in a concession stand (in minutes). Patience starts when a customer starts waiting and ends when a defined threshold is

reached and the customer decides to abandon the line and exit the system without performing a purchase.

<u>Level of detail, degree of accuracy and type of experimentation</u>

The level of detail is determined by the level of accuracy of the results and the output. For all sub-objectives the level of accuracy of the results (confidence interval) is specified at 95%. The experimentation type of this study includes the visualization of the system and comparison with alternative scenarios to achieve the specified objectives. The degree of accuracy includes the identification of logic and numeric data, which are illustrated in Table 10. A detailed data analysis can be found in Appendix A.

Table 10. Degree of Accuracy - Logic and Numeric Data

Data Name	**Data Type**	**Data Value**
Interarrival Times	Numeric Data	0.37 + Erlang(0.123, 3)
Service times	Numeric Data	1 + Gamma(1.71, 1.17)
Batch Size	Numeric Data	Empirical Distribution Cumulative Fraction / Discrete (0.339, 1, 0.816, 2, 0.934, 3, 0.934, 4,1,5)
Patience	Numeric Data	Triangular(10,15,20)
Balking Behavior	Logic Data	If the queue has reached the

Data Name	**Data Type**	**Data Value**
		maximum capacity, the customer decides to balk and exits the system
Reneging Behavior	Logic Data	If the customers patience expires, the customer decides to leave the queue (decides to renege) and exits the system

Selection of M&S Method(s)

In this section, we run the 3M&S framework with the manager of the MMCU system by selecting criteria that fit the problem, system and methodology perspective of each sub-objective and assign their numerical weights based on their relevant importance. The 3M&S framework returned the higher-scored M&S method for each sub-objective. Table 11 illustrates a partial list of selected criteria for each objective and summarizes the returned higher-scored M&S method for each of the three defined sub-objectives.

More specifically, for sub-objective o1, the framework recommended DE M&S to capture alternative line configurations, eliminate bottlenecks and improve MMCU system. For sub-objective o2, the framework recommended AB M&S to capture the balking logic of the customers and for sub-objective o3, the framework recommended SD to capture the reneging logic of the customers.

Table 11. Sample list for Selection of M&S methods

Criterion	VoIs	Selection for Sub-objective o_1	Weight w_1	Selection for Sub-objective o_2	Weight w_2	Selection for Sub-objective o_3	Weight w_3
Scope Level	*Operational*	*X*	*9*				
	Strategic					*X*	*5*
	Any			*X*	*2*		
Situation	*Queues*	*X*	*10*				
	Flows					*X*	*7*
	Rules			*X*	*8*		
System Process	*Discrete*	*X*	*9*				
	Continuous					*X*	*8*
	Discrete/Continuous			*X*	*5*		
Modeling Approach	*Process Centric*	*X*	*7*				
	Top-Down					*X*	*5*
	Bottom-Up			*X*	*7*		
Object	*Entity*	*X*	*7*				
	Feedback					*X*	*8*

Criterion	VoIs	Selection for Sub-objective o_1	Weight w_1	Selection for Sub-objective o_2	Weight w_2	Selection for Sub-objective o_3	Weight w_3
	Agent			*X*	*10*		
Control	*Holdings*	*X*	*6*				
	Stocks					*X*	*10*
	Transaction Mechanisms			*X*	*8*		
Time	*Discrete*	*X*	*8*	*X*	*5*		
	Continuous					*X*	*8*
M&S Method Selection		**Discrete Event**		**Agent Based**		**System Dynamics**	

Identify Interaction points

Interaction points describe variables of I/O information exchange among the different objectives. In this case, we have three sub-objectives that are captured and influenced by three sub-models. The mapping among DE, SD, and AB sub-models consists of input and output data of information exchange. For the MMCU 3M&S model, we identify the following interaction points of information exchange:

- Customer ID (DE) - Customer ID (AB)
- balking counter (DE) –balking counter (AB)
- reneging counter (DE) – counter reneging (AB)
- WaitInLine (DE) – Patience (SD)
- Patience Expired (SD) - Reneging State (AB)

<u>Formulate Relationships among DE, SD, and AB interaction points</u>

In table 12 we illustrate the interaction points and type of relationship for each pair of interaction points.

Table 12. Relationships for each pair of interaction points

	Interaction Points	**Type of Relationship**
Interaction points between AB and DE Models	Customer EnityID (DE) - Customer AgentID (AB)	*A.1 Direct replacement*
	Customer balking counter (DE) - Customer balking counter (AB)	*A.1 Direct replacement*
	Customer reneging counter (DE) – Customer reneging	*A.1 Direct replacement*

	counter (AB)	
Interaction points between AB and SD Models	Agent in state Waiting in Line (AB) – Patience Counter Clock starts (SD)	*B.4 Statechart control which transfers the flow to the SD model*
	Patience Expired (SD) – sent Agent in Reneged state (AB)	*B.3. Trigger of Condition Type (if patience <= 0)*

Phase 2: M&S Development Process

In this section, we describe the development process of the aforementioned simulation objectives (o_1, o_2 and o_3) for three alternative scenarios of the MMCU system. The developed 3M&S model consisted of three sub-models that interact with each other: a DE, a SD and an AB sub-model.

A DE sub-model was developed to describe alternative line configurations of the MMCU concession process system. In addition, the DE module was responsible for collecting statistics of the performance measures to reduce customers waiting time and total time in system, renegers and balkers.

Balking and reneging are queue-related behaviors demonstrated in the 3M&S model to better represent the overall behavior of the observed real-world MMCU system. Upon arrival, the customers are represented by DE entities. When they enter the waiting queue, the customers are represented by agents that exhibit internal decision-making based on the reneging and balking logic of the SD and AB sub-models, respectively.

An AB sub-model was developed to capture the balking decision-making logic of customers. This balking logic was developed by integrating the AB sub-model within the DE module to describe a deterministic logic of customer's decision-making. Upon arrival, customers observe the operation of the queuing system and decide if they want to enter the "WaitingInLine" state, or the "Balked" state. If all queues have reached their maximum capacity a customer decides to balk and exits the system. Otherwise, a customer enters the waiting state and selects one of the concessions queues to wait for purchase. The AB sub-model is also responsible for updating the DE reneging and balking counters.

A SD sub-model was developed to capture the reneging logic. Reneging logic considered to be customer's subjective probabilistic decision-making logic on an observed queuing behavior. We used a SD stock described by a triangular distribution with an average of 15 minutes to represent customer's "patience" or willingness to wait.

When a customer enters the AB state of "WaitingInLine" the reneging logic of the SD sub-model is activated and the "patience counter clock" starts counting. The AB transaction mechanism that connects the "WaitingInLine" state with the "Reneged" state checks every second if the condition of patience stock is equal or less than 0 and if the customer is not among the next three customers to be served, he/she decides to enter the "Reneged" state and abandon the line without receiving service. However, if the customer is among the three next customers that are about to be served, he/she remains in the "WaitingInLine" state until he/she is being served and moved to the "served" state, where batches exit the system after each member of the group receives service. Figure 19 depicts the reneging logic.

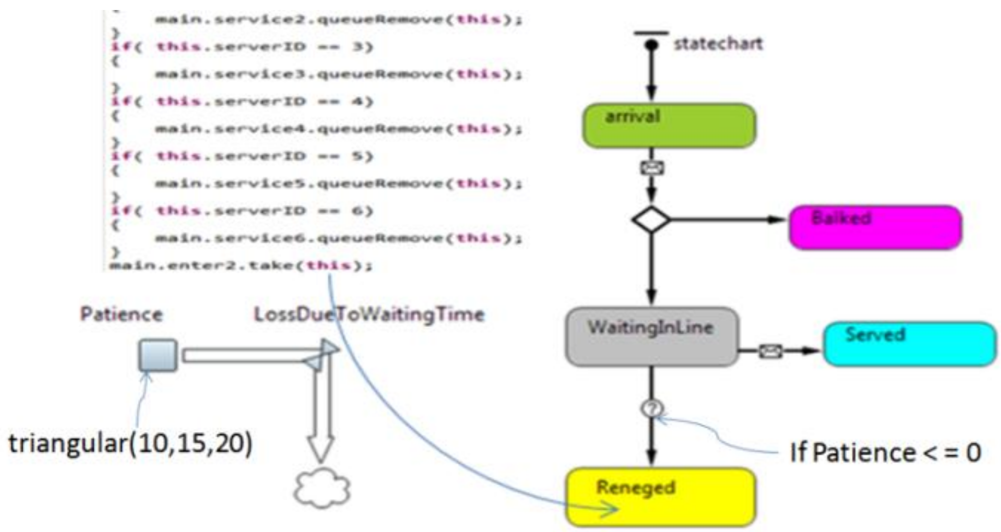


Figure 19. Reneging Sub-Model

<u>Phase 2.1 Scenario 1: MMCU Base System (max capacity per queue 10)</u>

Scenario 1 describes the current line configuration of MMCU Base System developed to represent the current operation of the concessions. MMCU Base Model consists of six servers, six queues and maximum queue length equal to ten (Figures 20 and 21).

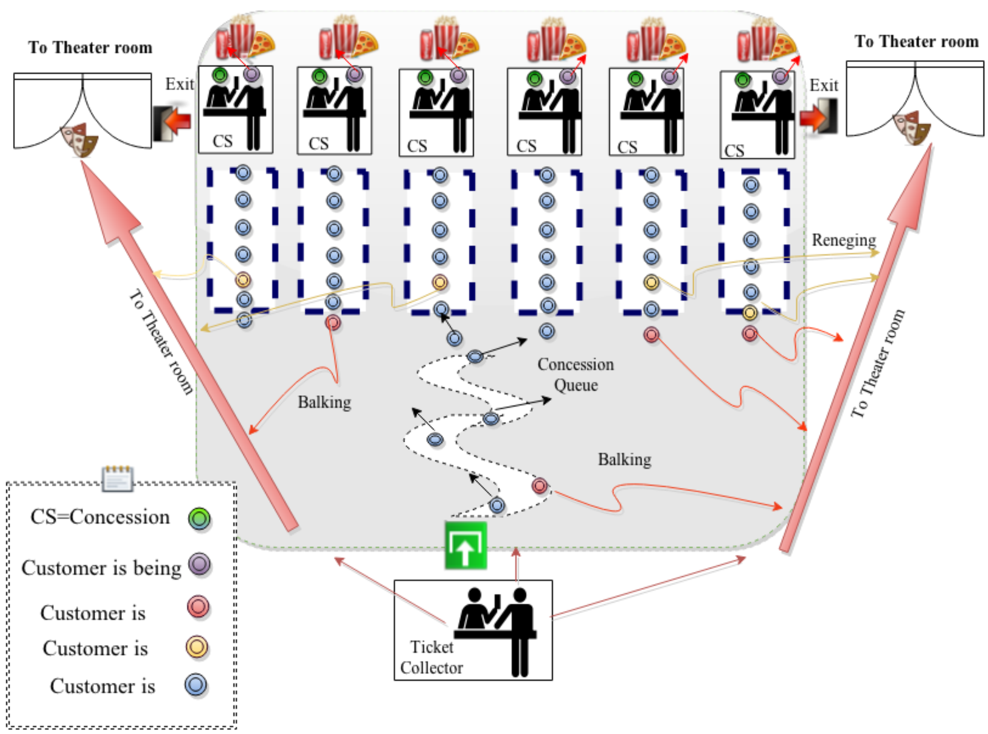


Figure 20. Scenario 1: MMCU Base Model

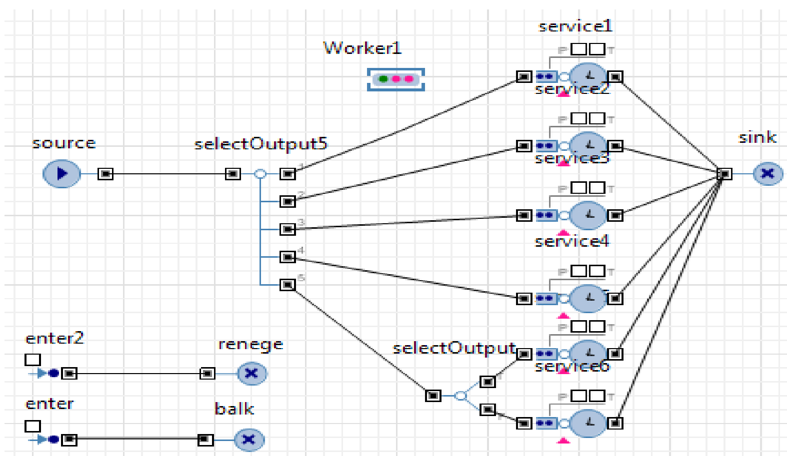


Figure 21. DE sub-model of MMCU Base Model

Phase 2.2 Scenario 2: Different Number of Queue Capacity (max capacity 13)

Scenario 2 describes an alternative line reconfiguration of the MMCU Base Model by increasing each queue capacity to fit three more customers. More specifically, it was observed that the maximum number of people that could enter the line was around ten, while the queue could be extended to fit thirteen. If more customers than thirteen want to enter the concessions lines, the lines exceeded the concession waiting area. Therefore, the capacity of each concession queue was increased up to thirteen, in order to fit the maximum possible number of customers (Figure 22). This model design (Figure 22) is similar to the MMCU Base System (Figure 21). However, the internal logic of the model has changed for the queue capacity which is modified to fit thirteen customers, and the balking logic which is activated for queue length greater than 10.

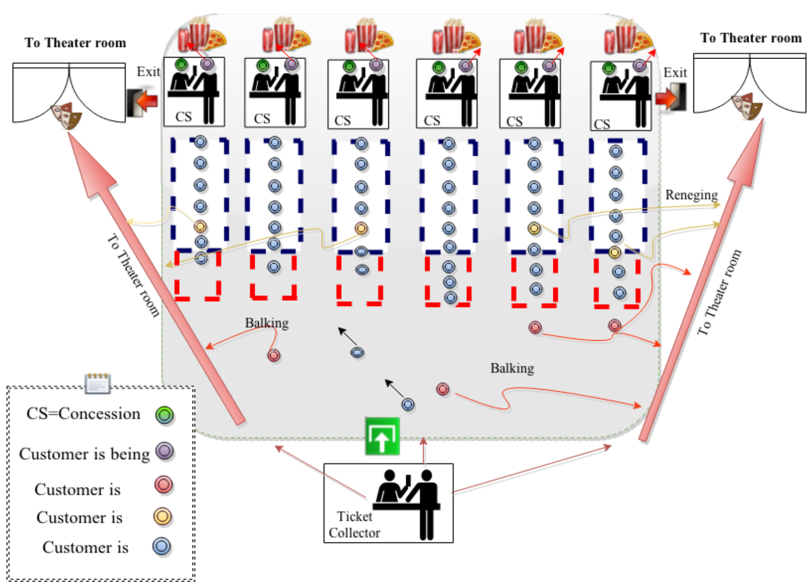


Figure 22. Scenario 2 with max capacity per queue 13

Phase 2.3 Scenario 3: Reconfiguration of the Main waiting queue (Alternative line configuration)

Scenario 3 describes an alternative line configuration considering one main waiting queue with maximum capacity of 60 customers that ends to six concession servers (CS). Figure 23 illustrates the customer's processes flow using the alternative line configuration of Scenario 3. The applied balking and reneging logics differ from scenarios 1 and 2 only in terms of the balking condition, that now is true when the number of customers in the waiting line is greater than 54 (Figures 23 and 24).

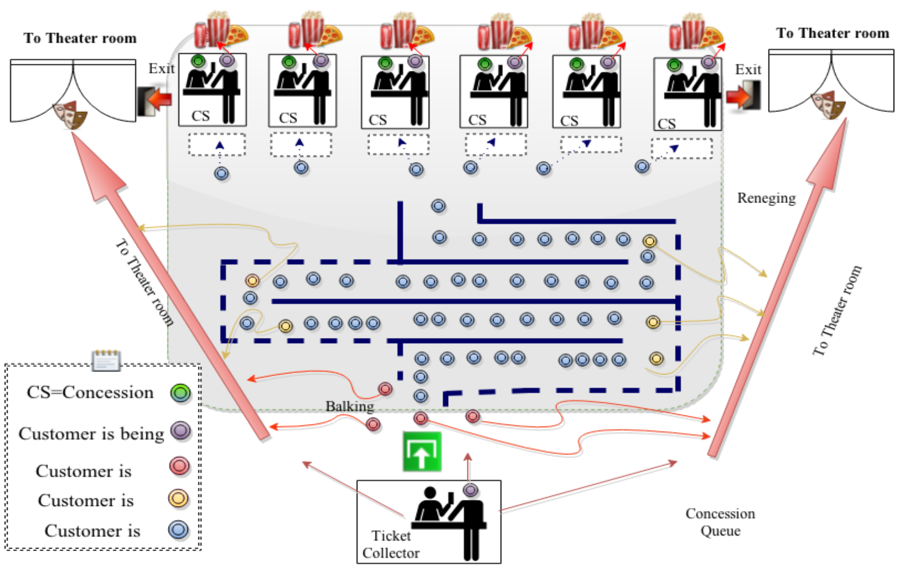


Figure 23. Scenario 3 Queue Capacity 60 balking >54

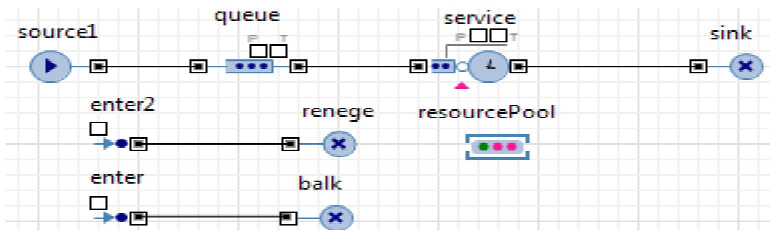


Figure 24. DE-sub model for scenario 2

Phase 3: Verification and Validation (V&V) of 3M&S model

Phase 3 provides information concerning the design, as well as the Verification and Validation (V&V) of the 3M&S Base Model of scenario 1, using real-world data. More specifically, the input data values from Table 10 were used to initialize the model. The data collection was based on observation and interviews with the manager of the MMCU. Distributions were fitted to each datum and statistics, such as mean and standard deviation, were calculated.

In order to accomplish the objectives stated in Section 4.2, a Base Model that represents the current operation of the concessions was developed, simulated, verified and validated through comparison with the real world observed system.

Warm-up Period of the Simulation

All the scenarios of the 3M&S model were run for 80 replications with a warm-up period of 75 minutes. Until that time the system had achieved steady-state. Since the period of interest is 3 hours, the total length of each replication was set to 4 hours and 15 minutes (255 minutes).

Verification and Validation (V&V)

Various techniques were used for verification and validation of the base model. First, the model was successfully tested for one customer in order to verify the total time in system. The 3M&S model was also verified by observing the animation of the simulation output. Moreover, the sample mean and sample variance for each simulation input probability distribution was computed, and compared with the desired mean and variance.

Validation included scheduled meetings with the movie theater's management, where the details of the simulated model were discussed and compared with the behavior of the real system. Quantitative measures were also examined for validity. The number of replications was set to 80 based on the approximation $n \approx n_0(h_0^2/h^2)$, where h_0 is the half-width from "initial" number n of replications and h is the desired level of precision. Table 13 summarizes the performance measures comparison between the data collected from the real-world system and the simulation output of MMCU Base Model Scenario 1 after 80 replications.

Table 13. Comparison of Real-world and Multi-Method Simulation output of Base Model Scenario 1

	Real Data			Simulation Output		
Measure Name	**Mean**	**Standard Deviation**	**C.I.**	**Mean**	**Standard Deviation**	**C.I**
Mean Wait Time	3.175	2.405	[2.72, 3.63]	2.812	5.204	[1.654, 3.97]
Renege Counter	20	N/A	N/A	24	N/A	[13.625, 32.999]
Balking Counter	21	N/A	N/A	19	N/A	[10.342, 25.882]
Total Time in System	6.066	2.474	[5.35, 6.77]	5.446	6.153	[4.077, 6.815]
Total Number Out	300-500	N/A	N/A	388	N/A	[285.165, 490.585]

We set-up two-sample t-tests to determine if there is statistical difference between the actual data and the 3M&S output of the Base Model for both the mean waiting time in queue and the total time in system.

The hypothesis test for the mean waiting time in queue is

- H_0: difference between means of 3M&S Simulated Output and Real Data = 0
- H_1: difference between means of 3M&S Simulated Output and Read Data ≠ 0

And the hypothesis test for the Total Time in System is

- H_0: difference between means of 3M&S Simulated Output and Real Data = 0
- H_1: difference between means of 3M&S Simulated Output and Read Data ≠ 0

The level of significance is a = 0.05. Table 14 summarizes the results of the two-sample t-tests. Since the p-value for both tests is greater than the level of significance, there is no significant difference between the observed data and the simulation output of the MMCU Base Model. Therefore, the simulated MMCU Base Model Scenario 1 was considered valid.

Table 14. Two-sample t-test Results

	Real Data		3M&S Simulation Output		t-Test results		
Measure Name	Mean	Std[a]	Mean	Std[a]	p-value	T-value	95% C.I. diff.
Mean Wait Time	3.175	2.405	2.812	5.204	0.559	-0.59	(-1.592, 0.866)
Total Time in System	6.066	2.474	5.446	6.153	0.431	-0.79	(-2.174, 0.934)

[a]Std refers to Standard Deviation

Validating the Base Model of scenario 1 allowed us the development, V&V of alternative scenarios, and gives sufficient evidence to show that implementing them in real world can improve the system.

Phase 4: Discussion of Results and Recommendations

The overall objective of this study was to simulate the concession process in the MMCU system in an attempt to reduce the average customer's wait time, total time in system as well as the number of customers that leave the concession lines or do not enter the lines, resulting in loss of profit for the movie theater.

The simulation output of each simulation scenario was used to determine which of the three alternative scenarios produce the lowest waiting time, Total Time in System, renegers and balkers. A comparison of means also determined if any significant difference exists between the performance measures of each scenario. Figure 25 illustrates a comparison of means that determined significant differences between the performance measures of each alternative scenario.

(a)
(b)
(c)
(d)

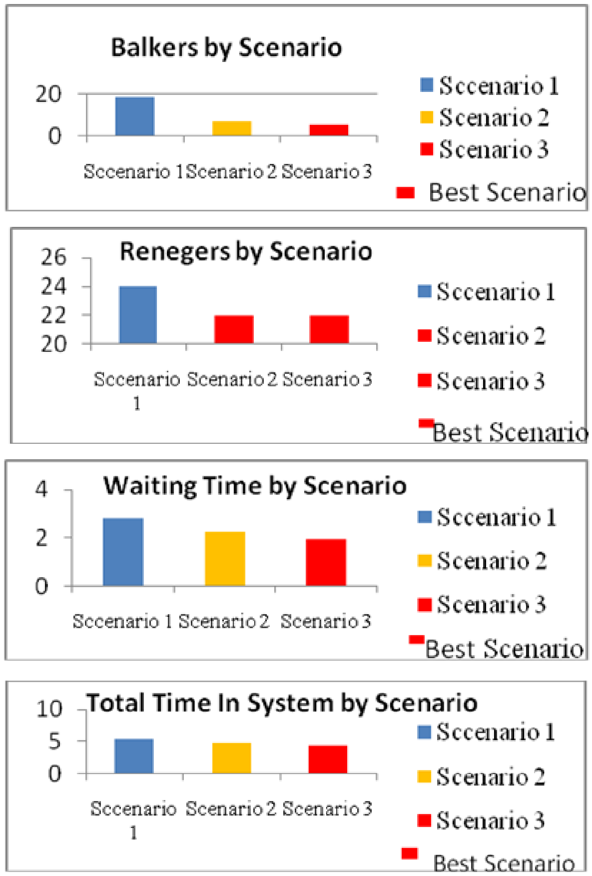


Figure 25. Comparison of means for alternative scenarios of MMCU system in terms of (a) number of balkers, (b) number of renegers, (c) average waiting time in queue, and (d) total time in system.

Based on the comparison of performance measures, the alternative scenario 3 produces the less balkers and renegers in the system, which could indicate reduced profitability loss since fewer customers abandon the system. In addition, this scenario was statistically and visually better than the Base model of scenario 1 and scenario 2 with respect to the total time in system and wait time at the concession stand. Table 15 summarizes the results of each scenario and suggests the best scenario for each performance measure.

Table 15. Comparison of Base Model and alternative Scenarios

Measure Name	**Statistics**	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Best Result**
Mean Wait Time	Mean	2.812	2.281	1.943	Scenario 3
	STD	5.204	5.785	4.68	
	Half-Width	1.158	1.287	1.041	
Renege Counter	Mean	24	22	22	Scenario 3 & 2
	Half-Width	9.687	7.635	7.744	
Balking Counter	Mean	19	6.925	4.162	Scenario 3
	Half-Width	7.77	3.468	2.256	
Total Time in System	Mean	5.446	4.745	4.428	Scenario 3
	STD	6.153	6.763	5.409	
	Half-Width	1.369	1.505	1.204	
Total Numb. Out	Mean	387.875	484.025	486.4	N/A
	Half-Width	102.71	106	111.79	

Recommendations

According to the discussion of the results, the concessions would present lower total time in system, as well as reduced number of people that abandon the lines, which can be achieved by reconfiguring the MMCU system to the alternative described by scenario 3. In addition, the number of people that abandon the lines could be reduced by reconfiguring the concessions' waiting area to have only one line that ends to the concession sellers. Another suggestion could be that cashiers should encourage customers to approach their concession stand as soon as they are available.

However, due to the various limitations, approximations and assumptions involved in this multi-method modeling and simulation study, a more detailed study would be beneficial in order to better guarantee that the results obtained in the simulations will be replicated if these changes were made to the real system.

Comparison of 3M&S model with the user's own selection

In this section, we compare the model proposed by the 3M&S framework with a model implemented based on the user's own selection without following the framework. In this case, we assume that the user is more familiar with DE simulation. Therefore, he/she decides to model the system using only DE for the same objectives, assumptions and constraints without using the suggestion of the 3M&S framework. The implementation of the DE model is described in the next section.

Implementation of DE model

The flow of the MMCU model, the reneging and balking logic were developed using only DE M&S. The customers were considered passive entities that do not exhibit any internal decision-making when they enter the waiting queue based on the reneging and balking logic of SD and AB sub-models described earlier. Upon arrival, if all the queues have reached maximum capacity the entities balk and exit the system, otherwise the customers wait in line until they receive service. However, if the waiting time exceeds a threshold and the customer is not among the next three in line to be served, he/she reneges and abandons the waiting line. The input data from Table 10 were also used for the initialization of the DE model.

Verification and Validation (V&V) of DE model

In order to evaluate the MMCU DE model, we set up two-sample t-tests to determine if there is statistical difference between the actual data and the simulation output for both the waiting time and total time in system.

We set-up two-sample t-tests to determine if there is statistical difference between the actual data and the DE simulation output for both the mean waiting time and total time in system.

The hypothesis test for the mean waiting time in queue is

- H_0: difference between means of Simulated MMCU DE Output and Real Data = 0
- H_1: difference between means of Simulated MMCU DE Output and Read Data $\neq 0$

And the hypothesis test for the Total Time in System is

- H_0: difference between means of Simulated MMCU DE Output and Real Data = 0
- H_1: difference between means of Simulated MMCU DE Output and Read Data $\neq 0$

The level of significance is a = 0.05. Table 16 summarizes the results of the two-sample t-tests. Since the p-value for both tests is greater that the level of significance, there is no significant difference between the observed data and the simulation output for the base model. Therefore, the simulated MMCU DE Model was considered valid.

Table 16. Two-sample t-test results

	Real Data		**DE Simulation Output**		**t-Test results**		
Measure Name	Mean	Std[a]	Mean	Std[a]	p-value	T-value	95% C.I. diff.
Mean Wait Time	3.175	2.405	4.04	4.57	0.122	1.56	(-0.234, 1.960)
Total Time in System	6.066	2.474	7.49	6.14	0.071	1.82	(-0.124, 2.980)

[a]Std refers to Standard Deviation

Comparison of output for DE and 3M&S models

In this section, we compare the outputs of the 3M&S and the DE simulation models with the observed data of the actual system to determine which model is more accurate representation of the real system. The mean waiting time and total time in system (TTIS) were used for a preliminary evaluation of accuracy. Table 17 shows that the mean waiting time and TTIS for the

3M&S model are 'closer' to the real system output. More specifically, the percentage difference between the 3M&S model outputs and the actual data are 12.9% and 11.38% for the waiting time and TTIS, while the percentage difference between the DE model outputs and the actual data are 21.3% and 19.055%, respectively.

Table 17. Comparison of 3M&S and DE models with real system

	Mean Waiting Time	**Mean TTIS**
Real Observed System	3.175	6.066
3M&S Base Model	2.812	5.446
DE Model	4.038	7.494
3M&S difference with Real	12.9%	11.38%
DE difference with Real	21.3%	19.055%

Based on the previous comparisons, we concluded that the 3M&S model implemented following the steps of the 3M&S framework is a more accurate representation of the real system than the DE model implemented based on the user's own selection. Moreover, the 3M&S model provides the capability to incorporate factors in the model that cannot be considered if the system is modeled using only DE simulation. Such factors include server behavior, interaction with friends, and service quality, among others. For example, the SD reneging logic of the 3M&S model could be modified and further expanded to incorporate more interactions for patience as depicted in Figure 26 [134]. The positive feedback loops demonstrate how customer's willingness to wait (patience) can be positively affected by various factors (i.e. interaction with friends, atmosphere, and queuing comfort level).

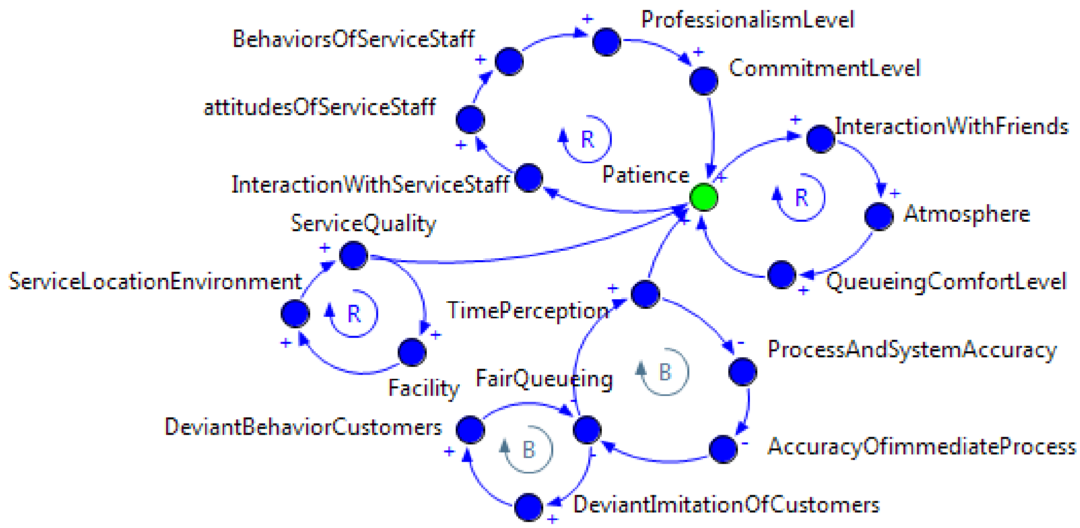


Figure 26. SD model that explores the interactions of reneging and patience adapted and modified by Yang et al. [134].

Moreover, the individual sub-models used for particular objectives to form the 3M&S model could be reused to design new models that satisfy similar objectives by saving developing time and cost. Therefore, following the 3M&S framework can improve model accuracy, and help the analysts save time and effort, particularly when they deal with CS problems or when multi-method M&S is required.

Conclusions and Future Work

In this case a novel Multi-Method Modeling and Simulation Framework termed 3M&S has been described. The steps of the framework were explained in detail and were applied to a case study for a movie-theater complex using the 3M&S framework. We also showed an alternative solution for the same problem when the user does not use the suggestion offered by the framework, but he/she decides to model the system using his/her own selection of method.
Two different simulation models were implemented with and without following the 3M&S framework. The one was a 3M&S model, which showed how the process-centric approach of DE, the bottom-up approach of AB and the top-down approach of aggregated feedbacks of SD can be deployed symbiotically to offer more realistic perspective and useful insights of CS problems. The other model was implemented using only DE simulation. The comparison of the two models showed that the 3M&S model provides more accurate representation of the real system and could allows for incorporation of other dynamical factors, such as interaction with friends, which cannot be captured using only the DE method (see Figure 26 “patience”).

Additionally, the 3M&S model may also be found more suitable than the DE simulation model in terms of future reusability. For example, if one wants to conduct another simulation study in the future, one can enhance, reconfigure and apply a pre-existing verified and valid module that has been used in a past 3M&S study since these models have been developed to communicate and interact with other models In the future, our work will focus on applying the 3M&S framework in different domains that require 3M&S approach as well as in the development of a decision support tool based on the 3M&S framework.

4.2 Case 2: Following the 3M&S framework for a Universal Task analysis Tool

The 3M&S framework was followed to aid in the design, development and evaluation of a Universal Task Analysis Simulation Modeling tool named "UTASiMo" [115], [135], [153]. The tool is capable of automating the modeling process and simulating individuals performing tasks in any domain in order to estimate task execution times, workload and error probabilities.

Phase 1: Conceptual Modeling

Define Problem

Task Analysis is a time consuming and static process, usually conducted using pen and paper. Existing task analysis tools require training or even programming skills to produce results, thereby requiring time and effort. Moreover, current task analysis tools do not always model the heterogeneity of agents across a population or they lack built-in modules for estimating human error and workload. Therefore, a more widely accessible and universally applicable simulation tool needs to be developed in order to perform a more comprehensive task analysis.

Identify Overall Objective "O" and decompose it into sub-objectives

The overall Objective was to develop a Universal Task Analysis (UTA) model capable of simulating tasks and scenarios performed by human operators, considering task execution times and workload for operators with different skills/characteristics and assessment of human error based on the skills of the operator and the dynamics of the task within a dynamic environment.

Next, we decomposed the overall objective to the following three sub-objectives:

- o_1: Provide quantitative prediction of human error over time influenced by the dynamics of the task and the properties of the operator
- o_2: Analyze a task network based on the task sequence, priorities, human skills and events to estimate task execution times
- o_3: Create a human operator model to capture variability of operator characteristics, indicate how the operators perform the tasks and estimate workload

Identify Constraints and Assumptions

- Each primary task can be performed by a single human operator
- Each human operator performs assigned primary tasks in a sequence
- All task execution times are assumed to follow triangular distribution
- Human error is influenced by six main factors
- The default walking speed for a human operator is 1.5 m/sec

Identify M&S Scope

The M&S scope is what helps achieve the objectives without violating the given constrains and assumptions. Therefore, we need to clearly define the aspects that will be included in the simulation for each sub-objective. Those aspects are described in the following sections.

Define Content and form of Results

The content and form of results is characterized by high detail as it includes animations, graphs and detail statistics such as: average task execution time and average workload of human operators.

Define Boundaries

The I/O boundaries for each o_i are illustrated in Table 18. As it has been noticed by Robinson, the detection of output boundaries is a standard process since it reflects a particular objective [131].

Table 18. Boundaries for each o_i

o_i	**Sub-objective o_1**	**Sub-objective o_2**	**Sub-objective o_3**
Beginning Boundary Inputs	Nominal Human Error Probability, Working Conditions, Quality of procedures	Task name, Task ID, Task location, Number of sub-tasks, Task complexity, Task Frequency, Skills, Priority, Critical time	Agent ID, Speed, Skills
Ending boundary Outputs	Total probability of human error	Total time in system, Mean time to perform task, Percentage of total time allocated to each task	Total Workload
Upper boundary Inputs	Agent ID, Workload, Skill, Task complexity	Agent ID, Skills (Agent)	Task location, Probability of human error
Lower boundary outputs	Probability of human error	Task duration, Task complexity, Task location	Workload, Skills (Agent)

Level of detail, degree of accuracy and type of experimentation

Parallel to the previous activities for each "o_i" we defined the level of detail, degree of accuracy for numeric and logical data and type of experimentation.

The experimentation type of this study includes the visualization of the system, the evaluation of a base model and experimentation with alternative scenarios.

The degree of accuracy includes the identification of logic and numeric data, which are illustrated in Tables 19 and 20.

Table 19. Numeric Data

Numeric Data
Task ID
AgentID
AgentLocation
Speed
Task location
Number of Subtasks
Skills
Priority
Critical Time
Duration

Numeric Data
Workload
Task Frequency
Task Complexity
Nominal Human Error Probability
Human Error

Table 20. Logic DATA

Logic Data
Task Name
Agent Name
Agent's internal model for executing tasks and adapting to events in the environment
Agent's State

Selection of M&S Method(s):

During this activity, the user selected from the list of criteria (Table 4 -6), those criteria that fit in each sub-objective and assigned numerical weight to each VoI. Then, the additive functions were ranked from best to worst and the framework returned the higher-scored method for each sub-objective, as illustrated in Table 21.

Table 21. Selected M&S Methods for each "o_i"

M&S Method Selection[a]	o_1. For sub-objective 1, SD was selected o_2. For sub-objective 2, DE was selected o_3. For sub-objective 3, AB was selected

Identify Interaction points

The internal and external interactions among o_1, o_2, and o_3 are listed as follows:

- Variation in task and operator characteristics, (interaction between o_2 and o_3)
- Human Error affected by task and operator dynamics, (o_1 is influenced by o_2 and o_3)
- Flow of the agents in the task network - Interaction between o_2 and o_3

In Table 22 we define the interaction points for all the models.

Table 22. Interaction Points

Identify Interaction Points	• Agent ID • Agent Location • Task Location • Workload • Task Complexity • Task Completion Time • Human Error

<u>Formulate Relationships among DE, SD, and AB interaction points:</u>

In Table 23 we describe the interaction points and the types of relationships that occurred between pairs of interaction points.

Table 23. Interaction Points and Type of Relationships

	Interaction Point	**Type of Relationship**
Interaction points between AB and DE Models	AgentID (AB) - AgentID (DE)	*A.1 Direct replacement*
	Task Completion Time (DE) - Skills (AB)	*A.3 Causal relationship* The task completion time in the DE model is calculated based on a function that takes into account the skills of each agent in the AB model

	Interaction Point	Type of Relationship
	Workload (AB) - Task Duration (DE)	*A.3 Causal relationship* The workload in the AB model is calculated based on a function that takes into account the Duration of each task in the DE model
	Task Location (DE) - Task Location (AB)	*A.1 Direct replacement*
Interaction points between AB and SD Models	Workload_(AB) – Workload (SD)	*A.1 Direct replacement*
	Skills (AB) - Skills (SD)	*A.1 Direct replacement*
	Human Error (SD) – Agent (AB)	*B.4. Statechart control* The AB statechart transfers control to SD model to calculate error.
Interaction points between SD and DE Models	Task Complexity_(DE) - Task Complexity_(SD)	*A.1 Direct replacement*

Phase 2: M&S Development Process

The hybrid SD-AB model is composed of Agents with a SD model inside. The SD inputs are guided by AB outputs and dynamic environmental factors. The human operators and their behavior were implemented with AB terms and conditions. The DE model is responsible for collecting statistics in regards to the defined measurements of performance. This multi-method simulation model exchange information through the DE-SD and DE-AB interaction variables. The detail description of the M&S development process of the task analysis tool is not within the scope of this dissertation. More information about the development process can be found in [115, 135], [153]. Figures 27, 28 and 29 illustrate the architecture of the tool, which was developed in AnyLogic.

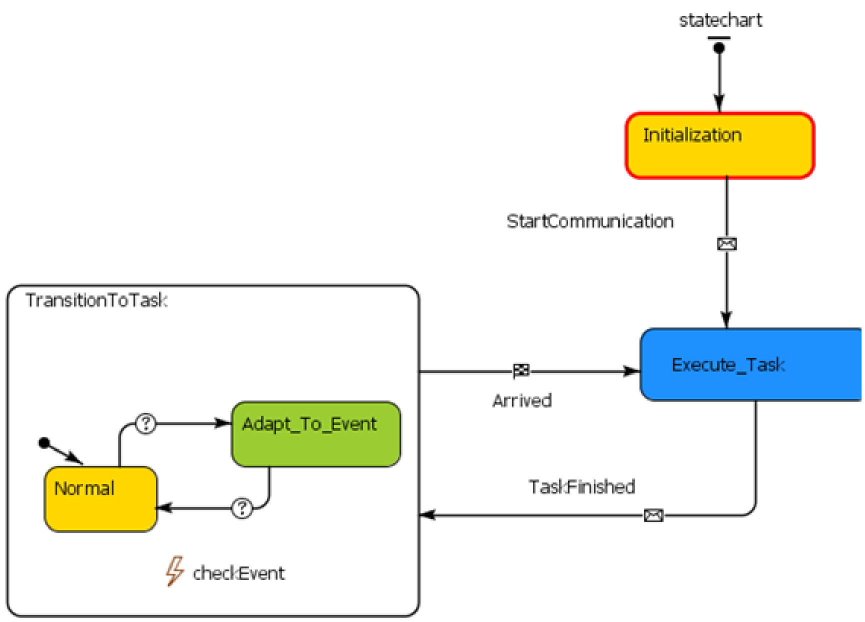


Figure 27. AB model of UTASiMo

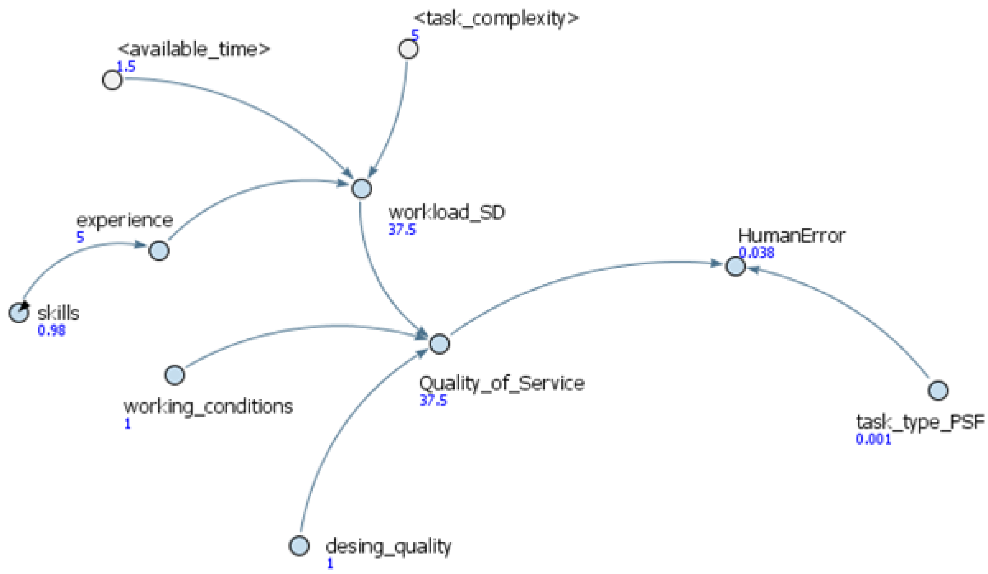


Figure 28. SD model of UTASiMo

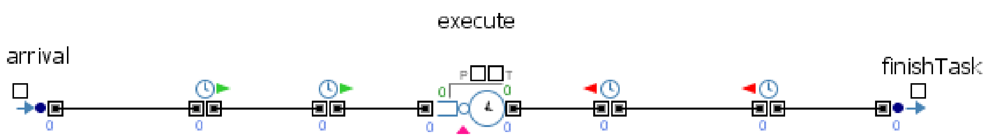


Figure 29. DE model of UTASiMo

Phase 3 and 4: V&V and Documentation of results

A 3M&S model of a power plant was produced using the UTASiMo tool to determine which system design produces the lowest average total time, workload and human errors. The model was verified and validated using various techniques. First, the model was successfully tested for one human operator in order to verify the total task execution time. The model was verified and validated by observing the animation of the simulation output. Validation also included comparison of the simulated system behavior with the behavior of the system. Figures 30 and 31 show the animation of the model and the simulation results accordingly. More information about the V&V process and documentation of results can be found in [115], [135] and [153].

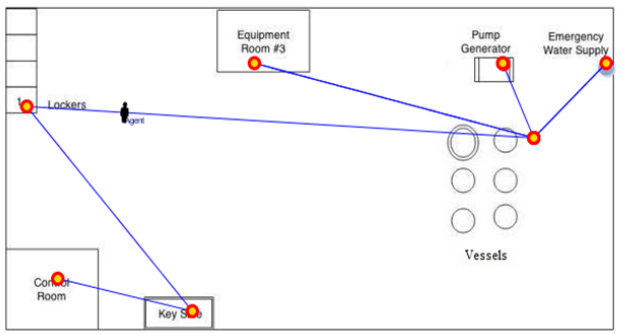


Figure 30. Animation of UTASiMo automatically constructed model

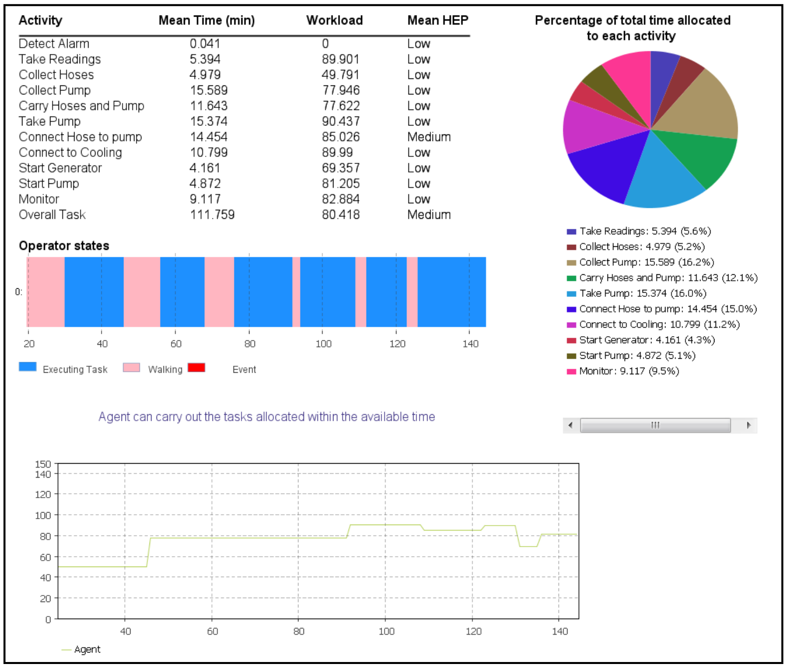


Figure 31. Simulation results of UTASiMo produced model

In this case study the 3M&S framework provided guidelines focused in the development of the conceptual modeling process. The framework was found helpful because it offers the option to combine, and/or integrate three M&S methods, while other frameworks provide guidelines for one or combination of two M&S methods. The problem, system and methodology perspective criteria (Table 4, 5 and 6) of the framework aided the user to understand when and why each M&S method is more suitable. The criteria assisted the user to conceptualize and include aspects that would be impractical or even impossible to be captured by one or two M&S methods. Finally, the 3M&S framework helped the user on how to connect the different models and formulate relationships between the interaction points using table 7 (Types of relationships for interaction points).

4.3 Case 3: Following the 3M&S Framework for Multi-Method Modeling and Simulation of face detection robotic system

Introduction

The 3M&S framework was applied in the field of robotics for modeling and simulating a face detection robotic system, named Cerberus [136], which was a part of a bigger effort, named ARTeMIS (Autonomous Robotic Technology Multitasking Intelligent System) [137]. In this case study, we focused on the multi-method modeling and simulation of a robotic system design with face detection capabilities . Figure 32 illustrates the main functionalities of the robotic system.

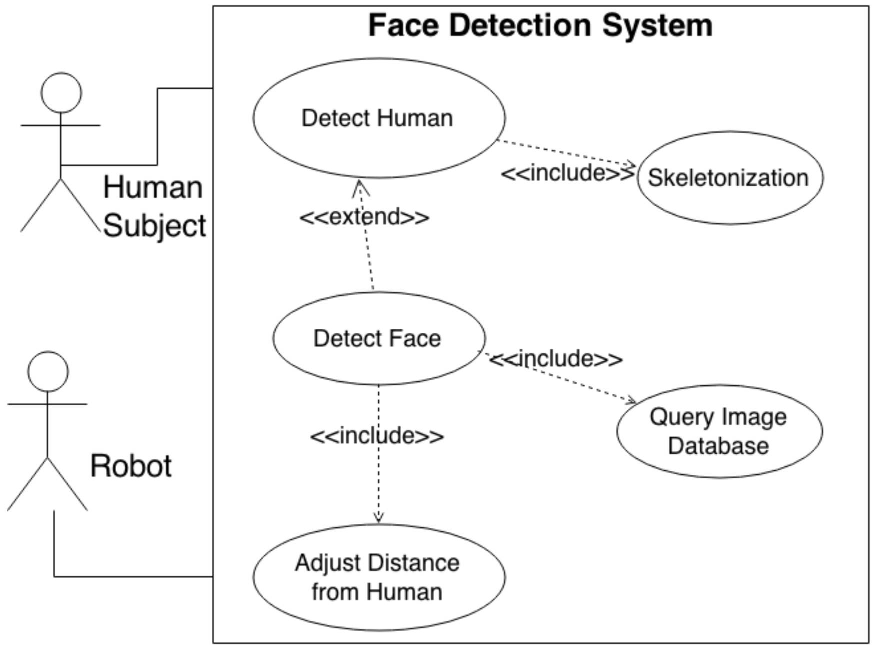


Figure 32. Overview of robotic system

Phase 1.

Define Problem

Constructing and setting up experiments with real robots is costly and time consuming. On the other hand, simulated robotic experiments are more convenient and cost effective. Thus, it is often useful to perform simulation prior to investigation with real robots. In addition, simulation is often faster than experiments with real robots, while all the parameters can be easily adjusted and displayed on screen. Simulation also allows for a better design investigation.

In this case study the main problem was that there are factors that cannot be captured during the actual experimentation. More specifically, we would like to investigate the effect of oscillation caused by the velocity and the acceleration on the face detection time of a robotic application. More information in regards with the activities of the robotic system and its architecture can be found in Appendix B.

Identify Overall Objective and Decompose to Sub-objectives

The overall objective of this study is to evaluate a robotic application of face detection by illustrating the behaviors of a robotic system and providing feedback in regards to the system's performance prior to the construction of the actual robot. Following the 3M&S framework, we decomposed the main objective to three sub-objectives.

- o_1. Define the robot rules and behavior that are required to perform face detection and to passively interact with the human.
- o_2. Determine the number of successful face detection events as well as the average time of the face detection process.
- o_3. Examine the effects of oscillation dynamics of the Kinect Sensor on the system performance.

Identify Constraints and Assumptions

For this simulation study we considered the following constraints and assumptions:

- The robot moves only forward and backward in a straight line until a face is detected.
- The robot approaches one person at a time.

- The Kinect sensor is massless
- The simulated human is assumed to be known, with his/her image stored in the database
- The human is assumed to be stable and still

Identify M&S Scope

The M&S scope is what helps achieve the objectives without violating the given constrains. Therefore, we need to clearly define the aspects that will be included in the simulation for each sub-objective.

Define Content and form of Results

During the design phase of the simulation experiment we define content and form of results. The form of results is characterized by high detail as it includes animations, graphs and detail statistics such as: average face detection time, average distance from the human and variation of oscillation periods of the pendulum-system.

Define Boundaries for Multi-method Simulation Model

The definitions of the input and output data are the following:

- Human location is defined as the coordinates of the human in a 2D space
- Control precision is defined as the exact distance that the robot moves forward and backward in order to detect a face

- Velocity is defined as the speed of the robot measured in meters per second
- Acceleration is defined as the rate of change of velocity in meters per second squared
- Resistance factor is defined as the sum of the environmental resistance factors such as air resistance and ground friction
- Gravity is defined as the force which is applied to the kinect-pendulum system by attracting its mass towards the centre of the earth
- Length of the pole is defined as the measure of the greatest dimension of the pole on which is mounted the kinect sensor
- x,y coordinates of the sensor are defined as the orientation of the sensor in a 2D space
- iRobot location is defined as the location of the robot after a successful face detection
- Face detection variable is defined as a successful face detection performed by the robot
- Oscillation movement is defined as as the variation of the pendulum-system position about a central point
- Average Face detection time is defined as the average time that takes for the robot to detect a face

Next, we describe the I/O data exchanged through the boundaries for each sub-objective.

Table 24. Boundaries for face detection Simulation Model

o_i	**Sub-objective** o_1	**Sub-objective** o_2	**Sub-objective** o_3
Beginning Boundary Inputs	Human Location, Control Precision	DE face detection timer	Velocity, Resistance factor, Gravity, Length of the pole, x,y coordinates of the sensor, initial angle of the pole
Ending boundary Outputs	iRobot Location, Face detection variable	Average Face detection time, Average distance from the human, Number of successful face detections	Oscillation movement
Upper boundary Inputs	iRobot Location	FaceID	Acceleration
Lower boundary outputs	FaceID	-	Oscillation movement

Level of detail, degree of accuracy and type of experimentation

Parallel to the previous activities for each "o_i" we defined the level of detail, degree of accuracy for numeric and logical data and type of experimentation. The level of detail was set up to 95% confidence interval for the average face detection time. The experimentation type of this study includes: the visualization of the system, and evaluation of the effect of oscillation on the face detection time. The degree of accuracy includes the identification of logic and numeric data. The *logic data* include: the navigation behavior of the robot (moving forward and backward) and the face detection information (face detection logic). The *Numeric Data* include all the input and output data such as: velocity, resistance factor, human location, gravity, angle and length of the pole, x and y coordinates of the sensor, average time of successful face detection and average distance from the human.

Selection of M&S Method

In this section, we describe the selection of M&S Methods. Table 4, 5 and 6 of Chapter 2 helped us justify which M&S method was more appropriate for each of these defined sub-objectives [27]. In table 25 we summarize the M&S selection for each sub-objective.

Table 25. M&S Method Selection for each objective

M&S Method Selection[a]	$o_{1.}$For sub-objective 1, AB was selected $o_{2.}$For sub-objective 2, DE was selected $o_{3.}$For sub-objective 3, SD was selected

Identify Interaction Points

Interaction points describe variables of I/O information exchange among the different objectives. The mapping among DE, SD, and AB sub-models consists of input and output data information exchange. For the robotic face detection application model, we identify the following interaction points of information exchange:

- FaceID(AB) – FaceID counter (DE)
- x, y location of sensor (SD) – iRobotLocation (AB)
- state “RIdle” (AB) – DE face detection timer

Formulate Relationships among DE, SD, and AB interaction points

In Table 26 we demonstrate the interaction points among DE, SD, and AB models, as well as the type of relationship that occurs.

Table 26. Interaction Points and Type of Relationships

	Interaction Point	**Type of Relationship**
Interaction points between AB and DE Models	FaceID(AB)- FaceID counter (DE) (Total number of successful detections)	*A.2 Aggregation/ Disaggregation*
	When AB state “RIdle” is active, the DE face detection timer is	*B.4 Statechart control combined with B.3 Trigger Event (arrival-*

	Interaction Point	**Type of Relationship**
	triggered by the simulated person's appearance	*agent arrives at the destination point)*
Interaction points between SD and AB Models	x, y location of sensor (SD) – iRobotLocation (AB) (irobot.get(x), irobot.get(y))	*A.1 Direct replacement*

<u>Phase 2: Development of the models</u>

In this section we describe the implementation of DE, SD, and AB models for the three defined sub-objectives. Anylogic [66] was selected as the software tool used in our subsequent modeling efforts.

- Discrete Event (DE) Model

In the present simulation study, the DE model was developed for collecting statistics on face detection performance, counting each successful face-detection event and calculating the average detection time.

- Agent Based (AB) Model

In this simulation study we used an agent to represent the scenario that occurs in the system using state-charts to understand the system's process. The use of state-charts helped us in the observation of the differences that occurred at each state, the transitions among the states, and the events that emerged during each transition state.

More specifically, in this simulation study a robot was implemented as an agent with a state-chart inside. The state-chart was responsible for the higher level controller of the robot's behavior and actions during the face detection process. A Systems Modeling Language (SysML) diagram (see Appendix B) was used to design the flow of the state-chart. The relations among each action (state) are established using conditional loops.

The robotic system was designed as closed-loop architecture (Figure 33): the initial state of the robot was assigned as idle (RIdle) and a transition was set to return to the same state after each successful face-detection. The conditional loops enable the simulated robot (agent) to evaluate its conditions and act accordingly. The High-Level interaction with the human (Person) was also captured.

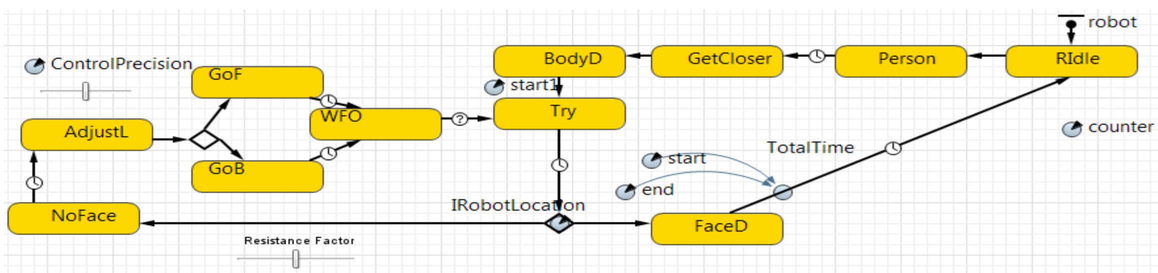


Figure 33. The state-chart describe r the robot's behavior and actions, while the robot attempts to detect the human's face

- System Dynamics (SD) Model

The multi-method simulation model also examined the effect of oscillation caused by the velocity and the acceleration of the robot. The capabilities of SD have here been used to capture the oscillation dynamics of the Kinect sensor. In order to analyze the effect of oscillation, we applied constraint control to the simulated robot in order to move on a particular straight line and to rotate at a constant angular velocity. The movement of the Kinect mounted on the robot follows a linear inverted pendulum model and is described using x and y coordinates [139]. Moreover, we assume that the Kinect sensor is massless (attached at the edge of the pole l). Figure 34 shows such robot model. A simplified SD model of oscillation was constructed in our case, as depicted in Figure 35.

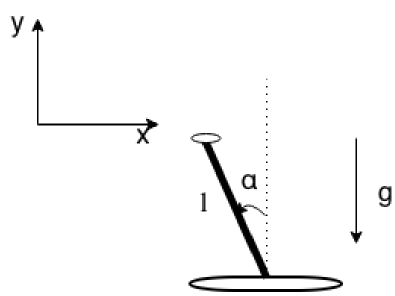


Figure 34. Robot Model

The variables and parameters of the robot model are displayed in Table 27.

Table 27. Variables of System Dynamics Model

Variable	**Description**	**Value**
x	The x coordinate of the Kinect – dependent variable	l*cos(alpha)
y	The y coordinate of the	l*sin(alpha)

Variable	**Description**	**Value**
	Kinect – dependent variable	
r	Resistance of the environment	[0,1]
l	Length of the pole	16.5 cm[a]
g	Gravity	9.81 Newtons
alpha0	Initial angle of the pole	180 ^{o}

[a]cm = centimeter, and ^{o} = degree.

The SD model includes two time dependent variables alpha and omega which represent the angle of the pendulum and the angular velocity, respectively. These variables are expressed using (4) and (5):

$$D\alpha/dt = \omega \tag{4}$$

$$d\omega/dt = (-g*\sin(alpha)-(r*omega)/(0.01*l)) \tag{5}$$

In order to be able to represent the movement of oscillation visually, gravity was assumed to be positive (as a force in the negative direction). This was specifically employed in order to test the evaluation graphs and the validity of the conditions embedded within the state diagrams.

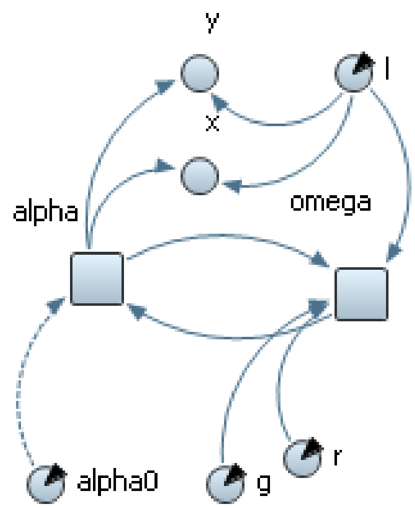


Figure 35. Systems Dynamics Model of Oscillation

Phase 3and 4: V&V of 3M&S model of robotic face detection system

We were able to design and run a multi-method simulation model of a face detection robotic system. As a result, we were able to test the capabilities of the software with respect to the oscillation effect. In order to test the analysis capabilities of the software, three performance variables were selected which are as follows:

- y – Coordinate location change of the Kinect. It is used for illustrating the oscillating motion of the Kinect along the vertical axis
- x – Coordinate location change of the Kinect and the robot. It is used for calculating the distance from human
- Average time to detect a face after a human body is detected.

The performance variables are displayed on time plots in order to check for any possible inconsistencies in the model, as depicted in Figure 36.

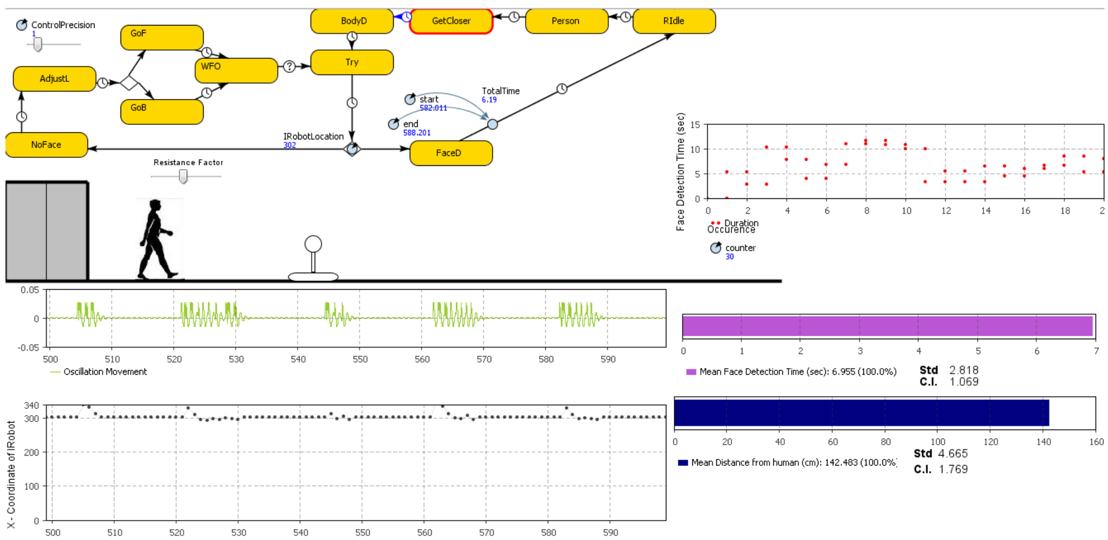


Figure 36. Simulation results of the robotic system

The model was tested by observing the animation of the simulation, as well as the average time for the face detection process. The simulation output for the average face detection time is 6.955 ± 1.069 seconds after 30 replications. The average face detection of the real system is 3.577 ± 0.509 seconds. As it can be observed, the confidence intervals of the simulated average face detection and the real average face detection do not overlap. Therefore, we can conclude that there is a statistical difference between the two means. This result is due to the oscillation effect which increases the average face detection time.

In this case study, the 3M&S framework provided guidelines focused in the development of the conceptual modeling process of a face detection robotic application. We designed an interface for testing a face detection algorithm and collected the appropriate data for the simulation study. The3M&S framework was found helpful mostly because it assisted the user to connect the three different models and identify the relationships of interaction points. Using DE, SD, and AB models, we included aspects that would be impractical or even impossible to be captured by one or two M&S methods. For example, the oscillation dynamics would not be practical to be captured by AB or DE and the robotic behavior could be better represented by using AB states and rules.

CHAPTER 5: SUMMARY OF DISSERTATION

This research describes the need for a generic multi-method modeling and simulation (3M&S) framework capable of addressing DE, SD, and AB M&S methodologies in order to assist in solving CS problems that may occur in different domains. Chapter 1 highlights the research needed for a 3M&S framework to offer useful guidance for combining and/or integrating M&S methods to deal with CS. In this research, it is claimed that attempts to model and simulate CS with stand-alone M&S methods or combination of two (hybrid M&S) may end in designing oversimplified models that exclude important factors. There is a realization that combining and/or integrating DE, SD, and AB methodologies can provide an inclusive way of representing and dealing with CS. Although the combination and/or integration of M&S methods has been reported in various domains in the past, there is an absence of a conceptual 3M&S framework to provide guidance to the potential users on when, why, and how to combine, and/or integrate DE, SD, and AB M&S to form 3M&S models. In addition, this research provides answers of what are the interaction points among DE, SD, and AB simulation models and how AB, DE and SD interact with each other to exchange information. This dissertation has attempted to fill these gaps by providing a generic guideline on how to tackle the overall simulation of CS by deploying the three M&S methods together.

The purpose of this research is to develop a generic 3M&S framework, to provide a guideline on the deployment of DE,SD and AB M&S methods in solving CS problems in various domains, such as in business and healthcare organizations. In order to achieve this goal and answer when, why, and how to form multi-method simulation models four main objectives are outlined. The first objective of this dissertation emphasizes the comprehension of similarities and differences among DE, SD, and AB methodologies. The second objective focuses on acquiring knowledge and understanding through existing M&S studies and frameworks that have been deployed in the past among DE, SD, and AB methods. These two objectives are described in detail in Chapter 2, where we provide a brief background of DE, SD, and AB M&S methodologies as well as a review of the literature for the combination and/or the integration of M&S methods across various industries. The review of literature served as the basis for the development of selection criteria for the appropriateness of each of the M&S methods based on problem, system and methodology perspectives. Chapter 2 continues with the establishment of different types of relationships of interaction points that can be applied among DE, SD, and AB models. Finally, Chapter 2 underlines the limitations of existing frameworks that combine, and/or integrate DE, SD, and AB M&S methods driving towards the concern of a research gap for the combination and/or integration of all the three M&S methods together. On the basis of the understanding and knowledge acquired from the review of the literature, a generic 3M&S framework capable of providing guidance of when, why, and how to combine, and/or integrate DE, SD, and AB M&S methods was proposed.

The third objective of the dissertation is the development of a generic framework for 3M&S. Therefore, Chapter 3 describes the framework that provides guidance as it concerns the research questions of when, why, and how to deploy DE, SD, and AB M&S methods.

Finally, the fourth objective of this dissertation is to evaluate the developed 3M&S framework. Chapter 4 provides the evaluation of the 3M&S framework by following its guidance for three different case studies.

Future work will include the development of a decision support tool based on the 3M&S framework. The decision support tool will address optimal selection of M&S method(s) based on given user requirements considering development time and accuracy of the simulation output under uncertainty. Furthermore, we will evaluate the 3M&S framework using existing studies that have been conducted with one or two M&S methods. We will compare these M&S studies with the framework's recommendations in terms of selection of M&S methods and simulation output accuracy.

APPENDIX A: DATA ANALYSIS FOR MMCU SYSTEM

Data were collected manually over a 2-day period (Friday and Saturday) for 3 weeks. Digital stopwatches were used to measure interarrival, travel, reneging, and service times. Digital counters were used to count the number of customers waiting in or entering each queue, as well as the number of people balking or reneging. All time measurements are expressed in minutes. The collected data were analyzed using Minitab, Microsoft Excel, Matlab and Arena Input Analyzer. Data were determined to be independent. Correlation assessment and raw data were tested to assure independence. Figures 37, 38, 39 and 40 illustrate the scatter plots and autocorrelation plots for interarrival and service times for two different days, Friday and Saturday.

<u>Interarrival Times Fridays - Saturdays</u>

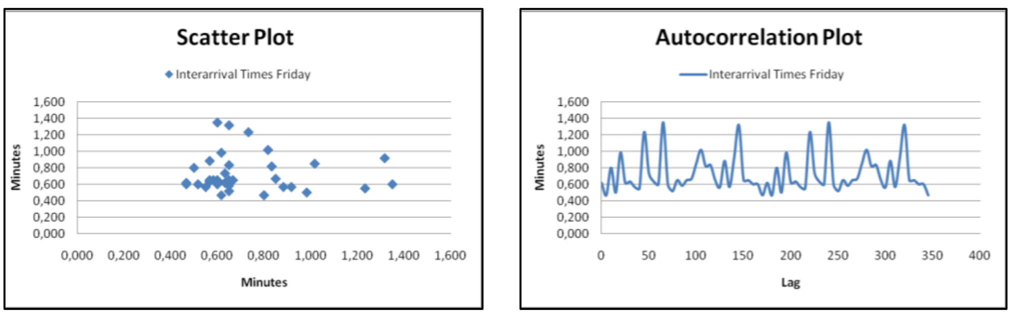


Figure 37. Inter-arrival times Fridays

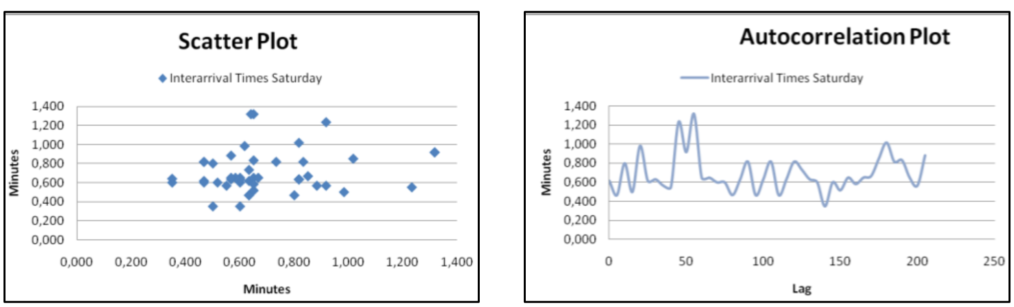


Figure 38. Inter-arrival times Saturdays

Service times for Fridays and Saturdays

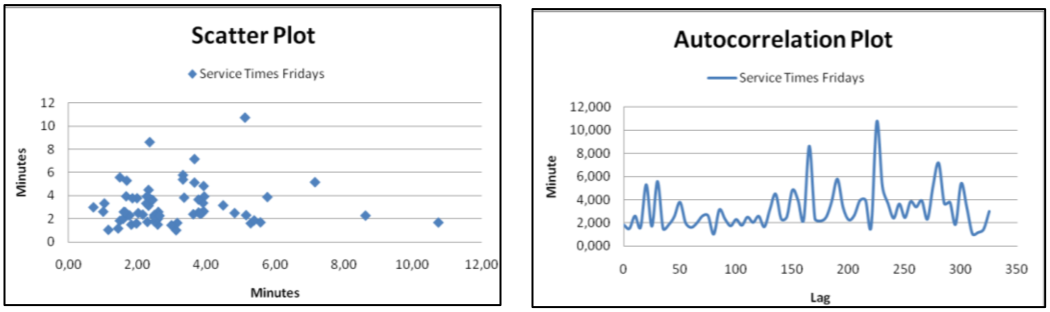


Figure 39. Service times Fridays

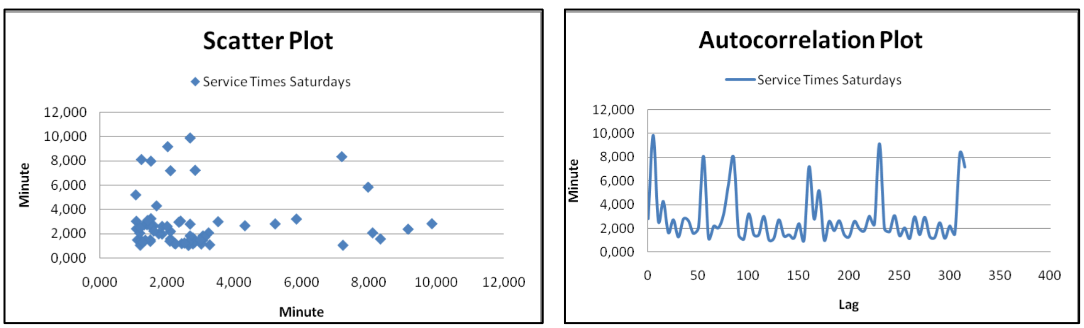


Figure 40. Service times Saturdays

Statistical tests (two-sample t-test and two-sample Kolmogorov-Smirvov test) were performed to statistically prove that data from Friday and Saturday come from the same population.

After assessing independence, MATLAB Statistical Toolbox functions ttest2() and kstest2() were used to perform the statistical tests for uniting the two datasets.

- Two-sample Test:

The function h=ttest2(x,y) performs a t-test of the null hypothesis H0 that data in x and y are independent random samples from normal distributions with equal means and equal but unknown variances, against the alternative H1 that the means are not equal. The result of the test is returned in h. If the result is h = 1, a rejection of the null hypothesis at the 5% significance level is indicated. If the result is h = 0, a failure to reject the null hypothesis at the 5% significance level is indicated.

- Two-sample Kolmogorov-Smirnov (K-S) Test:

The function h = kstest2(x_1,x_2) performs a two-sample K-S test to compare the distributions of the values in the two datasets x_1 and x_2. The null hypothesis is that x_1 and x_2 are from the same continuous distribution. The alternative hypothesis is that they are from different continuous distributions. The result h is 1 if the test rejects the null hypothesis at the 5% significance level; 0 otherwise.

The two tests were performed for two samples (Friday and Saturday) for interarrival, and service times. All the results were h=0, which means that data from Friday and Saturday come from the same population and the same continuous distributions. Therefore, the data from Friday and Saturday can be united into a single dataset. Table 28 summarizes the statistics for the Interarrival and Service Times for Friday and Saturday.

Table 28. Data Statistics for the two samples

	Data for Fridays		Data for Saturdays		
Name	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**	Unit
Inter-arrival Times of Batches	0.2219	0.2137	0.2788	0.2424	minutes
Service Time of Concession Seller	2.8678	2.1247	3.0987	1.7641	minutes

Since the tests failed to reject the null hypothesis that the data come from the same population, the two datasets were combined into one.

The input system characteristics include customer interarrival times and service times and were further analyzed to three alternative system designs. The fitting of distributions to each datum and the statistics, such as mean and standard deviation were calculated as follows.

Arena Input Analyzer was used to fit continuous probability distributions to inter-arrival and service times. Figures 41-44 depict the fitted distributions.

- *Interarrival Times*

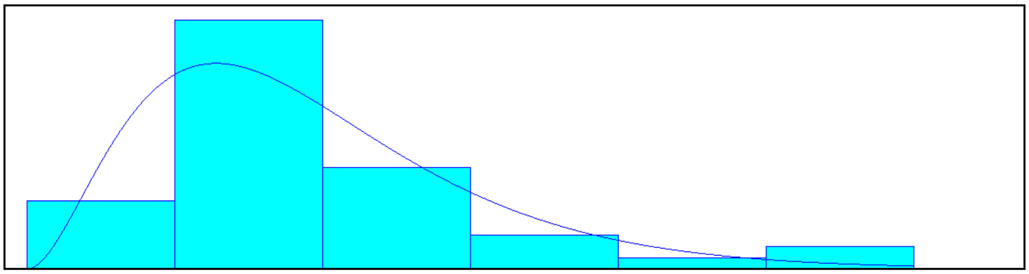


Figure 41. Interarrival times Histogram (6 bin intervals by default)

The Descriptive Statistics that Arena Input Analyzer provides are the following:

Table 29. Descriptive Statistics

Summary of Data	
Number of Data Points	= 43
Min Data Value	= 0.462
Max Data Value	= 1.35
Sample Mean	= 0.712
Sample Std Dev	= 0.214

Table 30. Erlang distribution

Distribution:	Erlang
Expression:	0.37 + ERLA(0.123, 3)
Square Error:	0.021115

The Chi-Square and K-S tests were performed for this distribution by defining the following null and alternative hypothesis:

H_0= the distribution of the data follows an Erlang distribution

H_1= the distribution of the data does not follow an Erlang distribution

Table 31. Chi Square and Kolmogorov-Smirnov Test

Chi Square Test	**Kolmogorov-Smirnov Test**
Number of intervals = 4	Test Statistic = 0.168
Degrees of freedom = 1	Corresponding p-value> 0.15
Test Statistic = 3.19	
Corresponding p-value = 0.0786	

Since the p-values in both cases are greater than the level of significance α=0.05, H_0 cannot be rejected. The two tests cannot reject the null hypothesis, so Erlang distribution with parameters ExpMean=0.123 and k=3 can be used.

For validation, the interarrival distribution was calibrated. Erlang distribution was adjusted to 0.739 + ERLA(0.123, 3) in order for the simulation results to be statistically similar to the real world.

- <u>Service Times</u>

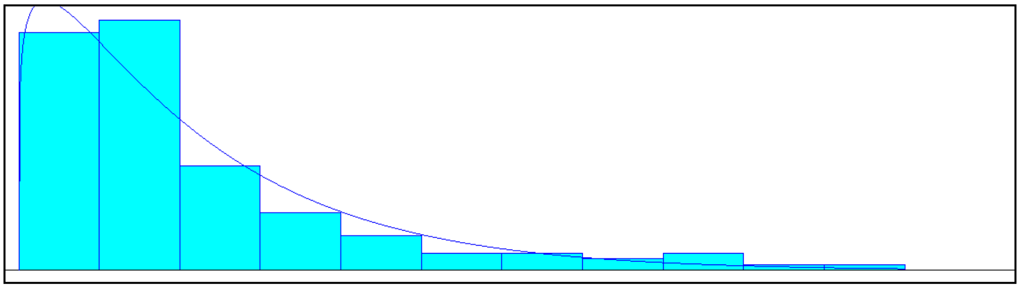


Figure 42. Service time histogram (11 bin intervals by default)

The Descriptive Statistics that Arena Input Analyzer provides are the following:

Table 32. Descriptive Statistics

Data Summary
Number of Data Points = 131
Min Data Value = 1.02
Max Data Value = 10.8
Sample Mean = 3
Sample Std Dev = 1.94

Table 33. Gamma distribution

Distribution:	Gamma
Expression:	1 + GAMM(1.71, 1.17)
Square Error:	0.008441

The Chi-Square and K-S tests were performed for this distribution by defining the following null and alternative hypothesis:

H_0= the distribution of the data follows a Gamma distribution

H_1= the distribution of the data does not follow a Gamma distribution

Table 34. Chi Square and Kolmogorov-Smirnov Test

Chi Square Test	Kolmogorov-Smirnov Test
Number of intervals = 5	Test Statistic = 0.0739
Degrees of freedom = 2	Corresponding p-value> 0.15
Test Statistic = 5.8	
Corresponding p-value = 0.057	

Since the p-values in both cases are greater than the level of significance α=0.05, H_0 cannot be rejected. The two tests cannot reject the null hypothesis. However, the p-values need to be improved. Therefore, the number of intervals changed to 15 (Figure 43)

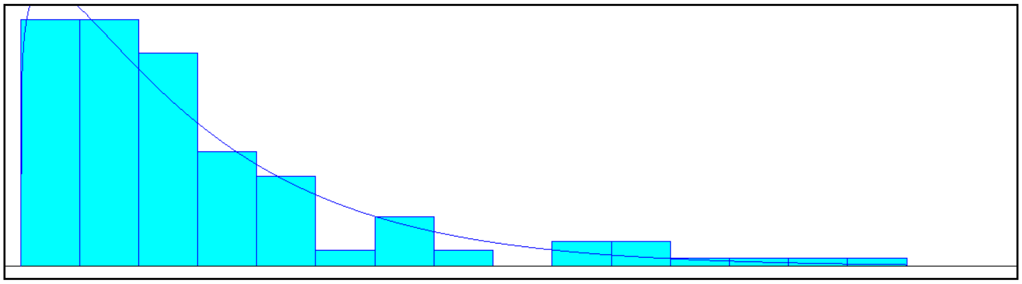


Figure 43. Service time histogram (15 bin intervals)

Both, Chi-Square and K-S tests were performed again for the same distribution by defining the following null and alternative hypothesis:

H_0= the distribution of the data follows a Gamma distribution

H_1= the distribution of the data does not follow a Gamma distribution

Table 35. Chi Square and Kolmogorov-Smirnov Test

Chi Square Test	**Kolmogorov-Smirnov Test**
Number of intervals = 7	Test Statistic = 0.0739
Degrees of freedom = 4	Corresponding p-value> 0.15
Test Statistic = 3.52	
Corresponding p-value = 0.48	

Since the p-values in both cases are greater than the level of significance α=0.05, H_0 cannot be rejected. The two tests cannot reject the null hypothesis and the p-values are improved, so Gamma with parameters α=1.71 and β=1.17 can be used.

- *Batch Size*

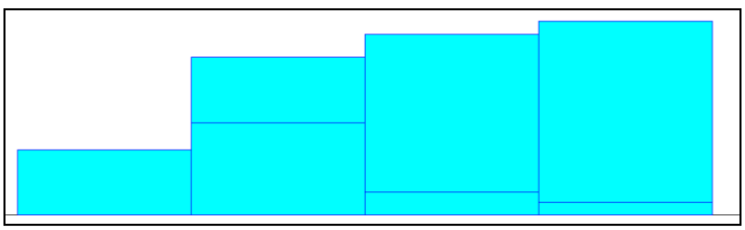


Figure 44. Batch size histogram

The Descriptive Statistics that Arena Input Analyzer provides are the following:

Table 36. Descriptive Statistics

Data Summary
Number of Data Points= 304
Min Data Value = 1
Max Data Value = 4
Sample Mean = 1.91
Sample Std Dev = 0.844

Table 37. Empirical distribution

Distribution:	**Empirical**
Expression:	DISC (0.339, 1, 0.816, 2, 0.934, 3, 0.934, 4,1,5)

Common random number streams (CRNS) were implemented with the input distributions to reduce variance within the simulation output. Table 38 summarizes the results obtained by the input data analysis.

Table 38. Input Data Statistics

Name	Mean	Standard Deviation	Unit	Distribution
Inter-arrival Times of Batches	0.712	0.214	Minutes	0.739 + ERLA(0.123, 3)
Service Time of Concession Seller	3	1.94	Minutes	1 + GAMM(1.71, 1.17)

In addition, Batch Size, Renege Time and Concession Queue Choice were analyzed. The Batch Size is defined as the number of individual customers who arrive together at the same time as a group of one, two, three, four or more customers. Although batches arrive at the same time in the system, each customer in a batch is processed individually as agent. A data fit for the batch size was attempted. The only discrete distribution offered is Poisson, which gives a very poor chi-square test fit. Consequently, empirical data were used to generate batch sizes.

Moreover, it was noticed that the arriving customers prefer the concession stands that they first see when they enter the movie theater (Concessions 3, 4 and 5), which are located in the middle of the concession area. Table 39 depicts the decision of customers to select a concession line.

Table 39. Queue Choice

Queue Choice	1	2	3	4	5	6
Cumulative Fraction for 180 minutes period	0.139	0.306	0.456	0.634	0.814	1

APPENDIX B: FACE DETECTION ROBOTIC SYSTEM

I. SysML Activity diagram of robotic system

The simulation process is illustrated in more detail in the SysML activity diagram of figure 45. The robot moves forward and backward in the environment until it detects a human through the skeletonization process. If the skeleton detection is successful, then the robot attempts to locate the user's face. In order to do this, the robot moves forward and backward until the face is successfully detected. If the face is successfully detected, the robot searches in the database for a matching face. Following successful detection, the user can receives visual information about the face detection and the robot returns to its initial position. The SysML activity diagram provided the foundation for the development of the state-chart in the simulation model.

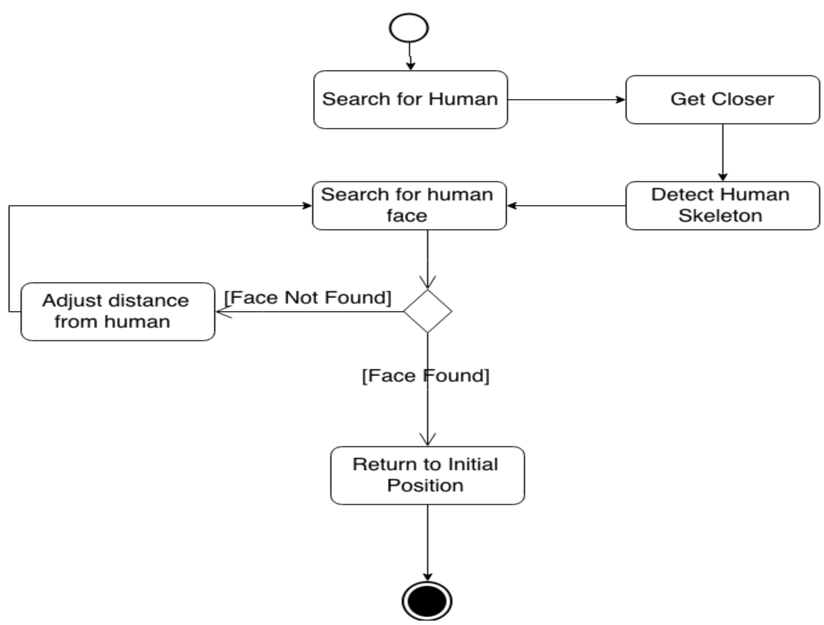


Figure 45. SysML diagram of robotic system

II. High-Level Architecture of Robotic Face Detection System

In this section, the robotic system architecture is presented. Figure 46 describes the components, relationships, and interactions between the different elements of the system. The developed application is based on Microsoft Kinect SDK and Biometric SDK. The bottom level of the system architecture is composed of the Kinect device and its driver. The Microsoft Kinect SD provides a set of API and interfaces to be used for the sensor data acquisition and the interaction with the face detection application. Biometric SDK provides another set of API used for face detection and interaction with the Kinect sensor. The top level includes the Microsoft Robotic Developer Studio (MRDS) Service and the iRobot. MRDS allows for communication with the robot in order to perform certain tasks. Finally, iRobot receives the commands/signals to move forward and backward until the face is detected.

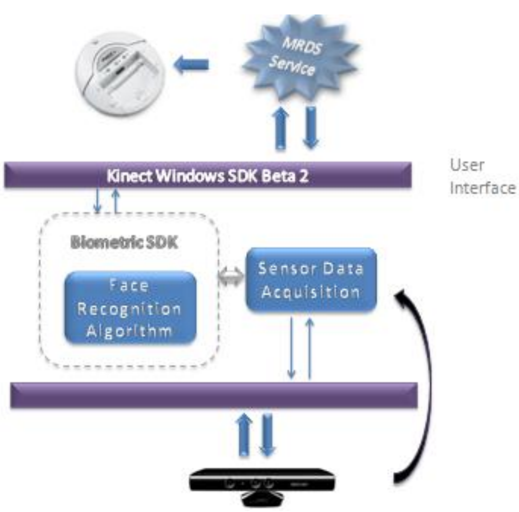


Figure 46. High-Level architecture of the robotic system

III. Skeleton and Face Detection Interface

The created interface for gathering the required simulation data of the face detection application is illustrated in Figure 47. The interface provides visual information about number of humans detected, skeleton and depth information, detected faces, and distance from the robot.

Human detection is achieved through a process termed "skeletonization" [152]. The Kinect depth sensor, in combination with the RGB camera, is used to provide a way for extracting the human silhouette for skeletal processing and to apply the information for facial detection. The skeleton tracking algorithm gives accurate information about joint positions. However, challenges arise due to various issues such as: background complexity, various human-body ergonomic parameters, lighting conditions, and higher dimensions of the search space.

The face detection algorithm works as follows: Once the skeleton of the human is detected, the algorithm stores in a database the pictures taken from the Kinect. Every time a new picture is taken, the algorithm checks for the presence of a face. If the face is found, a positive message appears on the interface. If the face is not found, the appropriate, message is displayed, as depicted in Figure 47.

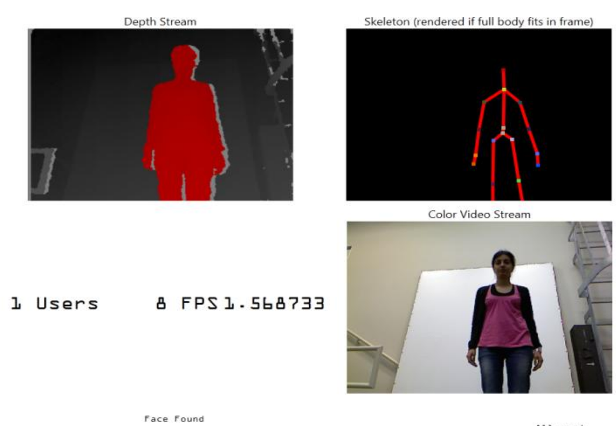


Figure 47. Face Detectionn Interface that provides visual information about number of humans detected, skeleton and depth information, detected faces, and distance from the robot.

IV. Data Collection and Analysis prior to simulation study

The present simulation study included the data collection and analysis of the robot component properties. These properties include the height of the pole, which is the distance between the robot and sensor, the angle of the Kinect, and the distance between the human and the robot.

An experiment was designed to understand the effect of each component on the performance of the face detection algorithm and to define the values of the relevant parameters. The Kinect angle and pole height were identified as the independent variables (Figure 48), while the distance from the human and the face detection duration were the dependent variables. For the purpose of measuring the performance, a temporary construction was mounted on the robot. The construction included an adjustable pole to change the height of the sensor.

Following the verification of the face detection algorithm, the behavior of the robot was tested using two decision criteria:

- “Average face detection time”
- “Robot’s distance from the human subject”

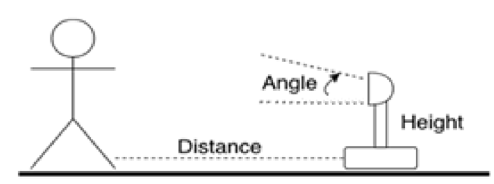
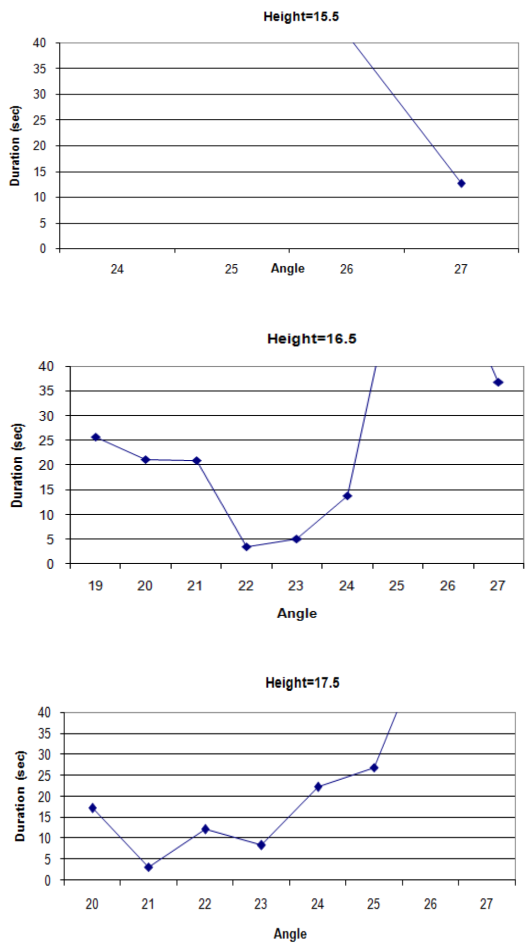


Figure 48. Variables considered for data collection and analysis.

Measurements were collected for each variable by keeping the other two variables constant. The collected results were then analyzed. The collected data were plotted in three graphs grouped according to their associated height values, 15.5 cm, 16.5 cm and 17.5 cm (Figure 49). In each graph, the duration performance was studied for different angles values of the Kinect sensor ranging from 19° to 27°.



(a)

(b)

(c)

Figure 49. Facial detection durations in seconds associated height values (a) 15.5 cm (b) 16.5 cm and (c) 17.5 cm

Two cases were found to be really close to each other (Figure 49b, 49c). However, considering the impact of height on the inertia, it was decided to select the combination which had the lower height and average of face detection time. Thus, height was set at 16.5 cm. Based on the collected data the minimum face detection time would be achieved by setting the angle of the Kinect sensor to 22^{o} for height=16.5 cm and distance equal to140cm. The estimated height, angle and distance values were then set as the default properties in the robotic simulation (Table 40).

Table 40. Properties of Robotic Simulation

Height	Angle	Distance
16.5cm	22^{o}	140cm

[9a]cm = centimeter, and ^{o} = degree.

During the experimentation, since the robot was assumed to be stable and still, some of the critical variables were not included in the tests. The effect of oscillation caused by the velocity and the acceleration was one such variable. Even though it was assumed to have no effect, for the actual experimentation, it would be wrong to design a system and a simulation without considering the impact of oscillation on the face detection time. Therefore, in the simulation study we considered the oscillation effect and investigated how it impacts the average time of detection.

Data were collected manually using digital to measure the actual face detection time of the robotic application. The distance between the robot and the human was constant and equal to 140cm, the height of the pole that the sensor was attached was 16.5 cm and the kinect angle was 22^{o}. Data were determined to be independent. Correlation assessment and raw data were tested to assure independence. Figures 50, 51 illustrate the scatter plots and autocorrelation plots of the face detection times for 30 observations.

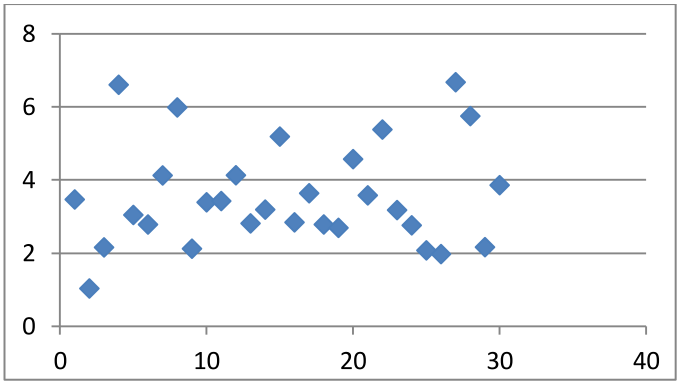


Figure 50. Scatter plot of face detection time data

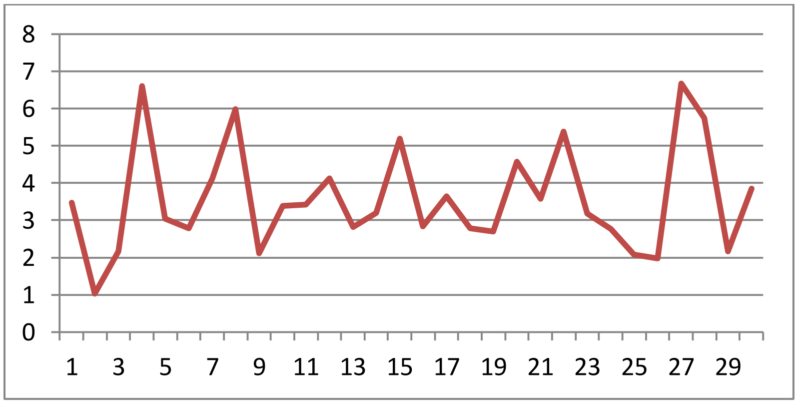


Figure 51. Autocorrelation plot of face detection time data

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