A MODEL DRIVEN ENGINEERING FRAMEWORK FOR HEALTHCARE SYSTEMS MANAGEMENT

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By

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CERTIFICATION

This is to certify that the thesis titled "*A Model Driven Engineering Framework for Healthcare Systems Management*" submitted to the school of postgraduate studies, African University of Science and Technology (AUST), Abuja, Nigeria for the award of the Doctor of Philosophy degree is a record of original research carried out by *Ignace Djitog in the Department of Computer Science and Engineering*.

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ABSTRACT

Traditional mathematical methods such as differential equations formalism have been used for centuries as the main tools for analysis of complex systems in varied areas. As opposed to the general solutions provided by analytical methods, simulation based techniques are effective methods for designing and analyzing complex systems while providing individual solutions for particular problems. Computer simulation is a technique of representing the real world by a computer program in order to manipulate that representation in such a way that it operates on time or space. A model is a simplified representation of the real world at some particular point in time or space intended to promote the understanding of its behavioral properties. Therefore, Modeling and Simulation (M&S) is the use of models, including emulators, prototypes, simulators, and either statically or over time, to develop data as a basis for making managerial or technical decisions in the design and analysis of complex systems. Such complex systems represent part of real world or human-made systems like manufacturing systems, management systems, transportation systems, urban traffic light systems, education systems, military systems, hardware systems, and social systems.

One of the areas that M&S has gained a tremendous popularity in these last decades is the domain of healthcare. Considerable efforts have been made in relation to simulation based study to healthcare systems (HS)s as witnessed by a huge amount of work published recent years. Simulation in HSs has a broad application around different disciplines such as clinical simulation, operational simulation, managerial simulation, and educational simulation. However, the domain of healthcare is characterized by a high degree of complexity and a diversity of perspectives, and modelers are often confronted with the challenge of formulating a simulation model that captures this complexity in a systematic and manageable manner. Frequently used methods to address the problems include discrete event simulation, optimization techniques, goal programming, and data envelopment analysis. We argue that none of the existing works provides an attempt to holistic view modeling of healthcare systems. Instead, the diverse perspectives of healthcare systems are studied in isolation and focusing on specific aspects like allocation of resources, disease outbreak control, and population dynamics using specific formalisms. Furthermore, unit specifics simulation are predominant in the literature. Such units include outpatient clinics, A&E (Accident and Emergency Departments), and inpatient facilities. As it turns out, answering questions concerning behavioral properties of the overall system becomes difficult and therefore not sufficient for an efficient design and analysis of the system under study.

In order to address the identified issues, this thesis suggests investigating the domain of HS using M&S with a whole set of activities: (1) an Ontology-based modelling framework, a real-world semantics and a formal specification of the core concepts and their relationships in healthcare simulation, for capturing modelling knowledge in a reusable and interoperable manner, (2) a Multi-perspective M&S Framework for HS, (3) an approach for holistic analysis of HS based on the multi-perspective framework and a systematic integration of simulation processes to form an integrated whole, and (4) a formalization of the integration approach through a concept based upon Discrete Event Systems Specification (DEVS) formalism called Parameterized DEVS, whereby concurrent simulation processes cause live update through output-to-parameter integration.

A top ontology for M&S is developed based on an extensive literature review and provides a framework that covers all the definitions of important concepts in the domain of healthcare systems and the descriptions of their properties. An ontology is a formal specification of a conceptualization that can be used to rigorously define a domain of discourse in terms of classes/concepts, properties/relationships and instances/individuals. The objective of the Ontology is to document knowledge that is formalized -machines and computers understand-, and assists in communication between humans, achieves interoperability, and facilitates communication among software systems.

A multi-perspective approach to modelling and simulation of HSs allows defining different perspectives that are integrated together to form a holistic. The integration between the isolated perspectives are done through concurrent simulations. Hence, studying HSs through multi-perspective modelling provides multiple levels of explanation for the same system.

A methodology for a "loosely" integration enables independent simulation processes of disparate concerns in HS to exchange live updates of their mutual influences. Such approach takes the results obtained closer to the reality of the interactions between health phenomena and help stakeholders to gain a holistic understanding of the whole healthcare system while deriving more realistic decisions.

A multi-formalism modeling approach to effectively capture the different concerns encapsulated into the multi-perspective framework is built to accommodate the diverse familiarities of the experts with modeling formalisms, reuse of existing models, easiness to reproduce realities using specific formalism for specific perspective accordingly. To realize that, we place the multi-formalism modeling feature at the top layer of the proposed framework and support it with the Model Driven Engineering (MDE) approach through which a co-simulation or a formalism transformation can be carried out

As a standards-based approach to system development, the concept of OMG's (Object Management Group) Model Driven Engineering (MDE) is a de facto theoretical unit guiding the investigation and definition of level of abstractions of a given system of interest. It aims at the development of source models of HSs and transforming them to multiple levels of abstraction until we get to a code level while at the same time increasing the power of models.

Finally, a case study is used to illustrate the application of our framework where models are built in isolation according to each perspective and their simulation results are integrated together to form a complete whole. The outbreak of Ebola in Nigeria in 2014 is used as a running example.

Keywords: Healthcare Systems, Multi-perspective M&S, Parameterized DEVS, Output-to-parameter Integration, Model Driven Engineering, Ontology, Multi-paradigm modelling, Model Transformation, Metamodel.

List of publications

The following are the journal and conference papers emanating from this thesis:

Djitog, Ignace, Hamzat O. Aliyu, and Mamadou K. Traoré. "A model-driven framework for multi-paradigm modeling and holistic simulation of healthcare systems." *SIMULATION* (2017): 0037549717744888.

Djitog, Ignace, Hamzat Olanrewaju Aliyu, and Mamadou Kaba Traoré. "Multi-Perspective Modeling of Healthcare Systems." *International Journal of Privacy and Health Information Management (IJPHIM)* 5.2 (2017): 1-20.

Djitog I., Aliyu H., Traoré M.K. 2015. Towards a Framework for Holistic Analysis of Healthcare Systems. *Proceedings of the 2015 European Simulation & Modelling Conference. ISBN: 978-90-77381-90-8.* October 26-28, Leicester, UK, 193-196.

To

My family ***Mahamat Tanro*** *and all my friends, making me who I am now with their love and support.*

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LIST OF ABBREVIATIONS

M&S	Modeling and Simulation
HS	Healthcare System
O4HS	Ontology-based modelling framework
EF	Experimental Frame
MDE	Model Driven Engineering
MDA	Model Driven Architecture
OMG	Object Management Group
C	Contribution
OR	Operating Room
SES/MB	System Entity Structure Model Base
RA	Resource Allocation
HD	Health Diffusion
PD	Population Dynamics
IB	Individual Behavior
DSM	domain specific modeling
OF	Observation Frame
IORO	Input/Output Relation Observation
IOFO	Input/Output Function Observation
IOS	Input/Output System
EVD	Ebola Virus Disease
WHO	World Health Organization
CSS	Coupled System Specification
FCT	Federal Capital Territory

ATL	ATLAS Transformation Language
EMF	Eclipse Modeling Framework
QVT	Query View Transformation
MOF	Meta Object Facility
LOS	Length Of Stay
CP	Clinical Pathway
CIM	Computation Independent Model
PIM	Platform Independent Model
PSM	Platform Specific Model
DeMO	Discrete-event Modelling Ontology
DESO	Discrete Event System Modelling
CM	Conceptual Model
DSL	Domain-Specific Language
DEVS	Discrete Events System Specification
AM	Atomic Model
CM	Coupled DEVS Model
CDEVS	Classic DEVS
PDEVS	Parallel DEVS
HiLLS	High Level Language for System Specification

Chapter 1
INTRODUCTION

With the mounting pressure of healthcare cost and the ever increasing demand for care services due to aging population of the world coupled with degrading quality of health delivery, today's healthcare systems face a wave of challenges. For example, total healthcare expenditure in the world stepped into over 5-trillion dollar economic sector [Barjis 2011] and it is projected to reach 8.7 trillion by 2020. The increasing waiting time for healthcare services by patients is another example of how much limited healthcare resources are, due to unlimited demands of healthcare services. The well-known three health competing goals, including access, quality and cost, represent the "iron triangle" such that any attempt of achieving anyone of them would significantly deteriorate the others. This makes the work of healthcare managers very challenging while trying to provide efficient management of health resources and patient-centered services such as developing strategic visions, hiring, training, assigning schedules and tasks, handling finances like creating budgets, calculating and issuing patient bills, negotiating insurance claims, and organizing and maintain patient records. Besides, understanding how well healthcare systems perform can be a difficult task, especially in today's complex world. It is difficult to say where a healthcare system starts and ends because there is a wide variety of healthcare systems around the world and every country has its own health system that reflects its own history, its own politics, and its own economy and national values that all vary to some degree. Depending on one country to another, healthcare may be fragmented or integrated among different organizations and this makes it even harder to disentangle each systems component's contribution since they are diverse and interrelated with complex relationships. As such, when evaluating the overall health outcomes, each unique intervention may be linked to a multitude of outcomes. Furthermore, the growing

market competition and the transition to electronic health records make healthcare management more challenging while every day, vast number of people lives (billions in Sub-Saharan Africa) rely on healthcare systems. The issue of healthcare efficiency - the need to produce more with less, despite the scarcity of resources- is becoming a widely acknowledged concern among policy-makers and healthcare managers [Shin et al. 2013], [Eklund 2008]. Hence, healthcare has become an attractive domain for scientific exploration using Modeling and Simulation (M&S).

Considerable amount of simulation research works have been dedicated to healthcare, seeking to address problems such as hospital scheduling and organization (like sizing and planning of beds, room, staff and patient flow), infection and communicable disease, cost of illness and economic, and screening. Healthcare systems is broad and complex, and more investigation need to be carried out to tackle challenges related to its management.

1.1. Research statement

Owing to a large number of components that are diverse, concurrent and distributed while interrelated with intricate processes, healthcare system (HS)s management become unquestionably a complex enterprise today. HS systems components are fragmented, loosely coupled and tightly cohesive. The component systems are fragmented, that is, without a strong relationships among the involving whole parts but rather each component is focusing on its own activities. This unbalanced and brokenness leads to failing structures that obviously subject healthcare systems to crises of cost increases, poor quality and inequality. For example, most of healthcare systems are designed to deal only with patient needs and fail to consider the interacting factors that can improve the health of the whole people within communities. HS are loosely coupled, i.e, organized in a modular way such that separate and semi-autonomous work units, e.g., neurology, cardiology, and

ophthalmology are weakly link to one another rendering difficult the flow of information within health organizations [Pinelle and Gutwin 2006]. The loose coupling can be seen both at horizontal and vertical level. At horizontal level, it is manifest between peers who are highly trained and self-directed with significant autonomy and can control their own tasks in their domain of expertise without necessary consulting others before taking any action even though they may collaborate. At vertical level, it is also seen between health workers who are head of departments in directing their daily activities on their own and the management of health units such as hospital administrators who have limited information on what is done at the operational level. As a result of this decentralization, the components are uncoordinated such that coordination of health services, and workers are difficult since the autonomous work units have limited awareness of others' activities. Additionally, HS are tightly cohesive, i.e, they depend on one another for the delivery of health services that meet patients' needs. For example, when services required for a patient are dependent to more than one work unit the collaboration between work units becomes a matter of necessity rather than of discretion.

Consequently, M&S related to healthcare systems has been paid a lot of attention over the last decades. Having a broad application in healthcare, it can be divided into different domains, including clinical aspects, operational aspects, managerial aspects, and educational aspects. The work of [Roberts 2011] reported on taxonomy for the use of computer simulation in healthcare into two categories: (1) Patient flow optimization and Analysis, and (2) healthcare asset allocation. Frequently used methods include discrete event simulation - to study problem related to performance modeling in healthcare [Gunal and Pidd 2010], [Mes and Bruens 2012], [Cote 1999], [Ozcan et al. 2011] -, optimization techniques, goal programming [Topaloglu 2006], and data envelopment analysis. Some few attempts are made to mix two methods such as combining

simulation with optimization techniques [Ahmed and Alkhamis 2009], or discrete event simulation (DES) and Data Envelopment Analysis (DEA) [Weng et al. 2011]. Merely integrating different simulation variables in the same model to address the multi-faceted challenges healthcare is facing and allowing a truly holistic systems view is only half the story [Brailsford et al. 2010]. Instead, unit specific studies that deal with specific problems have been predominant. Such unit specifics include outpatient clinics, A&E (accident and emergency) departments, and inpatient facilities that are addressed in [Ahmed and Alkhamis 2009], [Topaloglu 2006], [Khurma et al. 2013], [Choi et al. 2013], [Einzinger et al. 2013] and [Aboueljinane et al. 2013]. Common issues that are being addressed include, scheduling and patient flow, sizing and planning of beds, rooms, and staff. One of the major concerns in managing efficiently health resources is the control of patient movements across the healthcare facility referred to as care pathway. A care pathway is a sequence of treatments or services described as processes through which patients undergo during their medical journey. These processes are seen as key elements to evaluate the performance of healthcare providers since they reflect the amount of resources that are used, their order, and the time they are being allocated to patients. The movement of patients was monitored by a number of research studies that can be found in [Mes and Bruens 2012], [Morice et al. 2013], [Zeng et al. 2012] and [Verma and Gupta 2013].

However, when studying such complex systems, it is not sufficient to focus on the diverse components or aspects separately. This leaves a big gap of understanding the overall system by the decision makers and managers to make a consistent design and analysis of healthcare systems. Using unit specific and facility specific models for the analysis and design of healthcare systems can be misleading [Gunal and Pidd 2010]. Therefore, there is a need for a holistic approach to healthcare systems M&S. This research work aims at developing a framework that integrates all

relevant healthcare perspectives under a unifying umbrella, and allow a holistic simulation of healthcare systems. Such a tool has the potential to significantly help healthcare decision makers towards more efficient management of the "iron triangle".

1.2. Thesis contributions

In this thesis, we address the problem of healthcare management using Modelling and Simulation as a potential tool. The work of the thesis is based on the following contributions (C).

C1. Ontology for Healthcare Systems M&S

We propose an Ontology-based modelling framework (O4HS), a real-world semantics and a formal specification of the core concepts and their relationships in healthcare simulation, for capturing modelling knowledge in a reusable and interoperable manner. O4HS defines the domain of HS in terms of classes/concepts, properties/relationships and instances/individuals, and serves to document and formalize knowledge in healthcare simulation. We use System Entity Structure [Zeigler 1984] to formally express it. Prior to O4HS, ontology-based study has been widely proposed to address modelling challenges in large-scale and complex systems, e.g., ontology for discrete event system modeling (DESO) [Guizzardi and Wagner 2010], web-based ontology for discrete event modeling (DeMO)[Miller et al. 2004], ontology to deal with modelling problems such as composability and interoperability [Tolk and Turnitsa 2007], fundamental types of modelling errors - system description errors, and model translation errors- [McGinnis et al. 2011], simulation conceptual model [Balci et al. 2011], and model reuse [Durak et al. 2011]. O4HS is hoped to bridge the gap between healthcare domain experts and facilitate

communication among software systems while overcoming at the same time semantic problems of knowledge sharing

C2. Multi-perspective modeling and holistic simulation approach

We develop a multi-perspective approach to Modeling and Simulation of Healthcare Systems such that different perspectives are defined and integrated together. This contribution answers some key challenges related to HS modeling: (1) It offers to the modeler, through separation of concerns, a clear view on different perspectives proposed in the literature such as patient flow optimization and analysis, healthcare resource allocation, and disease propagation control that are most often intertwined [Gunal and Pidd. 2010]. Through separation of concerns in a well-defined manner, we then proceed to their integrations in order to form a holistic view of HSs modelling. (2) It proposes a multi-perspective modeling approach of HSs to overcome the problems of single-perspective modeling used in solving problems in individual HS units like outpatient clinics, A&E, and Inpatient facilities, as well as facility specific problems. Furthermore, a multi-paradigm modeling methodology is provided to support a holistic simulation of HSs using model transformation in which case models from System Entity Structure Model Base (SES/MB) framework [Zeigler 1984] are transformed from one formalism to another. This feature is capable of providing multiple levels of explanation, while the resulting global model allows deriving results that could not be accurately addressed in any of the perspectives taken alone. (3) It offers a DEVS-Based formalization of the loose integration of the different perspectives, and its implementation. DEVS formalism is chosen because it is universal for discrete event simulation as proven by [Vangheluwe 2000].

C3. Integrative healthcare M&S framework, with model base and automated code synthesis features.

To combine the different perspectives of HS defined in C2, we develop a novel approach for the integration via simulation parameters from experimental frame (EF) of models of perspectives based on dynamic update of models output-to-parameter during concurrent simulation. Most often, simulation-based studies assume that these parameters remain constant throughout the simulation. Hence, this approach will take the results obtained closer to the reality of the interactions between health phenomena and help stakeholders to take more realistic decisions. The developed integration approach is contrary to the classical models coupling through outputs and inputs interfacing of simulation models [Zeigler et al. 2000]. We make use of Model Driven Architecture (MDA), a standards-based approach to system development from Object Management Group (OMG), to investigate and define the level of abstractions in healthcare modelling [Blevins et al. 2004]. MDA aims at the development of source models and transforming them to multiple levels of abstraction until we get to a code level while at the same time increasing the power of models in a constantly changing world. The model driven architecture allows creating more or less, different models from different views that are combined in the final step to create a whole system. Additionally, we develop a software environment support for model-based healthcare systems management. This software environment for MB captures the dynamic behavior of HS components described in C1 using SES.

1.3. Thesis outline

The remaining of this document is organized as follows. Chapter 2 presents the background of our work, i.e., all theoretical and technological frameworks need to achieve our goals. Chapter 3 presents a literature review of research efforts that addressed healthcare systems M&S. Chapter 4 introduces our multi-perspective approach to healthcare systems M&S, through the ontology we've built, using the SES/MB knowledge representation framework. Chapter 5 presents the integration approach we propose to achieve holistic simulation of a multi-perspective-specified healthcare system. This approach is formally specified, using the DEVS framework. A case study is presented in chapter 6. Chapter 7 discusses our contributions, as regards to related works. Chapter 8 gives a conclusion and examines some perspectives of future work.

Chapter 2
BACKGROUND

We present in this chapter the research backgrounds to achieve the thesis contributions as presented in the previous chapter. Due to the fact that today's healthcare systems are multi-disciplinary complex fields, they require a sound simulation methodology based on multimethod and multi-paradigms to address them. As such, it is worth to investigate such domain with a combination of theoretical and technological tools to support the proposed Modelling and Simulation activities of the objectives of the thesis.

The rest of the chapter is organized as follows: The Discrete Events System Specification (DEVS) Modeling and Simulation framework is presented in section 1 followed by the High Level Language for System Specification (HiLLS) background. Section 3 discusses ontology in Modelling and Simulation. Then Multi-paradigm Modelling and Simulation a core concept to deal with multi-perspective modelling of the healthcare domain and multi-level of Abstraction is discussed in section 4. In section 5 we present the Model Driven Engineering (MDE) as related to different level of modelling abstractions and the concept of Model transformation to show how different formalisms can be related. Section 6 concludes the chapter.

2.1. DEVS Modeling and Simulation Framework

The framework developed by [Zeigler et al. 2000] is comprised of basics components in M&S and their relationships, a hierarchy of systems specification and a formalism corresponding to details of top levels in the hierarchy.

2.1.1. Basic Components in M&S and their relationships

Figure 2.1 describes the basics entities in the Modeling and Simulation framework and their relationships. A system under study is represented as a source of behavioral data and belongs to an experimental frame (EF). Entities such as model and simulator are interrelated by the modelling and simulation relationships. The EF is a specification of the conditions under which the system is being observed and defines the operational formulation of the objectives of the project and can be seen as a system that interacts with the system of interest based on three major components such as generator, acceptor and transducer. The system under studied is reproduced using rules or mathematical equations to an abstract representation called "model" that is used to replicate its behavior. The model is then used to build a simulator that is able to execute the model's instructions. Source system within EF is related to model by the Modeling relationship while model and simulator are related by the Simulation relationship.

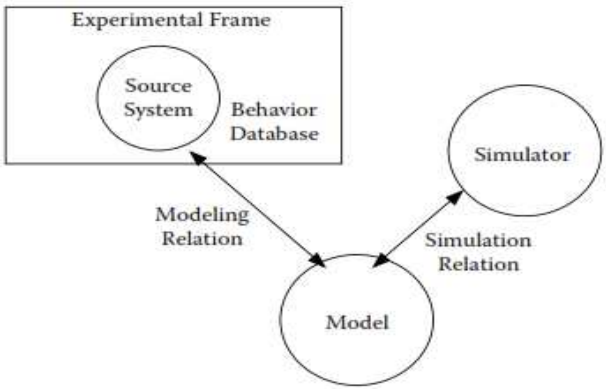


Figure 2.1. Basic entities in M&S and their relationships [Zeigler, B. P. et al. 2000]

2.1.2. Hierarchy of Systems Specification

The DEVS M&S framework [Zeigler 1976] suggests a specification hierarchy to capture the knowledge specific to systems behavior and structure. Hence, dynamical systems can be broken

down in knowledge levels and specified in a useful way to understand how they behave as captured in Figure 2.2.

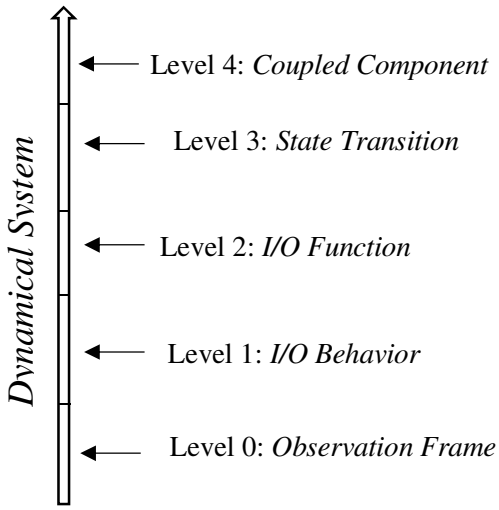


Figure 2.2. System Specification Hierarchy

- At level 0 the system is stimulated with input variables and observed over time to measure the output variable. Each input (I) variable is paired with the corresponding output (O) trajectories - I/O pair.
- At level 1 the collection of all I/O pairs observed are gathered and called I/O behavior of a system.
- At level 2 a system is observed with initial states and I/O pairs at level 1 are applied. This allows predicting the unique response to any input. The initial state establishes a functional relationship between input and output trajectories.
- At level 3 we are interested in knowing how the state changes when the input is applied with initial condition to a system as described at level 2. The level is called the state transition.

- At level 4 a system is specified by a set of sub-systems each having its own state and state transition while linked with a coupling structure to one another.

Each of the levels presented in Figure 2.2 has an associated set-theoretic structure (n-tuple) that allow to describe a system [Zeigler, 1976]. Going up the hierarchy (from behavior to structure) adds more elements to the n-tuple, since we know more about the system as levels increase. There are corresponding morphisms at each level, i.e., how to tell whether two descriptions of the same system at a level are equivalent or related at that level. Also, the morphisms at one level are consistent with those below, i.e., if two descriptions are equivalent at a higher level, then they are also equivalent at every lower level. Going down the levels is computationally done by simulation, while going up the levels (also known as structural inference) is much harder and can be realized under justifying conditions. These levels are often the most convenient to describe the structure of the system under study, while the well-defined DEVS simulation algorithms generate the behavior of these models which is described lower levels of the hierarchy.

2.1.3. The Discrete Event System Specification (DEVS) formalism

The DEVS M&S formalism was introduced by Bernard Zeigler in [Zeigler 1976] based on systems theory concepts to model discrete event dynamic systems (DEDS). Its formal background provides rigorous basis for the analysis and design, and modeling of a plethora of both discrete and continuous complex systems. DEVS formalism accommodates the specification of states of dynamic systems that change either once they receive an input event or after the expiration of a time delay. Models of system components are organized hierarchically such that components at higher level of hierarchy are decomposed into smaller elements and are coupled under closure

reducing the complexity of the system under study. The separation of concerns in terms of model and simulator and the hierarchical specification have led to successful proofs of formal analysis carried out on different systems studied.

DEVS provides two types of system behavior specification using atomic and coupled models for hierarchical and modular construction. A DEVS atomic model (AM) at the lower level describes the autonomous behavior of a DES in terms of transitions between different states due to an elapse time or input events received by the system generating output events. A coupled DEVS models (CM) at the higher level describes a system as a composition of subcomponents that can either be atomic DEVS models or coupled DEVS models in their turn. DEVS defines a network connection through which components use to influence each other by their output invents into other components input events. There are three kinds of couplings in DEVS formalism: External Input Coupling (EIC), Input Coupling (IC) and External Output Coupling (EOC). A coupling under closure suggests that for any network of components known as a coupled models it can be replaced by an equivalent atomic DEVS model.

DEVS formalism was initially known as classic DEVS (CDEVS) while presenting some limitations to perform parallel implementation. Some of its limitations comprise tiebreaking select function that handles simultaneous occurring internal transitions of the components of a CM, and the fact that it ignores an internal transition function while occurring at the same time with an external input event – collision - in which case the external transition function always takes place. [Chow 1996] introduced Parallel DEVS (PDEVS) to alleviate this drawback. For the rest of the work that will be presented in this thesis we will be referring to PDEVS formalism simply as DEVS.

2.1.3.1. The atomic DEVS model (AM)

An atomic DEVS model, *AM* is a structure $< S, X, Y, \delta_{int}, \delta_{ext}, \delta_{conf}, \lambda, ta >$, where S is a set of sequential states including the initial state.

$X = \{(p, v), p \in IPort \wedge v \in dom(p)\}$ is the set of inputs events received at the input port "$IPort$".

$Y = \{(q, v), q \in OPort \wedge v \in dom(q)\}$ is the set of outputs event sent by the output port "$OPort$".

$\delta_{int}: S \rightarrow S$ is the internal transition function

$\delta_{ext}: Q \times X^b \rightarrow S$ is the external transition function

$\delta_{conf}: S \times X^b \rightarrow S$ is the confluent transition function which defines the collision behavior between internal and external events

$\lambda: S \rightarrow Y^b$ is the output function,

$ta: S \rightarrow \mathbb{R}^+ \cup \{+\infty\}$ is the time advance function.

The operational semantics of an AM is informally described as follows: at the start, the systems is in an initial state and remains there until the time specified by ta is exhausted or until input event is received in the "$IPort$". In the former case, an internal transition function occurs then the system switches to another state after sending output event as defined by the output function λ to "$OPort$". In the latter case if input event is received before the specified time, then the external transition function is applied. When a collision occurs i.e., an external event is received concurrently with the elapsed time equal to the time specified by the time advance function, the confluent function is applied in such a way that the system sends output value and changes to a new state. All input values are gathered in a set called a *bag* of values.

2.1.3.2. The coupled DEVS model (CM)

A coupled DEVS model, *CM* is a structure$< X, Y, D, \{M_d\}_{d \in D}, EIC, EOC, IC >$, where

X and Y are the same as defined in *AM*

D is the set of component references ;

$\{M_d / d \in D\}$ is the set of components of the coupled model;

$EIC \subseteq \{((M, ip_M), (d, ip_d)) / ip_M \in IPorts_{M,} ip_d \in IPorts_d\}$ is the set of external input couplings

$EOC \subseteq \{((d, op_d), (M, op_M)) / op_M \in OPorts_{M,} op_d \in OPorts_d\}$ is the set of external output couplings

$IC \subseteq \{((a, op_a), (b, ip_b)) / op_a \in OPorts_{a,} ip_b \in IPorts_b\}$ is the set of internal couplings;

CM completely specifies the structure and behavior of the system at the coupled network level.

2.2. HiLLS Background

The High Level Language for System Specification (HiLLS) [Aliyu et al 2016] is a specification language for discrete event systems, based on system-theoretic concepts from DEVS [Zeigler et al. 2000] and software engineering concepts from Object-Z [Smith 2012] to specify models that are amenable to analysis by simulation, formal methods and enactment.

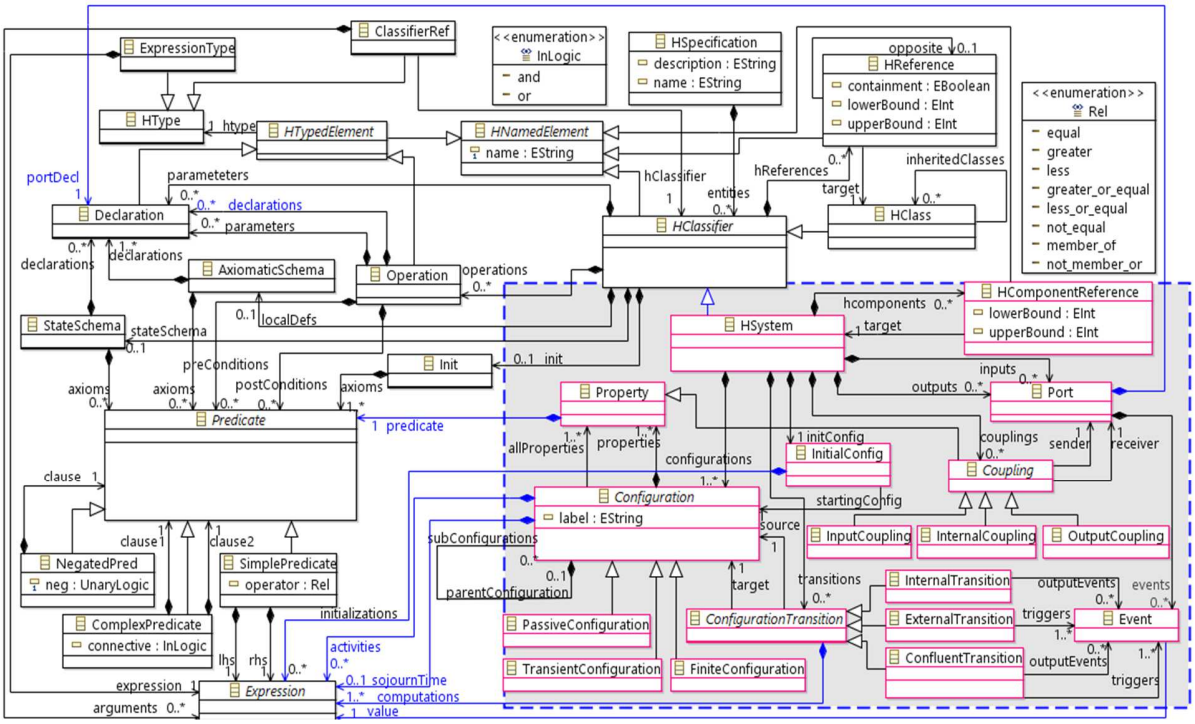


Figure 2.3. Simplified HiLLS' abstract syntax

2.2.1. Abstract Syntax

Figure 2.3 presents a simplified HiLLS' meta-model (abstract syntax). It integrates system-theoretic concepts from DEVS and software engineering concepts from Object-Z to produce a coherence whole. The choices of the two main underlying formalisms were inspired by two factors: 1) DEVS is considered suitable to most kinds of discrete event systems for simulation while Object-Z is an extension of Z, which is also considered suitable for modeling most kinds of state-based systems for formal analysis. 2) Both formalims separate system specification from analysis protocols thereby allowing the user to specify correct models based on the problem under study with limited influenced of the analysis techniques.

The dashed box at the south-east of Figure 2.3 contains most of the abstract system-theoretic concepts adopted from DEVS. A system is described by the class HSystem which is composed of *configurations*,

transitions, couplings, ports, and *hComponents*. Using the meta-model merge and interfacing techniques, class *HClassifier*serves as the bridge between the DEVS and Object-Z concepts. Through *HClassifier*, *HSystem* inherits the Object-Z concepts *StateSchema* to formally declare state variables, and *Operation* to encapsulate computation algorithms. Moreover, using meta-model refinement, Objec-Z's *Predicate* and *Expression* are used to provide detailed specifications of the *property* and *sojournTime* respectively of *configuration* where a configuration is a set of states that satisfy the same constraints called properties. Similarly, the concept *Declaration* in Object-Z refines the definition of *Port*.

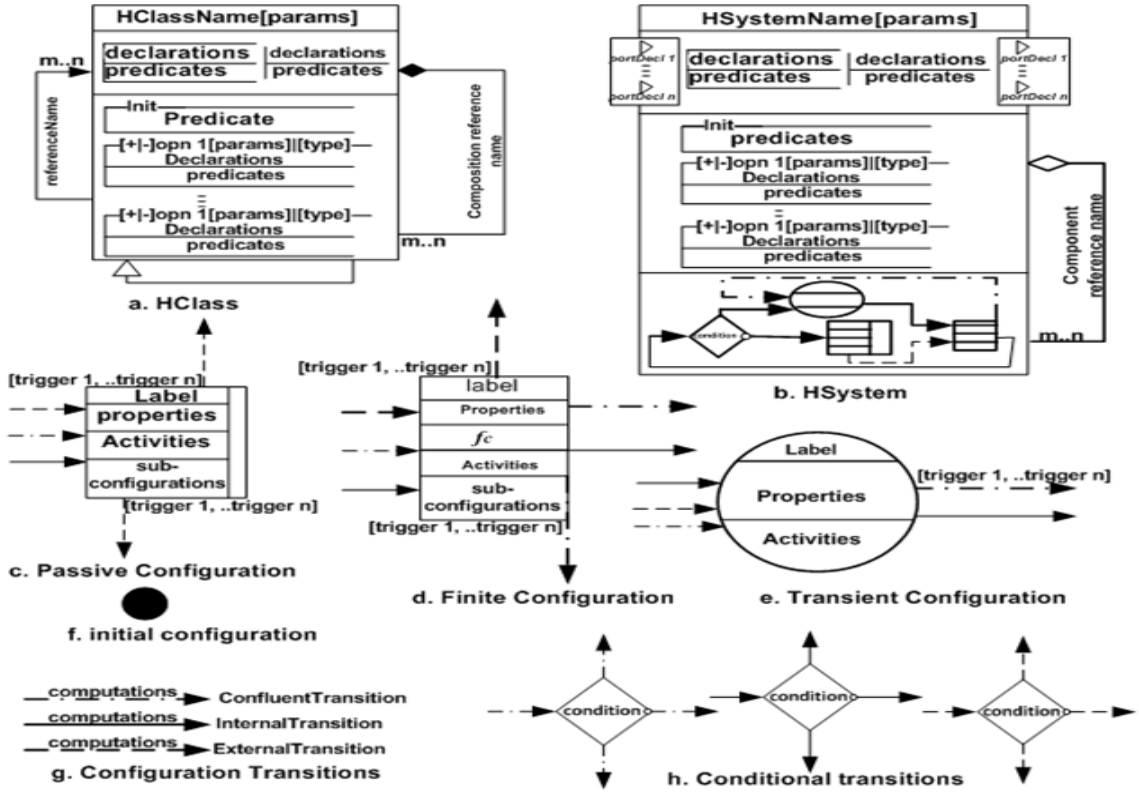


Figure 2.4. HiLLS' concrete syntax

2.2.2. Concrete Syntax

Figure 2.4 (a-h) presents the graphico-textual notations of HiLLS, which UML-like notations to represent system's structures of models so as to take advantage of the popularity of the later to ease the learning of

the language. It embeds Z-like schemas and formal expressions to formally specify the system variables, operations and behavior thereby combining the communicability and convenience of graphical notations with preciseness of formal specifications.

An HSystem (b) is denoted by a box similar to the UML class with the second compartment having the input and output ports to attached to its left and right sides respectively. The second compartment contains the state (resp. axiomatic) schema and within which state variables (resp. system parameters) are declared. The third compartment contains the definitions of operation schemas that use and manipulate the state variables. The system's behavior is described by the configuration transition diagram in the fourth compartment. Figures 2.4 (c - e) denote the configurations. The symbol fc in the third compartment of finite configuration (d) holds the expression that produces its sojourn time. Passive (c) and transient (e) configurations have predefined sojourn times positive infinity and zero respectively; hence they are not explicitly represented in the model. The three kinds of configuration transitions are denoted by the different labeled arrows in (g) with the computation expressions accompanying the transitions as the labels of the arrows.

2.3. Ontology in Modeling and Simulation

Many fields have developed ontologies to formally define and document concepts in their domains, while improving individual models, using ontologies. In modelling and simulation, considerable efforts have been made using ontologies to address modeling challenges like model reuse, composability and interoperability. This section is dedicated to such efforts. We present in sub-section 1 the various definitions of ontology provided by different authors according to the context of their work and sub-section 2 deals with ontology languages while sub-section 3 presents

some ontology tools. Sub-section 4 highlights M&S work using ontology and sub-section 5 presents the system entity structure (SES), a hierarchical knowledge representation for high level ontology construction as regards to DEVS formalism presented in the previous section.

2.3.1. What is Ontology?

Ontology is a vocabulary of terms and specification of their meaning including definitions and indications of how concepts are interrelated while collectively imposing a structure on a domain by constraining the possible interpretations of terms [Durak et al. 2011]. Shared vocabularies facilitate good communication between leading domain experts and the reason of using ontology is to structurally define knowledge within a given domain. This fact led [Zeshan and Mohamad 2012] to define ontologies as hierarchical definitions of important concepts in a domain and descriptions of the properties of each concept. As such, ontologies are used not only to describe knowledge but also to assist in communication between humans, achieve interoperability, and facilitate communication among software systems. When we speak of formal specifications says [Hofmann et al. 2011], ontologies are unambiguous description used to define and categorize concepts and the relationships among concepts within a particular knowledge domain - they are machine understandable language - . Ontologies are more powerful than taxonomies or glossaries - which collect and categorize concepts - but also define the relationships that exist between each other. For example, referential ontologies are used to store information about real world objects, their attributes and interrelations using symbolic representations. Most often, the type of semantic relationships that exist in Ontology are: “is a”, “has a”, “is part of”, etc. Ontologies are consequently seen as kinds of metamodels that enable modelers to define related concepts linked to real world. Being a formal specification of concepts about a topic, ontologies are usually used

to rigorously define a domain of discourse. At the conceptual and computational modelling phases, ontologies have been widely used as mechanism for capturing modelling knowledge in a reusable manner.

For practical applications,[Tolk and Blais 2005] reported that: "If a formal specification concisely and unambiguously defines concepts such that anyone interested in the specified domain can consistently understand the concept's meaning and its suitable use, then that specification is an ontology. Within the context of M&S composability and interoperability, this following working definition - formalizations of specifications of conceptualizations - is applied to ontology and explained as follows:

The objective of ontologies is to document the conceptualization, which is another word for the result of the modeling process.

This is done in a specified way, which means the application of engineering methods guided by rules and methods.

The result is formalized, which means that machines and computers can not only read the result, but also make sense out of it in the context of their applications.

Hence, using ontologies in large-scale and complex M&S application provides notable benefits such as promoting the "do not reinvent the wheel" principle while reducing development cost and time, leading to increased quality and risk reduction. By ontologies means, modelers overcome the key challenge of knowledge reuse of complex system development through solid documentation, reduced maintenance, and increased reliability. [Kerzhner et al. 2011] developed a formal framework based on concepts of modularity, reuse, and composition to capture knowledge and automate model transformation from system-level descriptive models to system-

level analysis models during systems design process. The proposed work promotes knowledge reuse as a solution to address the ever increasing complexity in system engineering problems such as the designer may not need to perform any additional work to create new models when the system components remain the same. The authors claimed that model reuse must rely on formal modelling. SysML(Systems Modeling Language) was used as formal modeling language and DSL (domain-specific language) for capturing knowledge about analysis models from the structural representation of the system while Model libraries called MAsCoMs (multi-aspect component models) composed of containers were used to store reusable knowledge.

The scope of an ontology for M&S system is hoped to cover all the things within a domain that the ontology will be used for. [Mahmoud 2014] provided the following four questions we must ask ourselves when developing an ontology to find the underlying domain and scope:

What is the domain that the ontology will cover?

What are we going to use the ontology for?

What types of questions should the information in the ontology provide answers for?

Who will use and further develop the ontology?

2.3.2. Ontology Languages

Ontology languages are used to explicitly represent ontologies in areas such as computer science as well as information science. In the semantic web, ontology is basically supported by languages like Resource Description Framework (RDF), RDF Schema (RDFS) and Web Ontology Language (OWL) [Ding et al. 2007]:

- RDF: is a graph model based on nodes and binary relations.

- RDFS: is an extension of RDF used to provide better support for definition and classification.
- OWL: is an extension of RDFS that emphasizes support for richer logical inference.

[Su and Ilebrekke 2002] presented a comparative study of ontology languages largely used in computer science as follows:

- *Traditional Ontology Specification Languages*
  - CycL: is a formal language whose syntax derives from first-order predicate calculus, and aims at proving a general ontology for commonsense knowledge.
  - KIF (Knowledge Interchange Format): is based on first-order predicate calculus, provides definitions for object, function, relation and logical constants. It has a declarative semantic.
  - Ontolingua: is referred to as both system and language. It is based on KIF and the FO (Frame Ontology) Ontology.
  - F-logic (Frame Logic): is a logic language integrated with object-oriented or frame-based paradigm.
  - CML (Conceptual Modeling Language): is an informal notation for knowledge modeling.
  - OCML (Operational Conceptual Modeling Language): is to provide operational knowledge modeling facilities and includes interpreters for functional and control terms.
  - LOOM: is a knowledge representation and reasoning system based on description logic.

— Telos: is a knowledge representation language with an object-oriented focus.

- *Web Standards*
  - — XML (Extensible Markup Language): is the universal format for structured documents and data on the Web.
  - — RDF (Resource Description Framework): is an infrastructure for encoding, exchange and reuse of structured metadata.
- *Web-based Ontology Specification Languages*
  - — OIL (Ontology Inference Layer): is both a representation and exchange language for ontologies.
  - — DAML+OIL: is a semantic markup language for Web resources, basically for ontological and metadata representation.
  - — XOL (XML-Based Ontology Exchange Language): is created to exchange ontologies for molecular biology as well as other ontologies.
  - — SHOE (Simple HTML Ontology Extensions): is an extension of HTML to incorporate semantic knowledge in ordinary web documents by annotating html pages.

2.3.3. Ontology Tools

We present some of the tools that support the development of ontology using the aforementioned languages. For more details we refer the reader to the work of [Su and Ilebrekke 2002]:

- Ontolingua: it provides users with the ability to browse, create, edit, share and reuse ontologies.

- WebOnto: is a web-based tool for visualization, browsing and development of ontologies and knowledge models specified in OCML.
- WebODE: is a scalable workbench for ontological engineering on the Web.
- Protégé-2000: is an integrated and platform-independent system for development and maintenance of knowledge-based systems.
- OntoEdit: is a development environment for ontology design and maintenance.
- OilEd OilEd: is a development tool for OIL and DAML+OIL ontologies.

[Abburu and Babu 2013] presented a detailed survey on ontology development tools that are used to build new ontologies from scratch or reuse existing ontologies. Figure 2.5 captures the comparison table of the ontology development tools.

Tool / Features	Ontolingua Server	OntoSaurus	OilEd	WebOnto	Protégé	SWOOP	TopBarid Composer	WebODE	OntoEdit	Neon Toolkit
Availability	Free	Free & Open	Free & Open	Free	Free	Free & Open	Commercial	Free	Free	Free & Open
Versioning	No	No	No	Y/N	Y/N	Yes	Y/N	No	Y/N	Yes
Collaborative	Yes	Yes	No	Yes	Yes (Collaborative Protégé)	Yes	Yes	Yes	No	Yes
Graphical Class/Property taxonomy	Yes	No	No	Yes	Yes	Yes	Yes	Yes	No	Yes
Back up management	No	No	No	Yes	No	Y/N	Y/N	Yes	No	Yes
Support growth of large ontologies	Yes	Y/N	No	Y/N	Yes	Yes	Y/N	Yes	Y/N	Yes
Querying	No	No	No	Y/N	Yes	No	Yes	No	Y/N	Yes
User Interface	No	Y/N	Yes	Y/N	Yes	Yes	Yes	Yes	Y/N	Yes
Consistency check	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
OWL Editor	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extensibility	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Ontology Libraries	Yes	No	Yes	Yes	Y/N	Y/N	Y/N	No	No	Yes
Architecture	Client/Server	Client/Server	Standalone	Client/Server	Standalone	Standalone	Client/Server	N-Tire	Standalone	Standalone
KR Paradigam of Knowledge model	Frames+, FOL	DL	DL	Frames+, FOL	Frames+, FOL+, Meta classes	DL	DL	Frames+, FOL	Frames+, FOL	DL
Import	Ontolingua, DAML+OIL, CLIPS	LOOM, IDL, KIF, C++	RDF(S), DAML+OIL	OMCL	RDF(S), OWL	RDF(S), OWL	RDBMS, OWL, RDF(S)	RDF(S), DAML+OIL, OWL	RDF(S), DAML+OIL	RDF(S), OWL
Export	Ontolingua, DAML+OIL, CLIPS	LOOM, IDL, KIF, C++	RDF(S), DAML+OIL, OWL	OMCL, Onto-lingua, RDF(s), OIL	RDF(S), OWL, CLIPS	RDF(S), OWL	OWL, RDF(S), XML	RDF(S), DAML+OIL, OWL, CLIPS	RDF(S), DAML+OIL, OWL	RDF(S), OWL
Storage	Files	Files	Files	Files	Files, DBMS(JDBC)	Files	Files	DBMS(JDBC)	Files	Files
Reasoner	JTP, Prolog, CML, Epikit	PowerLoom, Stella	FaCT	-	Pellet	Pellet	Pellet	Prolog	OntoBroker	Pellet2, Hermit, OntoBroker
Merging	Chimaera	None	None	None	Prompt, OWLDiff	Yes	Y/N	ODE Merge	Yes	Yes
Debug/Repair	No	No	Very Little	No	Very Little	Yes	No	No	No	Yes
Built-in Inference	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Y/N	Yes
Implemented in	Lisp	Lisp	Java	Lisp	Java	Java	Java	Java	Java	Java Eclipse

Figure 2.5. Comparison of ontology development tools [Abburu and Babu 2013]

2.3.4. Applying Ontology in M&S

The domain of M&S has been explored using ontologies in many ways. For example, [Tolk and Turnitsa 2007] developed conceptual modelling based on ontological spectrum that captures the data representation in a computable way for supporting composability and interoperability of information exchanged between distributed systems. Conceptual models are organized in a

trichotomy relationship based on ontological-entities representation rooted in system-entity definition to support multi-resolution modelling in a service oriented context.

Most often, two common fundamental types of modelling errors occur when modelling complex systems. These errors are: system description errors and model translation errors. To address these errors, [McGinnis et al. 2011] used a formal system modelling language based on OMG SysML (Object Management Group's Systems Modelling Language) for creating a usable ontology for a formal representation of knowledge, and a formal model transformation technologies for model automation. According to the authors, SysML has a significant benefit to support both ontology definition and specific models development.

Following the modelling of large-scale complex M&S application, [Balci et al 2011] discussed how reusability and composability (R&C) can be achieved using a simulation conceptual model (CM) to facilitate their design. Conceptual constructs, being independent of any design strategy and execution requirements, can be reused and composed at all possible levels of abstraction and promote the "do not reinvent the wheel" principle by providing significant benefits such as reduced development cost and time, effective use of subject matter expertise, increased quality, and reduced risk. A CM was defined as a repository of high-level conceptual constructs and knowledge specified in a variety of communicative forms such as animation, audio, chart, diagram, drawing, equation, graph, image, text, and video intended to assist in the design of any type of large-scale complex M&S application. Hence, through reusability an artefact is expected to be reused multiple times whether it has been developed in isolation or not. Using composability an artefact is constituted by combining things, parts, or elements.

According to [Ezzell et al. 2011], the purpose of ontology is to structurally define knowledge about a topic. This purpose led to the development of a methodology based on domain ontologies using a human-interface layer to construct dynamic models with their corresponding three-dimensional (3D) visualizations. The proposed ontologies are being manifested in the user interface to address the needs in education and medical training by integrating simulation with traditional teaching methods. An example of cardiovascular physiology model construction was presented to show how a 3D visualization is created after augmenting the visualized ontology with new attributes. Ontology can also be defined as a vocabulary of terms and the specification of their meaning, indicating how those concepts are interrelated among themselves in a particular domain.

In order to address the challenge of model reuse in large and complex systems, [Durak et al. 2011] adopted an otology-based approach to trajectory simulation called TSONT (Trajectory Simulation Ontology) that facilitates conceptual interoperability in trajectory simulation. According to the authors, a successful interoperability at the system implementation level is achievable through meaningful composability at the conceptual level. A conceptual platform independent model was constructed using model driven engineering concepts based on the domain ontology combined with the High Level Architecture (HLA) approach to achieve the underlying interoperability. The work was built upon MATSIX—MATLAB 6 DOF trajectory simulation framework using a model transformation tool for transforming an OWL ontology - that captures the domain knowledge of a trajectory simulation, specifically the static structure of the simulation, behaviour model and the definition of interfaces - into a UML class diagram. The PUMA federate

simulation object model resulting from the model transformation was then used to compute the flight path and flight parameters of munitions.

Ontology is considered as a practical approach of enhancing the conceptual interoperability and composability. While seeking to overcome the limitations of the current practices for composition of models and simulation systems, [Wang et al. 2009] proposed a framework that describes the Levels of Conceptual Interoperability Model (LCIM) as well as a descriptive and prescriptive model. The authors argued that the proposed LCIM was derived from many research efforts in various publications that dealt with different aspects on LCIM. Achieving conceptual interoperability and composability was reported to be a difficult problem. Therefore, seven levels of inter interoperability were differentiated, starting from level 0 - representing no interoperation - to level 6 - indicating conceptual interoperability- while intermediate levels such as level 1 represents technical interoperability, level 2 represents syntactic interoperability, level 3 represents semantic interoperability, level 4 represents pragmatic interoperability, and finally level 5 represents dynamic interoperability.

[Benjamin et al. 2011] developed a knowledge-driven framework for semantic simulation application integration (KSAI) and interoperability that captures ontological information in a context involving multiple domains, modelling paradigms, and software tools. KSAI is based on two categories for simulation application integration including design time integration and run time integration and is supported by five inter-related activities: (1) defining a simulation project scope, (2) assessing and filling knowledge gaps, (3) performing integration assessment, (4) generating executable information exchanges, and (5) running integrated simulation.

While investigating on epistemic and normative aspects of ontologies for M&S, [Hofmann et al. 2011] categorized ontologies for M&S into two classes: methodological ontologies and referential ontologies. The former defines modelling methods and simulation techniques while the later represents real world systems to be simulated. Arguably, ontologies are to be considered as formal specifications as well as means of knowledge representation. An advantage of being formal is that it provides an easy processing mechanism by computers in order to logically deduce higher order relationships between concepts. Referential ontologies are more powerful than taxonomies or glossaries as concepts are not only being categorized but also being interrelated to each other. As such, the strength of ontologies is based on their precision such as precision for a common terminology, precision for a common logical structure of conceptual relations, and precision for the denotation of concepts as far as possible by definitions. Precision, in this case, is essential for knowledge exchange and knowledge reuse such as compatibility with other ontologies. Hence, a notable benefit of using ontologies is to increase the interoperability of models while ontology-driven modelling significantly contributes in reducing time spent for finding the most appropriate formalism.

Seeking to address the lack of ontologically well founded conceptual modelling language for Discrete Event Simulation Engineering, [Guizzardi and Wagner 2010] presented a foundational ontology for discrete event system modeling (DESO) that addresses an agreed-upon precise definition of common concepts in discrete event simulation such as entity, object, event and state. Furthermore, DESO provides some basic properties for the evaluation of general-purpose discrete event simulation languages which are: soundness, completeness, lucidity and laconicity.

Similarly, [Miller et al. 2004] developed a web-based ontology for discrete event modelling called DeMO (Discrete-event Modelling Ontology) capturing knowledge about discrete event domain such as event-scheduling, activity-scanning, and process-interaction, known as three main world views for discrete-event simulation modelling. Consequently, Demo was built based on four types of discrete event models which are: State-Oriented, Event-Oriented, Activity-Oriented, and Process-Oriented Models. It is reported that the usage of DeMo provides several possible benefits such as browsing, querying, service discovery, components, hypothesis testing, research support, mark-up language, and facilitates collaboration.

In the field of healthcare, [Okhmatovskaiaet al. 2012] introduced ontology for simulation modelling of population health (SimPHO), a formal, explicit machine-readable specification of a domain of knowledge integrating both aspects of taxonomy and vocabulary in a form of logical axioms.

[Silver et al. 2007] developed ontology driven simulation model that promotes relationship between domain ontology and simulation ontology through an existing domain ontology called Problem-oriented Medical Records ontology (PMRO) in healthcare domain to derive simulation model as ontology instances. The resulting simulation models are then translated into executable simulation models that can be used by simulation tools. The authors based their arguments of mapping domain ontology into simulation ontology on four different world views of the modellers including state oriented, event oriented, activity oriented, and process oriented as suggested by the DeMo ontology (Discrete Event Modeling Ontology) as well as the influence of the application

domain. The selection of a world view modelling determines the choice of a particular modelling formalism.

[Zeshan and Mohamad 2012] presented domain ontology for IT-based healthcare systems that support knowledge sharing between devices and actors during the diagnostic process of patients in emergency department. Through a methodology called “methontology” the constructing of the proposed ontology was achieved following step-by-step guidelines that include entity extraction, taxonomy formation, relationships, and the axioms to add logical expressions using Protégé software for consistency checking at the evaluation phase.

Due to the growing needs of today healthcare, a single ontology is not sufficient to meet the need in the delivery of quality healthcare. As such, [Puri et al. 2011] proposed ontology mapping and alignment to integrate ontologies from heterogeneous sources together and to support data integration and analysis. As an example, patient information and domains of healthcare information were derived from different sources like Electronic Health Records (EHRs), Personal Health Records (PHRs), Google Health, and Microsoft HealthVault to provide a common vocabulary that enables interoperability and resolves ambiguity.

[Okhmatovskaia et al. 2012] developed an ontology for modelling population health called SimPHO (Simulation Modeling of Population Health). The proposed ontology was referred to as a formal, explicit machine-readable specification of a domain of knowledge that integrates both aspects of taxonomy and vocabulary in a form of logical axioms. SimPHO was reported to have a supporting set of software tools intended to facilitate simulation model development, validation,

comprehension and reuse. The authors argued that ontologies for modeling and simulation from findings are mainly domain-independent while SimPHO describes the content of the model in the specific context of the simulation modeling in population health. SimPHO combines existing knowledge from medical ontologies and vocabularies and is implemented in OWL (Web Ontology Language) using Protégé-OWL editor. Its domain coverage and scope include discrete event simulations, micro simulation models of population health (individual levels), and a wide range of diseases, their risk factors and outcomes, demographic characteristics of the population, health care associated costs and measures of disease burden. To characterize health simulation models using SimPHO one should consider 3 major parts: the general high-level definition, the characterization of the content of the model in terms of the relevant domain of knowledge, and the technical specification of modeling details. The high-level description provides a top-level class called Simulation and a number of sub-classes to represent different model categories based on logical axioms and class properties while the content of the model in health domain terms is focused on healthcare systems and public health policies. The technical details of the modeling that have been formalized by SimPHO include concepts such as data types and measurement scales of state variable, procedures for initializing state variables, model parameters, methods and data sources used for their derivation, and causal relationships between states and events. The authors presented a first prototype software application of SimPHO called Ophiuchus, implemented as a web-based application. It has been reported that after performing a preliminary informal assessment with a mixed group of twenty users the feedback that was received from the subjects was positive. The authors claimed that SimPHO provides a conceptual framework for clear, unambiguous, multifaceted representation of simulation models of population health and serves as

a foundation for a set of software tools intended to facilitate model comprehension, validation and reuse.

From the review presented so far, it is doubtless that the entire domain of healthcare suffers from the lack of standards and formal specification of agreed-upon concepts and their relationships to derive useful models for its simulation. To address this issue, we propose the Ontology for Healthcare Systems Simulation (O4HS) for capturing knowledge in healthcare domain in a reusable and interoperable manner. Contrary to the existing ontologies, O4HCS does not address the lack of unified vocabulary in clinical medicine such as formalizing and reorganizing medical terminologies and taxonomies like PMRO (Problem-Oriented Medical Records Ontology). Instead, O4HCS ontology is an attempt to describing terms, categories, and their relationships in healthcare simulation. Since the domain of healthcare is a complex domain and requires more than a single formalism for its modelling as reported in the work of [Barjis 2011], the existing reference ontologies - DeMO and DESO- that deal specifically with concepts that are related to discrete event simulation are not suitable for describing all information in healthcare simulation domain. Also, the scope of O4HS covers more than one system aspect modelling of healthcare, SIMPHO focuses only on the concepts of population health. O4HS is built based on an extensive literature review of healthcare simulation and addresses the concepts necessary for the simulation of the entire healthcare domain. Hence, O4HS is a way out for overcoming challenges related to healthcare simulation like unit specific and facility specific modelling while proving notable benefits including model reuse, composability and interoperability. More details concerning O4HCS will be given in the following chapter.

2.3.5. System Entity Structure / Model Base Framework

The system entity structure (SES) formalism is a hierarchical knowledge representation for high level ontology construction in a stepwise fashion way. We refer the reader to [Zeigler 1984] for more details. SES structures knowledge of a certain domain in terms of decomposition, coupling, and taxonomic relationships among different entities. A decomposition refers to the breaking down of an entity while the coupling refers to its reconstruction. The taxonomic relationship provides possible variants of the entity. SES is provided with a set of axioms and an expressive power for modeling and simulation of large and complex systems and data design engineering. Figure 2.6 shows an example of the basic elements in SES and the relationships that exist between them.

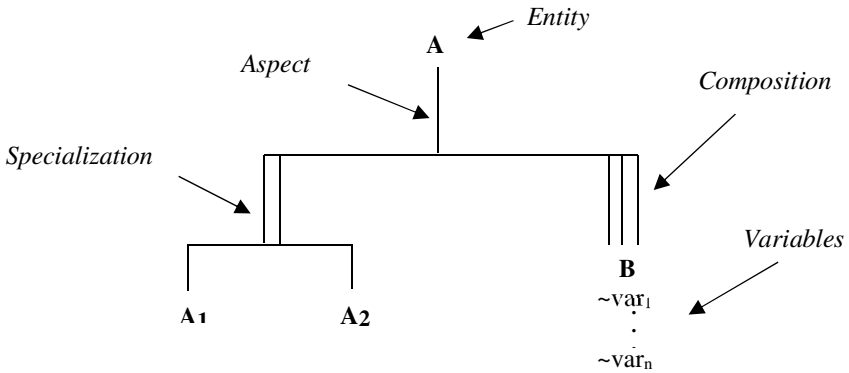


Figure 2.6. Basic System Entity Structure construction

SES consists of entities, aspects, specialization, multi-aspects, and variables. In Figure 2.6 A, A1 A2, and B are entities and represent things that exist in real world. An entity may have attached variables with assigned value within a given range and types. For example, entity B has variables var1… varn. SES defines two types of entities: composite entity and atomic entity. A composite entity, entity A is broken down into other entities, A1, A2 and B that are either composite or atomic while an atomic entity cannot be broken down into sub entities. An aspect represented by a single

vertical line provides ways of descripting entities into more detailed ones such as a decomposition relationship between a parent entity and its children. A specialization connected by a double vertical line from an entity expresses alternative choices between categorized sub entities. A multi-aspect specified by a triple vertical line represents ways of breaking down components of the same kind. The main axioms governing the SES are:

- Uniformity: Any two nodes with the same labels have isomorphic subtrees and identical attached variable types.
- Strict hierarchy: No label appears more than once down any path of the tree.
- Alternating entity aspects/specialization: a node is Entity, then the successor is either Aspect, Multi-Aspect or Specialization, and vice versa.
- Valid brothers: No two brothers can have the same label.
- Attached variables: No two variable types attached to the same item have the same name.

SES/MB is targeted to support the plan-generate-evaluate process in simulation-based systems design. The plan phase recaptures all the intended objectives of the modeler while the generate phase reproduces a candidate design model that will meet the initial objectives. The evaluate phase assesses the performance of the generated model through simulation. As such, the SES/MB organizes a family of alternative models from which a candidate model can be generated, selected and evaluated through system design repeatedly until the model meets an acceptable objective.

While complex systems are composed of large components and their structural knowledge can be broken down and systematically represented in SES, their behaviors can be specified in either atomic or coupled models and saved in model base - an organized library - for later use.

Once the models are saved they can be retrieved from their repository and reused to design complex systems.

SES/MB has been used to investigate many domains suing modelling and simulation. The following research works witness such efforts.

Systems Entity Structure (SES) is known as a support to development, pruning, and generation of a family of simulation models. [Zeigler et al. 2013] discussed on how to develop suites of simulation models using SES through concepts such as merging, multiple aspects and marketplace of models in the MS4 Modeling Environment (MS4 Me), a cloud-based repository. In merging process, individual models are composed to create hierarchical models in stage-wise fashion leading to a suite of models in which case some SESs become components of other SESs. Using multiple aspects in a single family of SESs provides different perspectives to associate an unlimited number of simulation models to work with them all together as a whole. The concept of marketplace of models was reported as a support in extending the development of suites of models using Web Services based on Cloud Technology. Hence, the authors claimed that SES can be regarded as an ontological framework for modeling and simulation. For example, in the composition of models, the SES serves as model repositories from which models can be drawn. Unlike common understanding of ontologies, the basics relationships in the SES are related to model structuring such as aspects, specialization and coupling, while supporting pruning and transformation. An example of suite of models related to Healthcare is used as illustration.

In an illustrative report [Pawletta et al. 2015] discussed on the implementation of an SES toolbox for MATLAB/Simulink used for variant modelling. SES Ontology was used for the

specification of a set of various system structures and parameter settings, while the MB repository was used for storing basic models describing dynamic behavior. Thus SES/MB has been advanced to a modelling and simulation framework of modular and hierarchical systems design.

SES was introduced by [Cheon et al. 2008] as a unique support for data engineering in the context of simulation modeling. Using a software tool called SES Builder for the implementation, the resulting model was transformed into an XML DTD (document type definition) schema. SES Builder also provides features such as pruning to create PESs (pruned entity structure), natural language representation and graphical interfaces. An application to data modeling of US Climate Normals was presented with automated generation of weather simulation models.

[Schmidt et al. 2016] used SES ontology for the specification of a family of model under test (MUT) in Model-Based Testing (MBT) scenario for objective fidelity evaluation in developing simulation models of complex systems such as Cyber physical systems (CPS). The MB was used to provide configurable basic models composing the experimental frame (EF) while a specific executable model consisting of an MUT and a test model was generated based on the SES/MB, and the implementation was done within MATLAB/Simulink.

[Lee et al. 2004] proposed a hierarchical and modular traffic simulation methodology for Intelligent Transportation Systems (ITS) that integrates the System Entity Structure/ Model Base in a four-layered approach on the basis of the object-oriented programming environment.

2.4. Multi-Paradigm Modeling & Simulation

The concept of formalism is referred to as the modeling paradigm with an underlying simulation paradigm representing the approach used to study the behavioral properties of the system under study. Multi-formalism modeling is the use of many formalisms - methods and techniques such as DEVS, Petri Nets, Differential Equations, etc. - in the same model to describe the different features of a system. Recently, there was a strong debate among scientists on which right paradigm to choose based on their weakness, strength and suitability because modelers, more often like to choose the formalism they are more experienced or are more comfortable with. Such choice usually leads to unnecessary complex and cumbersome models that are harder to explain and maintain with high consumption of computational resources in the best case, or result into a failure in worst case [Furian et al. 2014]. Healthcare is a complex industry, i.e., it is diverse and varies from one country to another while involving different stakeholders like governments, insurance companies, trade unions and religious groups with different interests. As such, it is worth to note that for a large and complicated system a single formalism may not be sufficient to cover all the features considering the diversity of the components as well as the complex interactions that exist among them [Fishwick 1995]. Hence the deficiencies of single techniques requires to model such systems using more than one formalism or combining them for an adequate study on various levels. Simulation techniques such as Continuous Simulation, Discrete Event Simulation, System Dynamics, Monte Carlo Simulation, Agent-Based Simulation, and Virtual Reality 3-D simulations are applied for various purposes in different industries. However, in healthcare the most commonly used simulation technique include Discrete Event Simulation (DES), Agent-Based Simulation (ABS) and System Dynamics (SD) [Furian et al. 2014].

[Vangheluwe et al. 2002] introduced Multi-Paradigm Modelling and Simulation along three orthogonal axes including multi-formalism modelling, model abstraction, and meta-modelling. Again, the author argued that complex systems are characterized by a large number of components and their diversities, so modelling such systems will require the understanding of the behavior of the overall system and it is not sufficient to study the individual components separately by focusing on the specific formalisms they were modelled in. The different components of complex systems are to be modelled with different formalisms such as Petri Net, Differential Algebraic Equations (DAE) or Bond graph, at different levels of abstraction. The levels of abstraction can be different for each of the components depending on the variety of views of the system, the available knowledge as much as the background and the goals of the modeler. When the components of a complex system are modelled in different suitable formalisms, different approaches are suggested: a super-formalism which subsumes the other formalisms, a common formalism resulting from the transformation of other models, and a co-simulation with the coupling at the trajectory level. The Meta-modelling gives a flexibility to a modeler to model a modeling language itself to support many formalisms while formalism transformation graph is used to relate different formalisms.

[Vangheluwe 2000] suggests that once the different views of the system are described in different formalisms, a Formalism Transformation Graph (FTG) would provide a mapping mechanism that guides models transformation in source formalism onto models in destination formalism. Above all, the DEVS formalism has been proven to be a common denominator which unifies continuous and discrete constructs in the context of hybrid systems models and provides a coupling under closure of different model components to form an overall model.

[Ross et al. 2014] proposed a guidance for selecting the most appropriate formalisms out of the existing plethora of M&S paradigms based on three system of systems (SoS) modeling "views. Such views include social view, physical view and socio-physical view that guide the modeler to choose the most-suitable paradigm for each of them according to his intention in creating simulation models. Social view corresponds to individuals and how they interact through formal, organizational policy or informal as well as through social norms within the SoS. Physical view represents the geography and structure of the SoS while socio-physical view refers to the combination of the two previous views along with the interactions that exist between them.

While it is hard to separate one of a large system's component and successfully study it in isolation, especially in a case like healthcare industry where "everything affects everything else", [Brailsford et al. 2010] proposed a step towards achieving the "holy grail approach as widely discusses over the past decade. The "holy grail" is referred to as a methodology that combines different approaches to provide a truly holistic systems view. The approach was illustrated by the combination of both Discrete Event Simulation (DES) and Systems Dynamics (SD) within the healthcare context.

Simulation paradigms fall into discrete simulation, continuous simulation, and hybrid simulation. The latter is a combination of the formers [Cellier 1979], [Praehofer 1991], and [Mostermann 2007]. Hybrid simulation can easily lead to model integration with the benefits and virtues of combining such variety of simulation techniques. Hybrid models of large scale systems provide more details of reality in a better way than highly customized single simulation techniques. Table 1 shows examples pertaining to each modeling/simulation paradigm.

Table 2.1. Modeling versus simulation paradigms

	Discrete simulation	*Continuous simulation*	*Hybrid Simulation*
Mono formalism modeling	Petri Nets DEVS Cellular Automata	Bond Graph Systems Dynamics Differential Equations Block Diagrams	DEV&DESS Hybrid DAE
Multi-formalism modeling	Cellular Automata combined with Petri Nets	Block Diagrams combined with Differential Equations	Cellular Automata combined with Differential Equations

In [Zeigler et al. 2000] three classes of "basic "system specification formalisms that build subclasses of systems were defined for model specification: DEVS (discrete event system specification) formalism, DESS (differential equation specified system), and DTSS (discrete time specified system). The term "basic" here represents fundamental formalisms in the sense that all other systems specification derive from them as well as they allow a local description of the dynamic behavior of the system from which case the global dynamic behavior of the corresponding dynamic system is derived. This is referred to as the dynamic interpretation of the system formalism. Furthermore, "basic" is to be distinguished from coupled system formalisms, which enable the creation of networks of systems. Since they encompass a wide variety of systems, these formalisms are seen as generic formalisms in contrast to a multitude of more specialized formalisms such as Petri nets and State charts, for the discrete event system specification side, and System Dynamics and Bond Graphs for the continuous side, dedicated to express models for particular classes of systems and problems. Today's real-world phenomena cannot be fit into one

formalism at a time and they cannot be modeled purely by a continuous or discrete paradigm. Instead, such systems need to be addressed by a combined discrete/continuous M&S methodology that supports a multiformalism modeling approach. Consequently two approaches to multiformalism modeling are developed. A combined formalism, DEV&DESS (Table 2.1) based on DEVS and DESS, the discrete event and differential equation system specification formalisms. Another approach to multiformalism modeling suggests to embed one formalism into another. As an example, the system dynamics and bond graph formalisms can be embedded in the DESS formalism while the Petri net and State chart formalisms can be embedded into the DEVS formalism.

2.5. Model Driven Engineering (MDE)

Model Driven Engineering (MDE) is a software development approach which considers models as central artefacts, being used throughout all engineering disciplines and in any application domain [Silva 2015]. It aims at raising the level of abstraction through models usage in program specification while increasing automation in program development by using model transformation between different levels of abstraction. Models at higher level of abstractions are successively transformed unto models at lower level of abstractions until code generation. Among other software development approaches that support MDE are Model Driven Development (MDD) [Atkinson and Kühne 2003], and Model Driven Architecture (MDA) [Blevins et al. 2004]. The MDD focuses on the requirements, analysis and design, and implementation phases. MDA is the vision of OMG (Object Management Group) on MDE using standards that focus on the technical aspects in software development.

2.5.1. Model Driven Architecture (MDA)

One of the major goals of OMG is to help reduce complexity, increase software development productivity, lower costs and time of software development through an architectural framework -Model Driven Architecture-. MDA is built around a number of OMG standards, which are used by the development community worldwide. In MDA approach, the use of models and the relationships between those models are addressed in a complete development lifecycle, from analysis and design to deployment and maintenance. As illustrated in Figure 2.7, the MDA architecture is composed of four layers: at the first inner layer (at the center) are standards such as UML (Unified Modeling Language), MOF (Meta-Object Facility) and CWM (Common Warehouse Metamodel). The second layer includes XMI (XML Metadata Interchange), Java, CORBA, .NET and web services. The third layer regroups services for managing security, events, directory, pervasive services, and transaction. At the final fourth layer, are frameworks for specific application domains such as healthcare, telecom, space, manufacturing, finance, e-commerce, transportation, Etc.

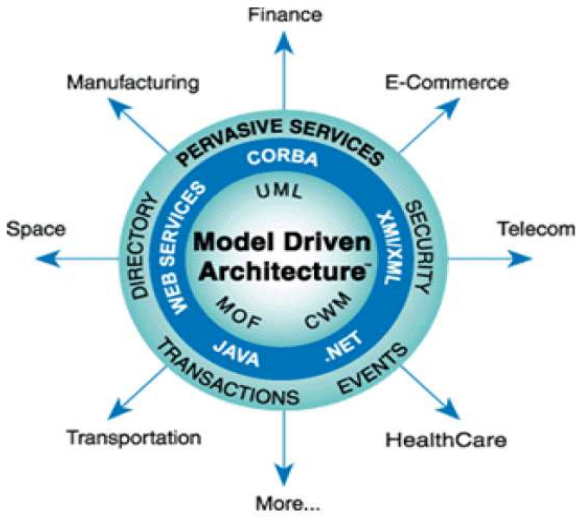


Figure 2.7. MDA Architecture [Truyen 2006]

2.5.2. MDA Concepts

It is appropriate to present some major concepts of MDA that give a better understanding on how to take advantage of modelling in the context of this thesis.

2.5.2.1. Model

A model is a formal specification of a system in terms of its structure, function and behavior, within a context that may include its environment for specific purpose. It is most often referred to as an abstraction of a system. A model is expressed using a combination of drawings and text. A specification is formal if it is based on a language having a well-defined semantic.

2.5.2.2. Viewpoint

A viewpoint is an abstraction technique that only focuses on specific concerns within a system under study. A representation of a viewpoint may include one or more models.

2.5.2.3. Platform

A platform is a set of technologies and subsystems that provide a coherent set of functionality through interfaces and specified usage patterns. Applications that are supported by the platform make use of it without concern on the details of how it is being implemented. Platforms can be for example, operating systems, Java Virtual Machine, programming languages, and middleware solutions.

2.5.3. MDA Viewpoint

In MDA, a system is specified from three viewpoints: computation independent, platform independent and a platform specific.

Computation independent viewpoint focuses on the requirements and the environment of the system. The details concerning the structure and the processing of the system are left out at this stage.

Platform independent viewpoint focuses on the operation of a system that is generic and can be used from one platform to another. Details that are particular to a specific platform are hidden while the specification of the system does not change due to a change of the platform. Usually, general purpose modeling languages are used and the implementation is independent by definition from the platform independent view.

Platform specific viewpoint extends the platform independent viewpoint by adding details that are peculiar to a targeted platform.

2.5.4. Model Transformation

Model transformation is the process of converting one model unto another of the same system. The model being converted is called "source model" and the model obtained as a result of the transformation is called "Target model". The conversion process is carried out based on transformation rules, as depicted in Figure 2.8. Transformation rules describes how source model elements are mapped to target model elements. It consists of left and right hand sides.

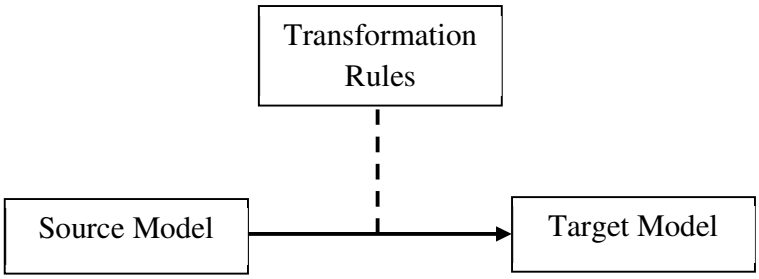


Figure 2.8. MDA Model transformation

2.5.5. MDA Models

In MDA, three models of a system are specified according to the three MDA viewpoints defined previously: Computation Independent Model (CIM), Platform Independent Model (PIM), and Platform Specific Model (PSM). These models are referred to as layers of abstraction with each one of them representing a specific viewpoint of the system.

A Computation Independent Model is a representation of a system from the computation independent viewpoint. CIM specifies the function of a system and focuses on the business process of the requirement in a way that is mainly understandable by the domain experts. It represents the bridge between business analysists and IT-professionals while abstracting all details related to the information technology from the specification.

A Platform Independent Model is a representation of a system from the platform independent viewpoint. PIM describes the construction of a system in a way that hides its implementation details and provides independence in the choice of the platform so that the model can be suitable for use with a number of different platforms such as programming languages, distributed

middleware, and messaging middleware. PIM focuses on how to achieve the business models and requirements models in terms of operational software systems.

A Platform Specific Model is a representation of a system from the platform specific viewpoint. PSM reflects the details in the PIM targeting a particular platform. Those details are necessary to produce the implementation of the system.

2.5.6. MDA Process

The MDA process consists of transforming higher levels model into lower levels model. The building process starts from the computational Independent Model that captures the requirement specified in a way that is understandable by domain experts. The CIM will be transformed into a Platform Independent Model by an IT-specialist that adds his knowledge without describing details that are related to a specific platform or technology. As a result, the PIM model is extended to a targeted platform by a platform specialist that adds technical details closer to its implementation. At each stage of the transformation, knowledge is added by different professionals till the completion of the building process. A complex system may require a set of interrelated models that are transformed within the same level of abstraction. For example, a CIM is transformed into another CIM with more details. A final model of that level of abstraction is then transformed into another model in another level of abstraction. When a transformation is performed within the same level of abstraction, it is known as a horizontal transformation. A vertical transformation is performed across different levels of abstraction. The described process is displayed in Figure 2.9.

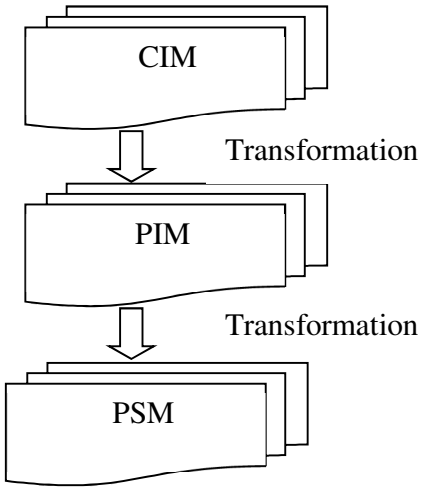


Figure 2.9. MDA transformation process

2.5.7. Model transformation languages

Transformations of model during development process are achieved through model transformation languages. There is a plethora of model transformation languages including natural languages, action languages, and dedicated transformation languages that can be used to transforming source models into destination models. When a model is specified as a graph, the transformation process is referred to as a graph transformation and the transformation tool that is being used is referred to as a graph transformation tool. We present some model transformation languages often used. More details about model transformation languages can be found in [Biehl 2010] and [Erata et al. 2015].

ATL (ATLAS Transformation Language) is a model transformation language and toolkit that provides a way to produce a set of destination models from a set of source models, in the context of Model Driven Engineering. ATL is built on top of the Eclipse platform and can handle models through the Eclipse Modeling Framework (EMF) while providing a number of standard development tools like a text editor with syntax highlighting, a debugger and an interpreter to ease

the development of ATL transformations. ATL supports both declarative and imperative constructs and enables defining three kinds of units including modules, queries and libraries that may be composed of a combination of ATL helpers, attributes, matched and called rules.

QVT (Query View Transformation) is a standard set of model transformation languages defined by the OMG and covers transformations, views and queries together. It transforms models that are conformed to the Meta Object Facility (MOF) metamodels, integrates the Object Constraint Language (OCL) and is aligned with the Model Driven Architecture (MDA). QVT captures three transformation languages:

- QVT Relational is a high-level declarative language that includes both unidirectional and bidirectional model transformation.
- QVT Operational is an imperative model transformation language extending QVT Relational for writing unidirectional transformations.
- QVT Core is a simple declarative model transformation language serving as a foundation for QVT Relational.

Acceleo is a model to text transformation language of the OMG while offering advantages such as easy kick off, high ability to customize, and interoperability.

2.5.8. MetaModeling

A common way of specifying a modelling language that is flexible enough to support many formalisms is to model the language itself [Vangheluwe et al. 2002]. Such process of specification is a metamodeling and a model of that modelling language is referred to as a metamodel. A

metamodel describes the abstract syntax of a modelling language and captures the class of all models expressed in that language. In the MDA context, metamodels are expressed using MOF and any model that is a representation of a system is conformed to the metamodel. From the metamodel specification, the modeling language, be it graphical or textual is used to specify models. For example, in Figure 2.10, the specification of the Petri net metamodel is depicted showing how to model a system using Petri net language. An instance of that metamodel is the Petri net model displayed in Figure 2.11. In simulation context, metamodeling is the construction of simplified models of complex systems that their modelling is quite subtle. As a result, the metamodel is a surrogate model that describes the complex behavior of the underlying system [Cetinkaya 2013]. Complex real world systems to be simulated are also referred to as reference systems including manufacturing system, a business, or a military conflict area. In this case, the conceptual representation of a reference system is coined referential ontology which is a kind of metamodel, enabling modelers to define the denotation of their conceptual representations within networks of related concepts linked to reality [Hofmann et al. 2011]. Representing knowledge about simulation models is also referred to as a form of meta-modeling [Okhmatovskaia et al. 2012].

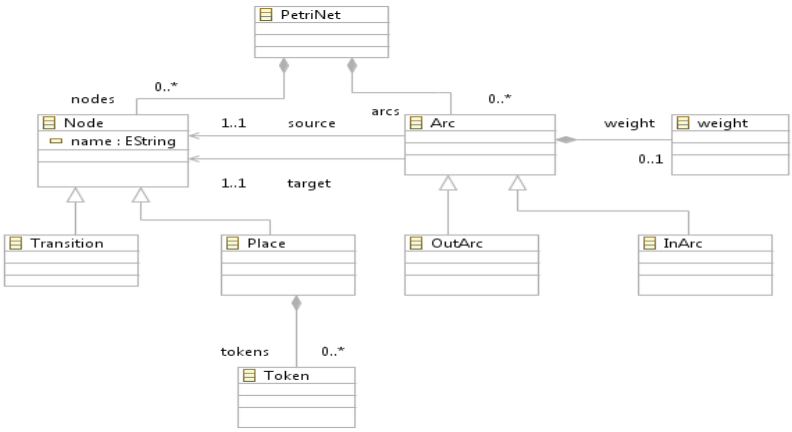


Figure 2.10. MDA transformation process

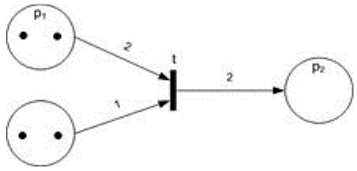


Figure 2.11. A Petri net model

A metamodel is specified in a metamodeling language that has its own metamodel as well. In this case, the metamodel of the metamodeling language is called meta-metamodel and is specified in its turned in a language called meta-metamodeling language. This meta-metamodel specification captures all the elements that are used in the specification of the meta-model of the modelling language. Thus, the chain of the meta-modeling specification goes on till an infinite level. However, OMG defines 4-level metamodeling architecture to be used in the UML specification as illustrated in Figure 2.12 consisting of a hierarchy of models. The level M0, at the bottom layer represents the user data of a real world system. M0 is an instance of the level above, M1. The next level M1 represents the model of user data at level M0. The models such as CIM, PIM, PSM, and UML are specified at this level. M1 is an instance of the level above, M2. The next level M2 represents metamodels of the modeling languages used at level M1. M2 is an instance of the level above, M3. Finally, level M3 represents meta-metamodels and is composed of MOF, used to represent metamodel of the metamodeling languages at level M2. This level is self-descriptive.

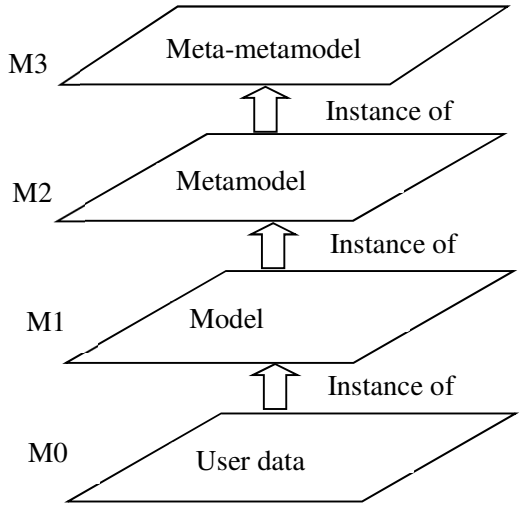


Figure 2.12. OMG four-level metamodeling Architecture

2.6. Conclusion

We presented in this chapter the foundations of our research work upon which the following chapters will be built on. The first section dealt with the description of the framework for Modelling and Simulation and section 2 provided the system behavior description at two levels: the DEVS Atomic Model representing the smallest entity at the lower level that cannot be decomposed and the DEVS Coupled Model representing the network components at the higher level of system specification. Section 3 discussed on the Multi-paradigm Modelling and Simulation as a way out to tackle complex systems with large and various number of components that their modelling in single simulation techniques is more challenging and cannot capture all the details viewed from different perspectives from the modeler. Section 4 presents the Model Driven Engineering approach with the concept of model transformations to show how components of the same system modeled in different formalisms can be transformed to a common simulation formalism. We will use the lessons learnt from these sections to support the modelling methodology proposed in this work in application to healthcare systems simulation which is at the heart of the contribution of this thesis.

Chapter 3
LITERATURE REVIEW OF HEALTHCARE SYSTEMS M&S

Today's healthcare systems (HS) face a wage of challenges while seeking to deliver quality services to patients, maximize resources utilization and control health costs. Decision-making concerning questions related to the performance of HS - such as the extent to which the system achieves its mission - have no clear or simple answers while the need to produce more with less resources despite the scarcity is becoming a widely acknowledged concern among policy-makers and healthcare managers worldwide [Shin et al. 2013].

The complexity of HS is rapidly increasing due to its multiple ramifications such as various healthcare specialties, and external laboratories that are intertwined with intricate processes. Hence, healthcare systems are characterized by a large number of concurrent, fragmented and diverse components interrelated by complex relationships. Consequently, a considerable volume of research work has been published in recent years dedicated to simulation-based study of HS. In this chapter, we present a literature review to show why the existing related works could not effectively address the main challenges of healthcare simulation. We focus on the methodologies that have been used, the specific problems that have been addressed as well as some other topics relevant to the objectives of the thesis.

The rest of this chapter is structured along the following considerations. In section 1 we present healthcare systems M&S scope with focus on unit specific problems modelling. Section 2 deals with M&S aspects related to healthcare simulation efforts. Section 3 presents modeling paradigms most used in the literature. Section 4 provides a review on healthcare simulation

paradigms and highlights M&S based healthcare systems analysis approaches used in the literature. Section 5 concludes the chapter.

3.1. Healthcare systems M&S scopes

M&S is a broad discipline with a variety of types of application being used both in science and engineering. More specially, in healthcare systems, simulation has enjoyed widespread application for a variety of reasons [Roberts 2011]. As a result, a considerable amount of research has been conducted to study individual units of HS this last decade. Such units specific include Accident and Emergency Department (A&E), Inpatient facilities, and Outpatient clinics.

[Mes and Bruens 2012] developed a flexible modeling framework for an integrated emergency post (IEP) within a hospital at Almelo (the Netherlands) that considers three main components including entities, resources, and processes. Entity components are referred to the moving parts of the IEP such as patients while resources are comprised of operating rooms, hospital beds, medical equipment, and medical staff. Processes are referred to sequence of services required by patients such as various treatments and are denoted by a care pathway for each patient going through IEP services. Such services include regular tasks, parallel tasks, and delay tasks.

[Zeng et al. 2012] presented a model of emergency department (ED) aiming at improving the quality of care in a community hospital that faces challenges of increase of patient visits, nursing workforce shortage, and long delays. The model was used to carry out analyses on patient throughput, waiting times, length of stay, and staff and equipment utilizations. Sensitivity analysis as regards to the number of nurses on duty was carried out and results showed that using such a

model the ED may require additional number of nurses may to ensure a minimum waiting time and length of stay for patients while the authors of the ED model claimed that the model can still be used to analyze the effects of potential improvement policies in the emergency department.

[Gavirneni et al. 2013] addressed the challenge of decision making in Concierge Medicine, a new development in the U.S. Healthcare system that provides comprehensive care in a timely manner. Concierge medicine is an alternative to traditional medical practices that provides better care services to registered patients. In the traditional medical practice a number of 2,500 to 3, 000 patients are registered per doctor while concierge Medicine practice facilitates a limited number of 600 patients to register per doctor with some guaranteed revenue streams. The developed model aims at improving HS efficiency at the primary care level while taking into account settings such as, physician settings, patient settings and society settings.

[Verma and Gupta 2013] developed a model to improve the performance of outdoor patient departments (OPD) in a general hospital in the state of Gujarat, India. While public health delivery in India is said to be in a very bad shape, the proposed model addresses critical issues within the OPD such as activities time of doctors - arrival time, examining time, break time, and treatment time -, and patient's arrival time, and number of personnel at registration counters. Surprisingly, the study showed that doctor's utilization time was rather below 100% pointing out the lack of good management skills in the OPD. Thus, the problem of maintaining discipline and scheduling of staff was highlighted against the general opinion of staff shortage problem in the hospital.

A better planning is referred to as a remedy to deal with delayed discharges at tertiary level health unit leading to degrading health service factors such as disruption in patient flow, blocked beds, frustrated patients and distressed unit staff. To address such obstacles, [Khurma et al. 2013] developed a patient-based discharge planning that reduces patients length of stay (LOS) at a tertiary acute care hospital working with 412 physicians, 305 beds while providing care to an average of 120,000 patients per year. The focus of the study was more on the top ranked medical units sending most patients (69.1%) to long term care. As a result, the study showed a significant resemblance and promising improvement of 4.5 days deduction in the LOS at the acute care hospital.

[Morrice et al. 2013] developed a patient-centered surgical home (PCSH) model for coordination of outpatient surgery process at the acute care facility for University Health System (UHS), Texas. The authors report that preparing outpatients for surgery requires intensive information while medical records in the current system are often inefficient and fragmented among different providers that more often lead to surgery delays and cancellations. The study was concerned with a systems-level process analysis for the Anesthesia Preoperative Clinic (APC) which is the key clinic for system-wide coordination in outpatient surgery. Thus, patients with more complicated medical conditions are referred to the APC for a pre-operative assessment prior to their day of surgery.

[Fletcher and Worthington 2009] presented a generic model of A&E department that captures key obstacles to its functioning. Such elements include process time - waiting time for a decision to admit patients-, resource constraints, and variability in demand. The developed model also

considers bottleneck factors faced by A&E department that are common to other hospital departments such as diagnostic processes of x ray and blood test, inpatient beds in assessment units and intensive care units that exert significant influences on A&E department.

[Bountourelis et al 2011] addressed the challenge of bed scarcity at a large scale Intensive Care Units (ICUs) in the Veterans Affairs (VA) Pittsburgh Healthcare System (VAPHS). The hospital under study was having 146 operating beds distributed among different departments such as medicine department, surgery department, neurology department, cardiology department and critical care department. The intent of the study was to alleviate the burden of blocking patients on ICUs having limited-capacity but are resource-intensive units that are designed for patients that require highest level of monitored cares.

[Cote 1999] conducted a performance based study of outpatient clinic department that addresses key factors such as patient flow time, examining room capacity, i.e., examining room utilization and examining room queue length, and physician's activities. The author reports that outpatient health care is a vital component of the American health care system while representing one of the strongest growth areas in the health care industry. The resources at the outpatient clinic department include examining rooms, nurses and physicians that work according to a predefined shift to provide general outpatient services.

[Sobolev et al. 2008] worked on perioperative processes of cardiac surgical care at the British Columbia hospital, Canada. Main activities within the surgical care include diagnostic, pre-operative, operative, and postoperative stages. Surgical care delivery is referred to as a reactive

system due to its features to interrelate processes that produce events in concurrent activities. As such, the study considered three categories of patients such as elective patient, inpatient, and emergency patient that their care pathways are intertwined with patients at the cardiac surgical care department within the hospital.

[Person and Person 2009] addresses the challenge of surgery department management with focus on both medical and economic constraints. The department of general surgery under study is overflowed with patients in waiting list divided into three medical priority groups according to surgical diseases. The study was motivated by a newly passed law in Sweden that states that patients who decide to receive surgery should not wait more than 90 days to be attended to. The study considers main factors such as patient arrival, operating room scheduling, and resource allocation related to surgery over time.

[Weng et al. 2011] conducted an operational efficiency based study to assess the Emergency Department (ED) at hospital research center in Taiwan. The goal of the research was to find an adequate formula that provides a right number of health resources including physicians, nurses and beds in the healthcare facilities such as resuscitation rooms, triage station, observation unit to maximize the efficiency of the ED. The ED department is equipped with beds distributed into the different sub-units. Patients are modeled from their arrival at the ED till when they are either released from the ED or admitted into the hospital inpatient department for further treatment.

[Price et al. 2013] worked on health service cost reduction at the Maryland proton treatment center by examining facility layouts and scheduling plans to minimize idle equipment and

maximize total patient throughput. The study aims at improving patient access to proton therapy, a highly expensive treatment. The treatment center is designed with each imaging and gantry rom servicing only one patient at a time with one cyclotron that provides protons for all different gantry rooms based on first come first served. The authors claimed that the study provides satisfactory results that can reduce the average total waiting time by over 55% at the Maryland proton treatment center.

[Choi et al. 2013] conducted a research study that addresses performance factors of outpatient departments at King Abdulaziz University (KAU) Hospital. Such factors include patients waiting time, workload and pressure on clinic staff, and exceptions handling. The obstetric and gynecologic outpatient department at the KAU hospital is known to be one of the most congested departments with longer waiting times despite its 21 clinics -each operated by a consultant-, a team of interns, residents, and nurses. The core components of the developed framework was comprised of three operation phases: preparation phase, service phase, and wrap-up phase while each phase was handled by a workflow management system.

[Topaloglu 2006] carried out research study that aims at tackling emergency medicine residents (EMRs) scheduling problem while considering both hard and soft constraints in assigning day and night shifts to the residents over a monthly planning horizon. It is widely acknowledged that emergency rooms (ERs) are stressful workplaces and shift work is more demanding than regular daytime work. As such, scheduling EMRs is one of the most difficult tasks among other groups of healthcare personnel. The authors claim that the research study is able to generate a

successful and high-quality monthly schedules in reasonable time considering all the constraints in the scheduling environment.

[Ma et al. 2012] presented a multilevel integrative approach to hospital case mix and capacity planning that considers both patient volumes that can be taken care of at a hospital and resource requirements management. The research study consists of three planning phases including case mix planning phase, master surgery scheduling phase, and operational performance evaluation phase. The three stages interact in an iterative way to make sound decisions both on the patient case mix and the resource allocation. The authors argued that one of the reasons of the increase in total health expenditures is the incapability of hospitals to handle decision making at strategic, tactical and operational levels of hospital operations.

[Ahmed and Alkhamis 2009] conducted a research study of an emergency department (ED) unit at a governmental hospital in Kuwait with focus on resource utilization. The authors report that most often health system managers and decision-makers face challenges of maximizing the utilization of their available resources while being at the same time constrained by high demands for service, high costs, and limited budget. The emergency department under study is a 24/7 working department, receives an average of 145 patients daily and shares resources with other hospital services. The designed decision support tool is hoped to help decision makers at the hospital to either evaluate different situations of staffing distribution or optimize the system for optimal staffing distribution at the ED unit.

[Yeh and Lin 2007] addressed specifically nurses' schedule problems at the emergency department (ED) of Show-Chwan Memorial Hospital in Central Taiwan. The ED is well-known to be a complex unit for the fact that fight between life and death is always a hair's breath away, thus requiring a high degree of coordination and interrelations between human and material elements. The ED under study faces serious challenges such as, high patient acuity, hospital bed shortage, high ED patient volume, radiology and lab delays, and insufficient ED space leading to overcrowding and staff availability. The results of the study assert that the quality care in the ED unit can be improved by making adjustments to the nursing schedules without increasing their number in the system.

[Harper 2002] developed a generic framework that integrates patient classification techniques for modeling of hospital resources. The author argued that the provision of healthcare services is perhaps one of the largest and most complex industries worldwide. As a result, one needs a sophisticated capacity models that takes into account the complexity, uncertainty, variability and limited resources to plan and manage the daily activities of a hospital system. The proposed framework was developed in response to the participating hospitals, including Reading, Portsmouth and Southampton hospitals. The author highlighted that the research work has proved to be very helpful in the planning and management of hospital beds, operating theatres and workforce needs.

[Aboueljinane et al. 2013] presented an extensive literature review on papers that deal both with timeliness and economic objectives to achieve analysis and improvement of emergency medical services (EMS). The authors addressed commonly faced problems by EMS providers such

as response time, recovery chances, and patients' disability. Reducing significant expenses that concern capital such as acquisition of facilities, emergency vehicles, equipment and communication devices, and operating costs like salaries, training and maintenance were widely discussed.

3.2. Healthcare systems M&S aspects

This section presents research efforts dedicated to healthcare simulation aspects such as resource allocation – human resource, finance resource and information resource -, population dynamics, and disease outbreak discussed in the literature. We also present some surveil papers that address taxonomies in healthcare simulation.

[Roberts 2011] presented a taxonomy of healthcare simulation that considers the following aspects: bed allocation and planning, admission control, room sizing and planning, patient flow, physician and healthcare staff scheduling, materials handling, and logistics. The underlying aspects are concerned with healthcare management challenges including outpatient scheduling, inpatient scheduling and admissions, and emergency department and specialist clinics, hospital departments like laboratory, radiology, surgery and recovery, pharmacy, and supply and support.

In a general classification, [Barjiis 2011] presented healthcare simulation along four axes including clinical simulation - used for studying and analyzing the behavior of certain diseases-, operational simulation -used for capturing and studying healthcare activities such as service delivery, healthcare operation, scheduling, and patient flow-, managerial simulation –used as

decision support tool for managerial purposes, strategic planning and policy implementation-, and educational simulation - used for training and educational purposes.

[Brailsford 2007] presented a review of applications of simulation in healthcare into three levels. Level 1 models refer to models at the cellular, organ or system level of the human body, or disease models and are used to study clinical effectiveness of healthcare interventions. They are also used to study human health behaviors, and some disease spreading. Level 2 models are used to study activities of health unit – hospital department, clinic or emergency room at operational or tactical level. Level 3 models also called strategic models are used for studying long-term problems.

[Onggo 2012] presented a review on simulation modeling for the provision of social care services. Main components of social care services that were considered include demand, supply, delivery methods and finance. The authors argued that health demand is generated by care users and its planning is linked to population projection that is partly influenced by healthcare system. They reported that one of the key challenges in demand projections is its dependence on factors such as health, culture and socio-demography.

[Gunal and Pidd 2010] presented a review of performance modeling in healthcare simulation that considers models according to the objectives of the studies. The models address simulation aspects such as scheduling and patient flow, sizing and planning of beds, rooms, and staff. The authors highlighted that healthcare simulation based studies are unit specific, that is, their focus is

on specific problems in individual units of healthcare systems. Additionally, those studies are facility specific, that is, the models were built for specific hospitals and are hardly reused.

The problem of emergency medical services (EMS) improvement and analysis has been addressed by [Aboueljinane et al. 2013] in a review of health simulation papers. They presented key characteristics of EMS operations as follows: operations - processes describing central and external operations-, decisions regarding EMS operations - long term decisions, mid-term decisions, and short term decisions-, and performance measures associated with EMS operations such as timeliness, survival rate and costs. The authors argue that a successful modeling of demand in EMS systems considers three key characteristics: the arrival distribution, the geographical distribution and the priority of calls.

A clinical Pathway (CP) is referred to as the path followed by an ill person through healthcare facility. [Ozcan et al. 2011] studied clinical pathway across surgery department at a public hospital and identified critical activities and scarce resources that represent process bottlenecks both from patients and facility point of view. The authors considered patients going through surgery department activities while competing against common resources such as personnel, ambulatory time, beds, and operating theatres. A Minimax optimization model was developed to generate optimal Operating Room (OR) allocation plans.

The problem of physicians' reimbursement schemes has been studied by [Einzinger et al. 2013] to analyze its influence on physicians' treatment decisions. The authors considered patients and medical providers with main attributes such as epidemiology, service need, and provider

utilization. In conclusion, they assert that the research study facilitates comparisons of different reimbursement system in outpatient care while being useful for testing assumptions.

[Davis et al. 2013] conducted a study on kidney transplantation challenges for improving policy allocation that gives more survival chance and quality of life to patients. Such challenges include high cost of services, donation shortage, and geographic disparities that more often result in considerable amount of waiting time and cause thousands of transplant patients to die each year. Three system performances were considered including average waiting time, probability of death, and probability of transplant.

[Lee et al. 2013] studied supportive care problem to allow individuals to remain in their homes or communities while receiving services. Demand for long-term care in the United States has witnessed rapid increase causing home care industry to face with shortage of home caregivers. A feedback control algorithm was used to obtain sequence of requested service departure times. The authors argued that the suggested study has great potential to solve a large scale scheduling problem in a short time compared to other studies based on operation research approaches.

[Charfeddine et al. 2007] discussed on generic aspects of healthcare simulation including population and healthcare delivery systems. The authors argued that simulation studies focusing on population and demand aspects are comprised of economic, epidemiologic and clinical modeling while simulation studies focusing on healthcare delivery networks are directed towards modeling care processes, patient flows and available resources within healthcare supply chains and facilities such as hospitals, clinics and care units.

A generic modeling framework has been proposed by [Mes and Bruens 2012] describing three major components including entities, resources, and processes to study emergency departments (ED). The flow of patients denoted by care pathway were captured by entities, the moving parts of the ED while resources include medical staff, operating rooms, hospital beds, and medical equipment. Processes represent services required by the entities. Sequence of activities through which patient undergo start from arrival processes and ends with treatment processes in the emergency room.

A better planning is referred to as a requirement to address nonmedical reasons for delayed discharges known as one of the causes of system obstacle that result in disrupted flow, blocked beds, frustrated patients and distressed unit staff. [Khurma et al. 2013] came up with such planning for discharging patients within a reasonable time by reducing their length of stay (LOS) in critical healthcare units. The authors reported that more people could stay in the hospital for lesser time and this will result into considerable savings (in dollar values).

Improving quality of care at emergency department (ED) has been addressed by [Zeng et al. 2012]. The authors studied the daily challenges faced by ED such as increase of patient visits, nursing workforce shortage, and long delays experienced by patients during their medical journeys. The model was used to carry out analyses on patient throughput, waiting times, length of stay, and staff and equipment utilizations. After comparing the results of the study with the collected data, the authors concluded that their work can be used for subsequent analysis.

Human resource utilization on a day-to-day basis affects significantly the performance of healthcare units. [Verma and Gupta 2013] conducted a study on doctors' utilization in outpatient department based on time factor in an outdoor patient department, one of the most congested department in the hospital. The authors investigated on doctors' activities times including arrival time, time spent to examine admitted patients, break time, and time taken by doctors to treat patients depending on illness. They concluded that the utilization of doctors' time was below 100% and increasing the number of doctors is not required in the hospital.

Healthcare managers are more often under financial pressure when trying to ensure the delivery of high quality care. However, the performance and quality of health systems ultimately depend on the quality and the motivation of health human resources. To tackle this challenge, [Vanhoucke and Maenhout 2009] developed a model based on four classes of performance indicators to characterize nurse scheduling problem (NSP) instances. Such indicators include problem size, preference distribution measures, coverage requirements of the schedule, and incorporated time related constraints.

[Fletcher and Worthington 2009] conducted a study on key issues affecting patients flow in A&E (Accident and Emergency) department in a hospital and causing significant patient delay. Such issues include waits for bed, waits for diagnostics, waits for a decision to admit, and variability in demand and process by time of day and day of week. The authors concluded that the natural level of performance of the A&E department under study may be around 89% based on performance factors such as process time, resource constraints, variability and time of day and day of week, and demand.

More specifically, [Bountourelis et al 2011] worked on challenges associated with hospital bed allocation within different departments like medicine, surgery, neurology, cardiology and critical care. The focus of the study was on patient blocking referred to as a patient that is medically able to leave a critical healthcare unit like Intensive Care Unit but might experience a prolonged stay due to unavailable beds downstream. The authors concluded that based on the performed analysis, the results of their study can faithfully represent the level of blocking and bed occupancies in the hospital under study.

[Cote 1999] addressed challenges related to patient flow and examining room capacity with focus on physician's activities in an outpatient clinic that has four general outpatient services, three examining rooms, and 14 physicians working according to a shift with a nurse aide that has been allocated to each of them. The study was conducted based on the assumption that each patient can select only one primary care physician while a choice of variables such as examining room capacity and arrival rate of the patients were independently considered. The author concluded that the assumption made based on a reduction in the number of examining rooms did not result in individual patient delays.

[Sobolev et al. 2008] investigated on the perioperative processes of cardiac surgical care at the British Columbia hospital, Canada based on three care paths of patients including elective patient, inpatient, and emergency patient with coronary artery disease. The challenge of surgeon's allocation was also addressed based on their activities like diagnostic, pre-operative, operative, and postoperative stages. Performance factors such as the availability of surgeons for

consultations, scheduled operations, and on-call duties according to the rotation and vacation schedules in the service were considered.

[Viana et al. 2012] addressed the problem of age-related macular degeneration (AMD) management that lead patients to interact with the eye clinic via appointment scheduling processes. The authors explored different scenarios from which new individuals are weekly added to initial individuals within a period of one year and the results of the study showed that improving the Eye Unit's capability by increasing the number of equipment will help more patients successfully completing their appointments.

[Ramirez-Nafarrate et al. 2013] worked on child obesity which is a public health concern for several countries leading to risk of diabetes, hypertension, sleep apnea, liver disease, stroke and some types of cancer. The authors argued that an estimate of 25% higher health expenditure is associated to an obese person than a person with a healthy weight while leading to 5% and 10% of the overall health expenditures in the United States. Excess caloric intake was reported as a main cause of child obesity.

[Harper 2002] discussed on performance factors related to hospital resources such as hospital admission and discharge dates, time of arrival, length of stay, emergency or elective status, and operation time of patients were considered. The model examined what if scenarios for hospital beds, operating theatres, use of human resources like nurses, doctors and anesthetists. The author conclude that the study was very helpful in the planning and management of hospital beds, operating theatres and workforce needs.

[Person and Person 2009] conducted a medical and economic based study that integrates both patient flow and resource constraint for surgery management decisions. The study considers performance factors such as patient arrival, operating room scheduling, and resource allocation. The scheduling of surgeries was done based on medical priority, time spent in the queue by patients and available resources like operating rooms, surgeons, and post-operative beds while two types of costs were considered including patient related costs - out-sourcing costs, rescheduling and cancellation costs-, and surgery costs - extra bed costs and overtime costs.

[Choi et al. 2013] addressed the problem of patients waiting time and staff scheduling in an outpatient department, one of the most congested departments in a hospital. The authors reported that patients have longer waiting times while the outpatient have 21 clinics, each operated by a consultant, a team of interns, residents, and nurses. Based on a test case performed on the outpatient department, the results led the authors to a conclusion that their study can significantly helped assessing key performance factors related to patients waiting time, workload and pressure on clinic staff, and exceptions handling.

[Ma et al. 2012] conducted a capacity planning based study to match patient demands and supplied resources. The study was directed both to patient volumes that can be taken care of at a hospital and the resource management. The authors argued that decisions regarding patient flows is based on the annual number of patients that can be treated per pathology group while decisions regarding resources consist of the capacity requirement of each specialty within the hospital. They concluded a hospital is assumed to possess a fixed number of different departments while it is

considered as a production system, in which the scarce resources are used to support the flow of patients.

[Bigus et al. 2011] proposed a general framework for studying the impact of incentives on healthcare that allows to control costs of health services and improve health by healthcare government and employers. The proposed framework considers healthcare main components such as decision-makers, regulations and reimbursement mechanisms. Decision-makers include patients, providers and payers. While patients drive demand for healthcare services, they seek to optimize the quality of life and maintain certain level of health.

In addition to research efforts dedicated to specific aspects of healthcare simulation such as resource allocations aspect and patient flow aspect, other simulation aspects have also been paid great attention in the literature including disease outbreak aspect and population dynamics aspect.

Ageing population is known as one of the major factors that influences both supply and demand for health and social care. [Brailsford et al. 2011] conducted a study that considers major factors affecting supply and demand targeting the UK health and social care system. The authors reported that demand for health is a function of need influenced by factors such as disability and disease, new technologies, changes in levels of income and wealth while supply for health is influenced by factors like demographic trends, economy, and policy environment.

[Paleshi et al. 2011] investigated on intervention strategies for handling disease spread within a generic US metropolitan area. The authors based their study on factors such as population

structure, disease characteristics within human body, and disease transmission between people. Population structure includes age groups: less than or equal to 4 years old, 5 to 18 years old, 19 to 64 years old, and 65 years old or older. Two intervention strategies were examined including home confinement and school closure for the mitigation of infected individuals during the pandemic outbreak.

Similarly, [Zhang et. al 2012] proposed a contact network-based study that incorporates different intervention strategies to assist policy makers to make decisions for containing the spread of infectious diseases. The authors examined major health interventions including public health interventions that are comprised of pharmaceutical interventions like antiviral treatment and vaccination and non-pharmaceutical interventions such as social distancing, hand wash, and face mask. In an illustrative case study, they studied intervention strategies based on social-distancing such as school closure and workforce shift for the mitigation of influenza spread in Singapore.

[Kasaie et al. 2013] addressed unanswered questions on tuberculosis (TB) transmission dynamics and the role of various contact networks. The authors defined three layers contact network comprised of close contact, casual contact, and random contact capturing social relationships of each individual with the rest of the population. Close contacts represent contacts among household members, casual contacts are social relationships among friends in places such as bar, store, and school, and random contacts represent encounters of people at places such as bus stops and museums. The authors concluded that the study of timing and distribution of TB transmission allows understanding the population heterogeneity with regard to personal characteristics and different contact networks.

Population projection is related to public health issues, political decision-making, or urban planning. Models concerning population projections include micro-level models - focusing on a sample population-, and Macro-level models - projecting a total population by age, sex, and other characteristics-. [Bohk et al. 2009] developed a probabilistic population projection model (PPPM) allowing detailed projections of a population. The proposed PPPM was based on macro-level projection model and integrated two variants: open type and limited type. The authors presented an illustration of open and limited PPPM types using data from the Federal Statistical Office of Germany and running 1000 trials for each of the PPPM types.

While healthcare is seen as a complex system with multiple ramifications and various aspects that interact with one another through intricate processes, we propose to investigate such domain using multi-perspective modeling and simulation where different aspects are captured by different views within a single model. Hence, modelling HS through multi-perspective modelling becomes more practical and richer with deep insights. We discuss some papers that address complex systems modelling in the next section.

3.3. Healthcare Modeling Paradigms

Healthcare systems have been investigated using different modelling paradigms such as petri net [Salimifard et al. 2013], cellular automata [White et al. 2009], and discrete event systems specification (DEVS) [Perez et al. 2010]. In this section, we discuss some of the modelling paradigms used to model different aspects of healthcare as highlighted in the previous section.

[Ng et al. 2011] worked on system dynamics modeling to study healthcare affordability problem in Singapore by investigating on different scenarios that evaluate the effectiveness and sustainability of policies over time. Major components of healthcare were considered including demand component, hospital resources component, and costing component and their respective relationships. Policies such as assigning a higher percentage of budget, changing migrant flow, differentiating subsidies according to income group, and shortening the length of hospital stay were tested. The authors concluded that the affordability problem will decrease significantly into the next three decades.

[Einzinger et al. 2013] developed an agent-based model to study reimbursement schemes, a factor that influences physicians' treatment decisions in the Austrian healthcare sector. The authors defined two types of agents including patients and medical providers. They argue that the model facilitates comparisons of different reimbursement system in outpatient care while it is useful for testing assumptions. However, the authors reported that the model is limited to a number of chronic diseases that will fit into it.

[Topaloglu 2006] developed a goal programming (GP) model to deal with emergency medicine residents (EMRs) scheduling problem that considers both hard and soft constraints in assigning day and night shifts to residents over a monthly planning horizon. While emergency rooms (ERs) are known as stressful workplaces with more demanding shift work than regular daytime work, the author used analytical hierarchy process (AHP) into the proposed GP model to assign weights to the deviations in the proposed objective function. They asserted that the developed GP model was capable of generating high-quality monthly schedules in reasonable time.

It has been argued that child obesity is a public health problem for several countries as referred to as the risk of diabetes, hypertension, sleep apnea, liver disease, stroke and some types of cancer, leading to 25% higher health expenditure for an obese person than a person with a healthy weight and causing between 5% to 10% of the overall health expenditures in the United States. Excess caloric intake is mainly known to be the cause of child obesity because obese children consume too many calories without doing enough physical activity whereas most of both the caloric intake and the caloric expenditure take place in school and at home.

While fight between life and death is always a hair's breath away, ED is a complex unit that requires a high skill of coordination between human and material resources. [Yeh and Lin 2007] developed a genetic algorithm (GA) to address nurses' schedule problems at the emergency department (ED) of Show-Chwan Memorial Hospital in Central Taiwan. The concerned ED is faced with management challenges of high patient acuity, hospital bed shortage, and radiology and lab delays that lead to overcrowding and staff unavailability. The authors considered ED processes such as triage, insurance procedures, recovery rooms, and diagnostic and respiratory therapy in their approach. They concluded that the quality care in the ED can be improved by making adjustments to the nursing schedules without increasing their number in the system.

[Ferranti and Freitas Filho 2011] developed a system dynamics model to study risk factors for age-related cardiac diseases. The model considered key parameters such as growth rate, reserve rate, and aging rate. The authors report the results of the study have shown that maintaining good blood pressure and participating in physical activities have an impact on a person's lifespan and

delaying mortality in the population while claiming that sex is related to a person's lifespan, thus anticipating mortality in the male population.

[Sobolev et al. 2008] used Statecharts, a system of graphical specification, to address perioperative processes of cardiac surgical care department. Statecharts specification paradigm was chosen because it extends the formalism of finite-state machines through notions of hierarchy, parallelism, and event broadcasting, for representing reactive systems. The authors modeled surgical activities such as diagnostic, pre-operative, operative, and postoperative stages while concluding that Statecharts enables the representation of surgical care features in a rigorous manner.

[Djanatliev et al. 2012] integrates system dynamics and agent-based models to investigate the effects of implementing new technologies in healthcare systems. Major modules such as population dynamics, disease dynamics, health care and health care financing were considered for the study. After using different use case scenarios, the authors concluded that the research effort has achieved an overall credibility from all domain expects including doctors, health economics, medical informatics, and knowledge management experts.

In a similar way, [Viana et al. 2012] combined agent-based modeling (ABM) with system dynamics (SD) for the management of age-related macular degeneration (AMD) problem. Individuals were modeled as agents in the population developing AMD that lead them to interact with the eye clinic via appointment scheduling processes. SD was used to model progressive sight loss from AMD which affects agent eyes. The authors reported that the integration ABM and SD

in a health care context is rare in the sense that the main conceptual challenges lie in designing those sub-components and achieving their interactions.

[Paleshi et al. 2011] developed an agent-based simulation model of a pandemic within a generic US metropolitan area in order to study how the disease spreads and to prepare for handling the consequences by implementing intervention strategies. The proposed model consists of three main subroutines including the structure of the population, disease characteristics, and transmission of the disease between people. The population was structured into four age groups: less than or equal to 4 years old, 5 to 18 years old, 19 to 64 years old, and 65 years old or older. The authors conducted 50 replications for each scenario and concluded that all intervention strategies have positive effects on the attack rate representing the percentage of infected people during the pandemic.

[Bigus et al. 2011] used multi-agent modelling to study the impact of alternative healthcare incentives. The simulation model considered four components that are: disease model, patient, medical intervention and provider components. Based on 'state abstraction' from the perspective of a Markov disease model, relevant disease states and the estimation of transition probabilities between disease states were automatically extracted. Statistical estimation of certain patterns of intervention was used for characterizing provider's behavioral model.

[Kasaie et al. 2013] developed an agent-based simulation (ABS) model to study tuberculosis (TB) transmission dynamics and the role of various contact networks. People in the population were represented as agents in the model. The population was structured into different groups

including households, neighborhoods and communities. TB natural history was modeled at the individual level using five main TB health states including susceptible, early latent TB, late latent TB, active TB, and recovered states. The authors defined a three-layer contact network referred to as close, casual, and random contacts representing the social relationships of any individual with the rest of the population.

[Ramirez-Nafarrate et al. 2013] presented an agent-based simulation (ABS) framework that can help policy-makers to design meal menus and physical activity programs for school-age children that reduce the prevalence of obesity during childhood. The authors argued on the proposed modeling framework that ABS models are used because they allow analyzing a complex system with autonomous agents. Children were represented with eight attributes including age, gender, weight, height, body mass index (BMI), weight status category, daily caloric intake, and energy expenditure. The results of the study showed that the fraction of children with healthy weight increases significantly as they increase the intensity of their physical activity.

[Charfeddine et al. 2007] presented a conceptual framework for healthcare delivery systems with focus on two major components: population generating the demand for healthcare services, and healthcare delivery network representing the organization of the healthcare system in order to satisfy the population demand. Population demand for healthcare services is expressed as the probability distribution through the stochastic modeling of the health state evolution of each person (represented as an agent) while the model of healthcare delivery network was based on a strategic mapping framework and agent oriented modeling methodology.

[Brailsford et al. 2011] presented an integrated model of supply and demand of both health and social care of the UK health and social care system. UK society was modeled with Statistical models using theories from social models of disability. An agent-based model of the demographics of aging and social care was constructed to investigate the effects of individual-level behaviors. A high-level system dynamics simulation model was developed to study health and social care at the institutional level. The authors reported that these three approaches are linked to build a suite of models which represents UK health and social care at multiple levels: population, individual and institutional.

3.4. Healthcare Simulation Paradigms

Several papers studied management of healthcare using different simulation technics such as discrete event simulation (DES), continuous simulation, and hybrid simulation. For example, [Price et al. 2013] proposed a DES model to examine facility layouts and scheduling plans that minimize idle equipment time while maximizing total patient throughput in a proton treatment center. The authors formulated the treatment steps for each patient throughout in discrete time starting from waiting room till imaging room where the treatment begins using a computer tomography (CT) scanner.

[Gavirneni et al. 2013] developed a DES model of Concierge Medicine, a new development in the U.S that provides comprehensive care in a timely manner. The scope of the model takes into account settings such as physician, patient and society. Results of the study have shown that concierge medicine is attractive to both patients and physicians and could lead to better health

outcomes for the entire society. The authors concluded that the research effort should be implemented under the right circumstances and managed effectively.

[Davis et al. 2013] developed a DES model for alternative allocation strategies of kidney transplantation system that reduces geographic disparities in the US. The kidney transplant system is divided into 11 regions of neighboring states with patients being registered in different waiting lists. The simulation study was driven by three main events including patient arrivals, patient deaths, and organ arrivals. The authors reported that there was not a significant difference between simulated and actual average waiting times from all scenarios performed while concluding that the study provides valid estimates of kidney transplantation system outputs.

[Morrice et al. 2013] conducted a DES study that addresses the impact of health information necessary to preparing outpatients for surgery at Anesthesia Preoperative Clinic (APC). The authors considered the problem of staffing and scheduling requirements for resources and patient flow process from patient arrivals, provider assessment, and provider wrap-up times within the APC. They concluded that the simulation results were given the go-ahead to be implemented while a registered nurse has been added to the clinic staff to pilot the screening.

Likewise, the simulation model proposed by [Price et al. 2013] for the proton therapy center (PTC) was run in discrete time considering patient flow processes' time including the amount of time waiting for entry into the imaging room, and the amount of time waiting in the gantry room. The model was built to accommodate more complex PTC components interactions between patient, facility, and personnel. A simulation was run for 250, 000 ticks with patients arriving

whenever an imaging room became available and the results showed that by adding more gantry room leads to little throughput increase with longer patient wait times.

[Lee et al. 2013] developed a continuous-time dynamic model for controlling home care crew scheduling problem that minimizes delay and transportation costs between requested service time and starting service time. Homecare is referred to as a supportive care provided to individuals in their respective homes. The authors used a complete graph to describe home care crew problem in which case vertex set corresponds to locations of residents and home care agency location having caregivers while vertices set corresponds to travel time between two consecutive residents.

[Brailsford et al. 2003] developed a DES model integrating both psychological and human behavior model to evaluate attendance for screening of diabetic retinopathy. Human behavior factors such as physical states, emotions, cognitions and social status of the persons involved were considered. Each patient was modeled as individual entity with his or her own characteristics assigned with numerical attributes between 0 and 1 representing low, medium or high value. Attributes like anxiety, disease knowledge, and educational level have been taken into account. The authors concluded that the model would have great potential value as a policy analysis tool to design efficient screening plan that will attract more non-attenders and improve the overall health of the population.

[Djanatliev et al. 2012] argued on the effects of new innovations using a new approach of simulation techniques called Prospective Health Technology Assessment (ProHTA) that loosely integrates system dynamics and agent-based models within a hybrid simulation environment. A

use-case scenario with an innovative stroke technology as Innovative health technologies was presented as having the power to improve the life quality of populations and to make healthcare more effective. The authors argued on the idea of using hybrid simulation that it helps to easily handle complex simulation architectures while profiting from the advantages of different modeling approaches.

More narrowly, some models use simulation combined with other methods to investigate the domain of healthcare. For example, [Weng et al. 2011] developed a mixed method combining Discrete Event Simulation (DES) and Data Envelopment Analysis (DEA) to assess operational efficiency in Emergency Department (ED) at hospital research center in Taiwan. The goal of the research is to find the mix of physicians (PH), nurses, and beds to achieve ED efficiencies. A benchmarking approach based on DES and DEA was presented using ED simulation model to generate different ED operation alternatives considering the available budget while DEA as a mathematical programming model is used to evaluate the relative efficiency of decision making units. The authors concluded that their approach consolidates the benchmarking sets and provides better references when ED efficiency is considered.

[Ahmed and Alkhamis 2009] developed a DES model combined with optimization techniques to investigate the operation of an emergency department (ED) unit at a governmental hospital in Kuwait. Patients arriving at the ED are classified into 3 categories according to their conditions. The optimization problem aiming at maximizing patient throughput has been represented as a discrete stochastic optimization problem with two deterministic constraints and one stochastic constraint. The authors concluded that the designed decision support tool is to help decision makers

at the hospital to either evaluate different situations of staffing distribution or optimize the system for optimal staffing distribution.

[Ozcan et al. 2011] combined DES model with optimization methods to study the allocation of scarce resources in a surgery department. The simulation model considers the flow of patients going across the system as they compete against the same common resources of the specialty such as personnel, beds, and operating theatres while the optimization model generates optimal Operating Room (OR) allocation plans. The DES model and the simulation output were used as model input data for the optimization.

[Yeh and Lin 2007] presented a simulation model combined with a genetic algorithm (GA) to address nurses' schedule problems at the emergency department (ED) of Show-Chwan Memorial Hospital in Central Taiwan. The simulation model takes into account processes such as triage, insurance procedures, doctor's clinical care, diagnostic, laboratories, recovery rooms, and respiratory therapy. The simulation model was developed using eM-Plant while the GA was developed by the simulation language, SimTalk.

[Person and Person 2009] developed a DES model integrated with optimization technics that considers both medical and economic constraints for surgery management decisions. The simulation model takes into account patient arrival, patient and operating room scheduling, and resource allocation related to surgery over time while the optimization model deals with the scheduling of surgeries based on medical priority, time spent in the queue and available resources such as operating rooms, surgeons, post-operative beds.

3.5. Conclusion

We present in this chapter a literature review on healthcare simulation starting with some taxonomies commonly used in healthcare and publications that most often focus on unit specifics like outpatients, inpatients and emergency departments. Following that, we discussed specific aspects corresponding to simulation problems in the literature. Such aspects include but are not limited to health resource allocation - scheduling and patient flow, sizing and planning of beds, rooms, and staff-, patient flow, population dynamics and intervention measures for disease outbreak control that are more often modeled in isolation. We highlight research efforts that dealt with commonly used modeling paradigms like systems dynamics, petri net, and agent based modelling in the literature. Simulation paradigms such as discrete event simulation, continuous, and hybrid simulation were likewise discussed. Modelling and simulation based healthcare systems analysis approaches that use simulation combined with other methods to study problems related to healthcare management were also considered.

From what we discussed, we argue that there is a need to provide a simulation base study framework that could reliably specifies the various aspects of healthcare systems as an integrated whole while reflecting at the same time how these components interact among themselves. Such a framework will definitely serve as a foundation for measuring its performance in terms of efficiency, effectiveness, and ability and achieving equity between populations. This concern is the main objective of our thesis and will be addressed in the following chapters.

Chapter 4
MULTI-PERSPECTIVE APPROACH TO HEALTHCARE SYSTEMS MODELING AND SIMULATION

This chapter presents a multi-perspective approach to Modeling and Simulation (M&S) of Healthcare Systems (HS) such that different perspectives are defined and integrated together with the interactions that exist among them. Most often, simulation-based studies of HS in the literature focus on specific problem like resource allocation, or disease propagation. In the context of HS M&S study, we refer to the scope of an approach as the extent to which it covers the different perspectives of the domain. In the current context, a single-perspective simulation approach – as reported in most of the cases in the literature review – refers to a simulation study focusing on specific healthcare problems. A multi-perspective approach refers to the concurrent studies taking into consideration two or more perspectives of HS and their interactions at the same time such as associating the study of resource allocation with disease outbreak within an area. The contributions of this thesis are specifically in the multi-perspective modeling approach of HS. To the best of our knowledge, it is the first effort to investigate HSs through multi-perspective modeling and simulation where different aspects of healthcare are captured by different views within a single model. Hence, modelling HSs becomes more practical and richer with deep insights. Since healthcare systems M&S is nothing but a domain-specific application of M&S principles, it is noteworthy here to state that both approaches may use one or more formalisms and their underlying M&S paradigms.

We first lay the basis of our approach with an ontology for healthcare systems M&S. Based on that, we secondly suggest a modeling framework of four perspectives that can serve to develop

models at each level of abstraction and couple them. Consequently, a top model within each of the perspective is coupled with its experimental frame to run simulations and derive results. Perspectives are identified by the categories of questions that the corresponding experimental frames can allow to answer.

The rest of the chapter is organized as follows. Section 1 discusses multi-perspective modelling approach to HSs followed by section 2 that presents ontology for healthcare M&S. Section 3 presents model abstractions in HSs while section 4 emphasizes on abstraction stratifications in HSs and the interactions that exist between them. Section 5 presents model based, a repository of the implementations of the models and section 6 concludes the chapter.

4.1. Multi-perspective Modelling of Healthcare Systems

Being composed of concurrent, fragmented and diverse components interrelated with intricate processes, modeling the domain of healthcare will require the understanding of the behavior of the overall system [Barjis, 2011]. Decision-making concerning questions related to the performance of HS - such as the extent to which the system achieves its mission - have no clear or simple answers while the need to produce more with less resources despite the scarcity is becoming a widely acknowledged concern among policy-makers and healthcare managers worldwide [Shin et al. 2013]. As a result, simulation based studies dedicated to HS have increased considerably over the last decades. Specific research efforts focusing on specific aspects of HS are numerous in the literature. However, they are more often narrowed into specific health units while rendering their reuse and understanding difficult if not impossible for a holistic simulation approach of HS. Different aspects are regularly addressed using different modelling and simulation technics. Such

aspects include patients flow, allocation of scarce healthcare resources, and healthcare intervention during disease outbreaks. Daily management activities such as resource allocation and planning - bed allocation, room planning, materials handling, and physician and healthcare staff scheduling - patient flow, and admission control are challenging tasks faced by healthcare managers overseeing different health units. More specially, allocating scare resources is a difficult task due to an increasing demand of healthcare services from various units such as emergency department, outpatient unit, inpatient and admissions unit, specialist clinics, and hospital departments like laboratory, radiology, surgery and recovery, pharmacy, and supply and support.

While healthcare managers are under financial pressure to deliver quality care with wide access that can meet the demand of health, questions such as how to improve health performance factors in a way that the volume of patients that can be taken care of can match resources supplied have not found convincing answers. Such performance factors are related to capacity planning due to resource constraints and patient flow like patient waiting time, resource scheduling of medical doctor, nurse, and health service costs, workload and pressure on health units staff. Demand for healthcare services is generated by care users from the population and includes different health phenomena like cancer, diabetes and infection diseases that are influenced by demographic factors such as immigration, emigration, death and birth. Simulation based studies related to disease outbreak that occurs in the population seek to address challenges of investigating on disease characteristics within human body due to human behavior and disease transmission between people for containing the spread of the infection. Consequently, studies related to disease outbreak include public health interventions that are comprised of pharmaceutical interventions such as

antiviral treatment and vaccination and non-pharmaceutical interventions such as social distancing, hand wash, and face mask.

The diversity of healthcare components and the complex relationships that exist between them impose the limitations of understanding the overall system as an integrated whole. We argue that a viable approach to address the challenging problem of healthcare systems management is a multi-perspective modelling. We propose to investigate the domain of healthcare system through multi-perspective modeling and addresses the challenges that come with modeling such a complex system. Multi-perspective modeling allows constructing distinct and separate models from different aspects of healthcare system for a better understanding of its complexity. Furthermore, an integrative approach based on live updates of output-to-parameters translation is developed to allow the simulation output of a model of a given perspective to update the simulation parameters of another perspective dynamically. Arguably, a closer representation of the real situations can be achieved if these parameters are systematically modified at runtime in such a way that the outputs of the simulation models corresponding to different perspectives provide live updates of their parameter(s) in concurrent simulations. This will be discussed in details in the next chapter.

Modelling complex systems such as HSs characterized by a large number of components that are diverse while interrelated with complex processes is a challenging task since the interactions between the different components are more often uncoordinated and semi-autonomous where each health unit is focusing on its own activities. At the same time healthcare systems also operate as an integrated organization, e.g., a care requested by a patient may depend on more than one specialty. This makes the collaboration between health units even tighter. In such case, to

understand the behaviour of the overall HS, one of the common ways is to impose on them a hierarchical design by separating the different subcomponent parts representing the different healthcare aspects and define relations between them in a common simulation framework [Seck and Honig 2012]. While different aspects of HSs are modelled at micro level with focus on specific problem, an ideal solution is to model the entire system at the macro level as large loosely coupled and distributed system of systems. As such, we model HS as a set of sub-systems that are linked to one another with a coupling structure [Zeigler 1976].

Multi-perspective modelling approach has been successfully adopted by a lot of research works where distinct models are constructed to model the same system and each model focuses on the particular aspects of that system [Reineke and Tripakis 2014], [Seck and Honig 2012], and [Tekinay et al. 2010]. Hence, multi-perspective modelling of HS is more relevant to improve the understanding of its complexity and allows overcoming the limitations of single-perspective modelling that encompasses all different views within a single model. More practically, multi-perspective modelling of HS provides a richer way of studying its complexity that results from the observation through different perspectives and the corresponding influence that each sub-system exerts on its counterpart. Such influences are remarkably seen between different health units where the allocation of scarce resources becomes a competing factor affecting patient needs during their medical care pathways.

We describe HSs through a disciplined stratification of concerns where each layer focuses on a particular problem. We base our argument on multiple layers of healthcare aspects representing various problems in healthcare simulation. These aspects regroup a family of models that describe

specific concerns in healthcare simulation such as allocation of scarce resources associated with patient flows, demand generated by the population, and human behaviours in disease outbreaks. Consequently, we view HSs as a collection of perspectives as depicted in Figure 4.1. Different perspectives are shown, perspective1, perspective2, perspective3,…, perspective n, being each associated with a unique healthcare aspect. These perspectives are described by the positions from which one looks at healthcare systems as indicated by arrows from the current positions of the viewer.

Figure 4.1 enables us to look into HS with multiple views and derive different explanations of the same system. When we look from the top of Figure 4.1 following the arrow pointing down through a downward motion, we perceive a stratification of layers different from one another describing each a specific problem of healthcare domain. Each of the perspectives can represent a family of questions that one may want to answer according to the objective of the model. Similarly, a look from the bottom of the figure using the arrow pointing up through an upward motion describes a set of views that are all different while describing the same system under study which is still the healthcare domain. The arrows from the left to the right and from the right to the left give us a clear idea on the concept of separation of concerns that are more often addressed in healthcare simulation with focus on specific problems and specific healthcare units. As such, modelling HS using multi-perspective modelling is more practical and suitable for the understanding of the overall system as well as for the integration of those perspectives to form a complete whole.

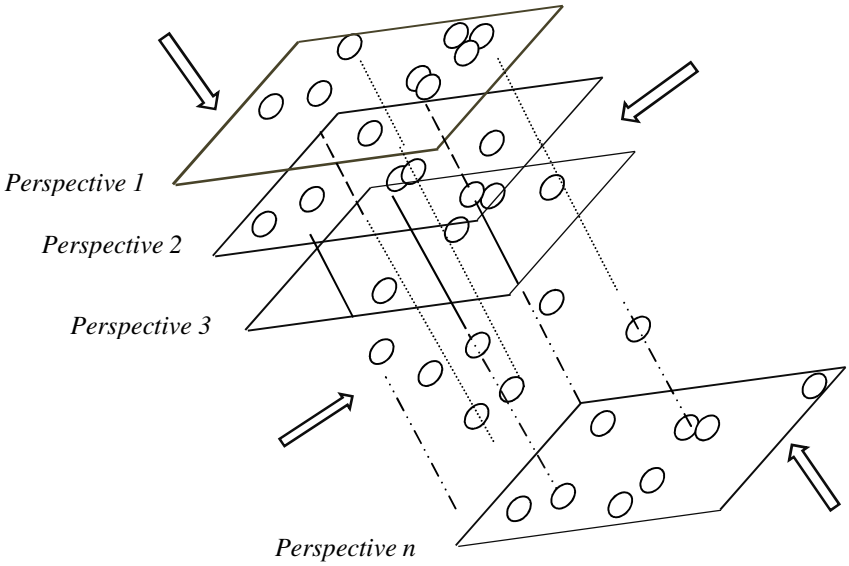


Figure 4.1. Multiple perspectives of HSs.

4.2. Ontological view of Healthcare Simulation

When developing an ontology for HS, it is essential that we provide, at some general level, a framework that captures all the knowledge that might be in the range of healthcare domain that the ontology is likely to be used for [Partridge et al 2013]. Consequently, based on an extensive literature review, we have built an ontology to capture and share a common understanding of knowledge available in the range of healthcare M&S. We adopted a useful way to begin building this ontology by surveying existing taxonomies of healthcare models as offered by [Brailsford 2007], [Gunal and Pidd 2010), and [Roberts 2011], and we used the System Entity Structure Model Base (SES/MB) [Zeigler 1984] framework to formally express it.

Figure 4.2 presents the SES hierarchy of the ontology. SES/MB provides an ontological framework for knowledge representation of decomposition, taxonomy and coupling of systems. We use SES Ontology for the specification of a set of various healthcare system structures and parameter settings while the MB repository is used for storing basic models describing the dynamic behaviors.

The systems entity structure (SES), presented in chapter 2, is known as a support to development, pruning, and generation of a family of simulation models [Zeigler et al. 2013]. While complex systems such as healthcare systems are composed of large components with complex relationships, their structural knowledge can be broken down and systematically represented in SES and having their behaviors specified in either atomic or coupled models and saved in model base, an organized library for later use. Once the models are saved they can be retrieved from their repository and reused to design complex systems. Hence, through SES/MB we can organize a family of alternative models of healthcare systems from which a candidate model can be generated, selected and evaluated through system design repeatedly until the model meets an acceptable objective. Additionally, combining multiple aspects in a single family of SESs provides different explanations associated to an unlimited number of simulation models to work with all together as a whole. Based on the principle of plan-generate-evaluate process in simulation-based systems design, SES/MB also enables us to develop a complete software cycle for healthcare domain. As such, at the plan phase all the key concepts in healthcare simulation are captured according to the intended objectives of the modeler while at the generate phase a library of models are built and stocked in the model base repository to reproduce a candidate design model that will meet the initial objectives. Such candidate model may encompass a family of aspects representing various

concerns in healthcare simulation while at the evaluate phase, those candidate models that have been generated are assessed through simulation based on their performances. This feature allows us to develop healthcare models that are easily understandable by domain experts and most likely reusable in a larger community of healthcare simulation.

The developed Ontology for Healthcare Systems Simulation (O4HS) is a real-world semantics and a formal specification of the core concepts and their relationships in healthcare domain, for capturing modelling knowledge in a reusable and interoperable manner. We hope that O4HS will be useful to researchers, domain experts, and software engineers to share a common understanding of the concepts and their relationships in healthcare simulation while its application will allow facilitating modeling components, meta-modeling as well as multi-perspective modeling of healthcare systems. Hence, it is hoped that O4HS will become a standard effort for modelling HSs while being both useful in itself and an illustrative ontological foundation for other fields that are developing ontologies for their subdomains. Let us now introduce the O4HS in a stepwise fashion way, starting with high-level concepts and then gradually adding concepts related to lower levels of consideration.

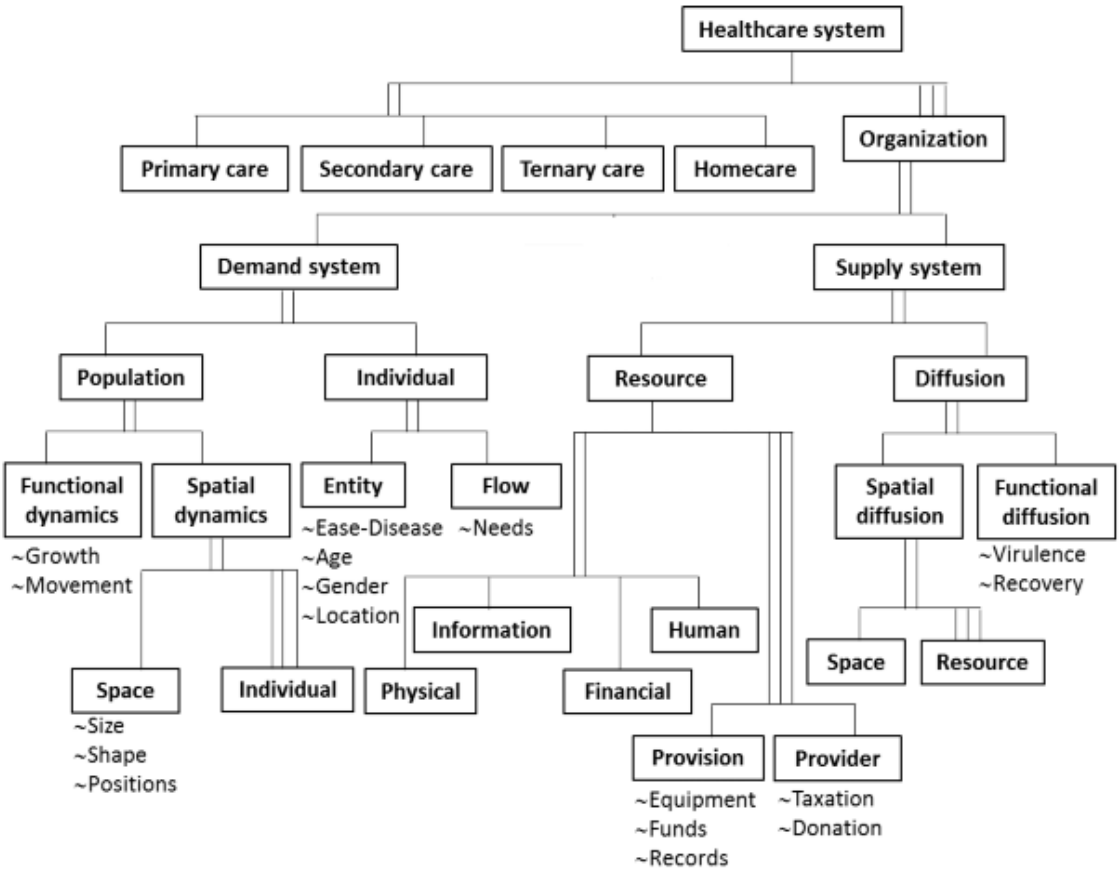


Figure 4.2. Ontology for healthcare systems M&S

4.2.1. Healthcare Systems Hierarchy

Healthcare systems are composed of organizations and health providers at different levels of care including primary care level, secondary care level, tertiary care, and home and community care level.

A primary care level can be a clinic, a practitioner office or a primary care center and is known as the first point of consultation of patients within the healthcare system. Health care professionals at this level are general practitioners, family physicians, and non-physician primary care providers

such as assistants to physicians and nurses, who operate in multiple settings like primary care center, provider offices, clinics, schools, colleges, prisons, and worksites. However patients may be referred for secondary or tertiary care depending on the nature of the health condition.

A secondary care level is a hospital providing necessary such services as acute care treatment for a brief but serious illness, injury and other health condition to patients in healthcare units like emergency departments. This level of care also provides services such as skilled attendance during childbirth, intensive care, and medical imaging services. Health professionals working there are medical specialists including cardiologists, urologists and dermatologists.

Tertiary care level is an advanced referential hospital that provides specialized care services mainly for inpatients referred from health professionals of primary or secondary health centers. Those services include cancer management, neurosurgery, cardiac surgery, plastic surgery, treatment for severe burns, advanced neonatology services, palliative, and other complex medical and surgical interventions.

Finally, home and community care level provides care interventions of public health interest such as food safety surveillance. Services provided at this level also include the distribution of condoms and needle-exchange campaign for the prevention of transmissible diseases, usually outside of health facilities, services in support of self-care, home care, long-term care, assisted living, treatment for substance use disorders and other types of health and social care services.

4.2.2. Healthcare Organization

We present a higher level of O4HS ontology by abstracting healthcare organization into its core concepts: demand system and supply system. While healthcare demands grow increasingly, its supply however remains limited due to the scarcity of healthcare resources. Nowhere in the world is there a healthcare system that devotes enough resources to meet up with all demands of healthcare of its people. As such, we suggest to explore the domain of healthcare using demand and supply system considering the various constraints surrounding the provision of the expected care. As a market brings together demand of goods from consumers and its supply by suppliers, in this actual context, healthcare is mainly demanded by a population to improve health while its supply deals with how resources, costs and services are related to each other within a productive process. The provision of healthcare can be regarded as a process by which resources such as personnel, equipment and buildings, land and raw materials are transformed into services. However, demand for healthcare is driven by individuals in the community. Such demand is referred to as the amount of care a population needs and can be evaluated in terms of inpatient admissions with a high number of admissions indicating a high demand for a service, for example a high number of admission seen in an aging population. Another factor of demand is hospital catchment population that reflects the number of people who fall within the catchment area of a healthcare provider such as a clinic, healthcare practitioner office, or hospital. Consequently, demands expressed by patients who seek such care will be evaluated based on factors such as distance from the patient household to the service provider, ease means of access, quality of care and cost of care. Furthermore, average length of stay is also considered in how healthcare demand is estimated, for example in case of good discharge planning the corresponding demand maybe more while it is less in case of poor discharge planning when some scare resources are still in use.

An illustrative example of the concepts presented in Figure 4.2 is the allocation of health resources as intervention measures to control the spread of disease in a given population. In this case the labor time of healthcare practitioners and the resources being allocated represent the supply of care while the disease being propagated prompts demands of healthcare from individuals of that population. A campaign of vaccination can be seen as the productive process that combines resources to produce the expected service which in return impacts the outbreak by reducing the illness attack rate (attribute). Likewise the illness attack rate affects the allocation of the resources by consuming or reducing those resources.

4.2.3. Supply System

The supply of healthcare consists of health resources dedicated to meet up with health phenomenon diffusion – processes. Healthcare supply includes many different things such as labor time of various trained professionals: general practitioners, specialists, nurses, consultants, managers, medical technicians, pharmacists, and many others. Healthcare supply takes into account procedures and testing, like magnetic resonance imaging (MRI) scans and laboratory analyses, operating theatres, pharmaceutical products, ability to manage waiting times, and budget like surplus, debt, available funds for investment, and other source of income.

Core processes in healthcare are: clinical processes, educational processes, research processes and environmental processes. Clinical processes are carried out through activities of healthcare professionals on subjects of care (patients) by which policies and plans are translated into the interventions of the public health system. Educational processes consist of mobilizing and educating communities. Through research processes practitioners seek to identify causes for health

problems in the population. Environmental processes refer to contamination outbreak surrounding a given population.

Resources in healthcare and their relationships are necessary to carry out the important processes involved in service (care) provision. A resource can be human, information, financial (fund) or physical. An information resource can be a patient medical record such as laboratory report, medical history or clinical record. Reliable information is crucial to health planners and decision-makers in formulating their policies and regulations. Such policies include personal health care policy, pharmaceutical policy, vaccination policy, tobacco control policy and breastfeeding promotion policy. Regulations concern prices and the use of public health facilities for private purpose. Information resources are also used to evaluate the performance of healthcare in terms of availability, accessibility, quantity and use of health services, responsiveness of the system to users' needs, financial risk protection and health outcomes. These outcomes can be seen in multi-dimensional perspective and they are grouped in three major categories: clinical outcomes, patient reported outcomes and economic outcomes. Clinical outcomes refer to mortality, morbidity, intermediate clinical outcomes, symptom, and clinical events. Patient reported outcomes are health status such as pain, vitality, perceived well-being, health risk status, as perceived by the individual. Economic outcomes consist of health service utilization and cost per episode of care. However, hospital records are the bases for statistics on performance related to inpatient activities. These records include the number of beds, admissions, discharges, deaths and the duration of stay, while outpatient records are the bases for utilization data. Health human resources are all people who provide healthcare services. Progress towards national health systems performance depends on health human resources defined as one of the core building blocks of

health systems. Human resource can be generalist physician or specialist physician, nurse, dentist, pharmacist, allied health profession, community health worker, social health worker and other health care provider, as well as health management and support personnel such as health service managers, administrators, health information technicians, medical laboratory technologists, health economists, health supply chain managers, medical secretaries, and others. Physical resources represent healthcare facilities like building, drugs, furnishing and equipment known also as supply. A physical resource can also be a room such as operating, waiting or emergency room.

Health resources are composed of provision and provider. Health provision is described by equipment, fund and records. Health provider is characterized by health financing which accounts for one of the largest areas of spending for both governments and individuals in the world. Healthcare systems are composed mainly of five sources of funding including general taxation, social health insurance, private health insurance, out-of-pocket payments – incomes-, and donations to charities. While healthcare is seen as a fundamental commodity that is essential to people well-being, its demand however can be limited by financial constraints such as poor income. Health insurance is provided through social insurance programs or private insurance companies to pay medical expenses for coverages like disability, long-term nursing and custodial care needs for insured people. In such case, the person having health insurance will have to pay a price that is much lower than the normal price of healthcare. The demand of healthcare is also known to be relatively inelastic, that is, a person who is sick does not have other choice than to trade off spending on other things just to purchase the medical care he needs. Such person can even be bankrupted as reported often in some countries. Health insurance may also be obtained based on employer and employee mandate in which case an employer must procure health

insurance for its employees and their dependents. Under the individual mandate, workers are obliged to purchase health insurance either from private insurance, or religious groups and the poor are subsidized in their purchases through government taxation. A donation refers to a gift such as cash offering, services, new or used goods like clothing, toys, food, and vehicles given by physical or legal persons for purposes of charities in order to benefit the health of a population.

One of the areas that health system expenditures increase remarkably these last decades is wage costs. While health system expenditures consist of investing in people, building and equipment, wage costs represent approximately 65% to 80% of renewable health expenditures in most countries. As such, healthcare systems are composed of three ways of paying healthcare practitioners: fee for service, capitation and salary. General practitioners (GPs) are paid based on services provided in case of fee-for-service arrangements while in capitation payment systems, GPs are paid for each patient registered in their list based on factors such as age and gender. In case of salary mode of payment, governments employ and pay general practitioners (GPs) on salaries basis.

4.2.4. Demand System

Health demand is either generated by a population – in case of an outbreak- or an individual – a care seeker- in time of needs. Healthcare seekers can be military communities, civil societies, ageing population, or pregnant women. A Population is characterized by either functional dynamics or spatial dynamics. Functional dynamics includes growth rate and movement of the population subject to demographic flows such as immigration, emigration, births, and deaths. Spatial dynamics refers to space with its coordinates - size, shape and position-, and individuals.

While an individual can be soldier, employer, employee, unemployed, and even health worker, he is described as an entity with his medical flow. During a medical journey, processes under which an individual undergoes are referred to as flows and they reflect the amount of resources that will be used to meet his needs. An individual has a behavior characterized by factors such as diet, smoking habit, alcohol use, sexual activity, education level and income level. Each individual – entity- is described by his personal data such as social security number, age, gender, location, and insurance coverage while having a health state at a particular date. Hence, his health state can be affected by health issues such as disease -infectious or non-infectious disease-, injury, mental or sensorial disability and pollution -air pollution, and water pollution-. An individual has a medical record -information resource- that covers his name, weight, height, temperature, care need. He has a lab report with properties like proposed test, status and date. He has his parent medical history as well as his own medical history including complaints and dates. Finally, he has his clinical record showing complaints such as symptoms, diagnosis and treatment plan reflecting all the clinical processes he went through.

In the following section, we present a modeling framework derived from O4HS that can serve to develop models at each level of abstraction and couple them together to form an integrated whole.

4.3. Healthcare System Model Abstractions

From what we discussed so far, it becomes obvious that the domain of health is a complex field with multiple ramifications. As such, the main challenge of healthcare simulation is the understanding of the interactions between different components, the separation of the levels of

abstraction and their specifications in a common simulation framework. We present the levels of abstraction in healthcare systems with the relationships that define the interactions between them in order to simulate healthcare system as an integrated whole.

4.3.1. Stratification of Abstractions in Healthcare Simulation

Along with the SES-based ontology, we have identified the categories of healthcare problems studied in the literature. They fall into 4 perspectives (as presented by Figure 4.3), each encompassing a family of questions that can be formulated through experimental frames (Zeigler, 1984) with which models are coupled to derive answers. They are comprised of:

(1) Resource Allocation (RA) perspective. It encompasses all scheduling and planning problems, mostly in the context of limited resource provisions (as beds, rooms, medical records, doctors, nurses, funds…), to meet the healthcare demand.

(2) Health Diffusion (HD) perspective. It covers simulation studies of contagion spreading, whether positive (like information or vaccination), or negative (like disease or panic).

(3) Population Dynamics (PD) perspective. It comprises all studies of the dynamics in the population of a community (immigration, emigration, birth, death…).

(4) Individual Behavior (IB) perspective. It covers the studies of social behavior in relation to how its components (such as educational level, physical state, emotion, cognition, decision…) affect the willingness/ability of individuals in a community to effectively access available healthcare services.

Figure 4.3 shows that we place this stratification of abstractions in the context of the hierarchy of systems specification introduced by [Zeigler 1976]. Consequently, models can be developed within each perspective and coupled together. The resulting top model in each perspective can be

coupled with its experimental frame to derive results specific to this perspective. The stratification of perspectives (and thus of M&S objectives) provides multiple levels of explanation for the same system, while modelers are assisted in selecting suitable model components from the Model Base introduced in the next sub-section (or in deriving new ones from existing models).

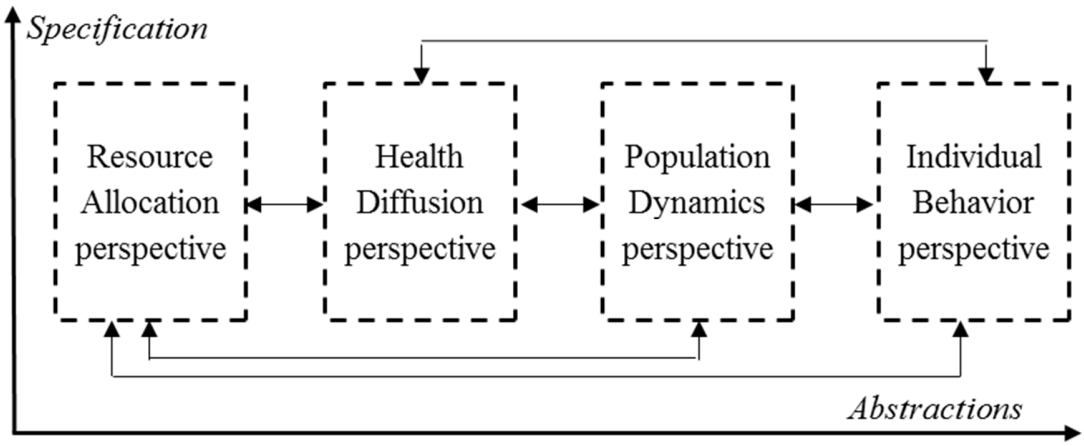


Figure 4.3. Multi-perspective framework for holistic M&S of healthcare systems

To facilitate a holistic simulation study of healthcare systems, which encompasses both the isolated simulations in the four perspectives and their influences on one another, we have defined an integration mechanism to enable live exchange of information between concurrent simulations in the different perspectives. More details on this topic will be given in the next chapter.

4.3.2. Foundational and computational specification for Healthcare

Being fragmented, uncoordinated and loosely coupled with multiple component systems that are interrelated with intricate processes, HS is doubtless a complex system rendering difficult to achieve the expected common objectives of healthcare managers while seeking to improve the

overall healthcare service performance. Hence, HSs require a modelling and simulation method directed to the whole system. We consider HS as a hierarchically structured system that is composed of interrelated subsystems [Simon 1962]. As such, a system of system modelling approach that would evidently provide useful knowledge on how HS performs at the holistic level rather than focusing on specific problems in isolation for specific solutions is an appropriate means to address its complexity.

A system of systems is referred to as multiple, heterogeneous, distributed, occasionally independently operating systems embedded in networks at multiple levels, which evolve over time [Eusgeld et al. 2011]. In a systematic view, a system of systems approach supports the modelling of large loosely coupled distributed system of systems that target the optimization at the macro level which is the entire system itself instead of the micro component system level. However, it is a challenging task to model such complex systems and one has to carefully choose the levels of abstractions that fit into the holistic view of the entire HS in order to gain multiple explanations and more efficient computational results. To this end, we adopt the hierarchy of system specifications with the discrete event system specification (DEVS) [Zeigler 1976] as a computational basis and the SES/MB to more practically model the whole system at different levels of system organization. DEVS formalism rooted in system hierarchy specification represents a systems as DEVS atomic models that can be coupled together to form an abstraction network that is able to answer a number of questions about the whole system behaviour. Using SES/MB we can organize a family of alternative models of healthcare systems from which a candidate model can be generated, selected and evaluated through system design repeatedly until the model meets an acceptable objective. Such family of alternative models allows maintaining a

multilevel view of a system while permitting stakeholders to observe system output at several abstraction levels. Thus, we could have the very same system under study, HS, being specified and modelled simultaneously at each of the different levels. The hierarchy of system specification provided in the theory of modelling and simulation characterizes different elements at different levels ok knowledge including, observation frame (OF), input/output relation observation (IORO), input/output function observation (IOFO), input/output system (IOS), and coupled system specification (CSS). We base our modelling at the CSS level where components at lower levels are coupled together to form a generative system and the resulting top models are integrated together through model output to input parameter from their respective experimental frames to form an integrated whole in a concurrent simulation.

In Figure 4.3, the vertical axe represents the level of specifications and the horizontal axe shows the different abstractions in healthcare simulation. These level of specifications allows a complex system to be broken down repeatedly until some lowest level of elementary parts referred to as DEVS atomic models while through hierarchical design, we impose on HSs the separation of concerns and understand in a better way the intricate relationships that exist between them.

In Figure 4.3, the allocation of healthcare resources perspective and the health diffusion perspective influence each other during concurrent simulation such that the former affects the latter through health services like clinical and non-pharmaceutical interventions and the later affects the former through public health concerns like chronic ailments like cancer, hypertension and diabetes or disease outbreak. Likewise, the population dynamics perspective is affected by the resource allocation perspective. For example, when we consider factors such as geographic regions and

subpopulations, the allocation of resources such as deploying healthcare units or training more healthcare workers – human resources- have a significant effect on access to healthcare services. Similarly, human resources are integral part of population and determine the service capacity, and the number of health practitioners required even in long-term planning, thus affecting in return the allocation of health resource. The individual behavior perspective such as educational level, physical state, emotion, cognition and social status influences the allocation of health resources as well. For example, the resources that are allocated for patients screening are consumed or not based on patient daily attendance behavior. Such behaviors are commonly found with elderly people coming for screening and timely treatment that can allow them to have long and safe lifestyle despise their cognitive or educational limitations. The flows of individual patients around the system determine also the capacity planning, resource allocation and process redesign for identifying and eliminating bottlenecks. Health diffusion perspective influences the population dynamics through health factors such as local birth-death process, replenishment of susceptible individuals via the loss of immunity, and random immigration. As a result, human populations with close physical interactions contribute massively to the disease spreading. In return, a certain portion of the population that decides to seek for medical treatment or other medical interventions during an outbreak event can change the disease dynamics. Individual behavior perspective influences the disease spread through behavioral factors also known as risk factors such as needle-sharing, condom use and number of sexual partners during epidemic spread like HIV/AIDS. Poor sanitation and housing conditions are also risk factors from individual behaviors that can easily contribute to disease outbreak like cholera outbreak. Finally, population dynamics perspective is influenced by individual behavior factors that can lead demographic changes such as mortality, birth, immigration and emigration.

Hence, the idea of the multi-perspective modelling of healthcare systems is to adopt a holistic approach through concurrent simulation in such a way that the transmissions of the outputs of the simulations in one perspective provide live feedbacks to the simulation parameters in other perspectives. In this way, we provide a closer representation of the real situation that would help to capture interactions between seemingly independent concerns and the effect of such interactions in simulation results. Most often, simulation-based studies of HS in the literature focus on specific problem like allocation of resources, disease propagation, and population dynamics that are studied with constant parameters from their respective experimental frames throughout the simulation. The next chapter provides more details on the proposed idea of the integration.

4.4. Model Base

SES/MB introduces two mechanisms to allow interactive or automatic generation of an executable simulation model: the Model Base (MB) and the pruning process. While the MB is a repository where basic models (i.e., entities of the SES tree) with a predefined input/output interface are organized, the pruning is the process of extracting from the SES tree a specific system configuration (called PES for Pruned Entity Structure), resolving the choices in Aspect, Multi-Aspect and Specialization relations (i.e., selecting particular subsets of Aspects, cardinalities of Multi-Aspects, and instances of Specializations) and assigning values to the variables. We are implementing in the MB for healthcare systems M&S, a large spectrum of DEVS-based parameterized theoretical models, organized along the stratification of abstractions proposed in our framework. This includes SIR [Kermack and McKendrick 1927] and its derived SEIR, SIRQ, MSEIR… models [Hethcote 2000] for the HD perspective, Prey-Predator [Voltera 1931] and

cohort-component models [Leslie 1945] for the PD perspective, Queueing theory models [Gelenbe and Pujolle 1987] for the RA perspective, and agent-based models [Fishbein and Ajzen 1975] for the IB perspective.

We regard HSs as a collection of perspectives that are each associated with a unique system component and highlight some key contributions of the thesis as follows:

- It offers to the modeller, through separation of concerns, a clear view on perspectives like patient flow optimization and analysis, healthcare resource allocation, and disease outbreak control that are most often intertwined [Gunal and Pidd 2010]. In this paper, the different concerns are separated into four generic perspectives for a holistic view of HSs modelling.
- It proposes a multi-perspective modelling approach of HSs to overcome the problems of single-perspective modelling used in solving problems in individual HS units like outpatient clinics, A&E, and Inpatient facilities, as well as facility specific problems. The proposed approach presents a broader view on healthcare modelling including various perspectives than the ones proposed by [Charfeddine and Montreuil 2010] that dealt specifically with population and healthcare delivery network perspectives.
- It presents a novel approach for integrating the isolated perspectives in HSs based on dynamic update of models output-to-parameter integration during concurrent simulation contrary to the classical models coupling through outputs and inputs interfacing of simulation models [Zeigler et al. 2000] with parameters that are usually assumed to be constant throughout the simulation.
- It provides a DEVS-Based formalization of the loose integration of the different perspectives, and its realization. DEVS formalism is chosen because it is universal for discrete event simulation as proven by [Vangheluwe 2000]. This solution differs from the

one proposed earlier by [Seck and Honig 2012] that represents the dynamic parameters as input ports that are coupled to the respective sources of live feedbacks. Furthermore, concrete implementations of both aspects are provided while to the best of the authors' knowledge these aspects have not been addressed both together before.

As depicted in Figure 4.4, the idea is to follow the plan-generate-evaluate process employed in simulation-based systems design. HS structure is represented in the System Entity Structure base called O4HS previously discussed in Section 2. The components are separately implemented and saved in organized libraries called model base. The model base encompasses a collection of different perspectives in healthcare including RA perspective, HD perspective, PD perspective, and IB perspective being each a family of models from which a candidate model can be selected. Thus, the plan phase enables us to define the set of objectives, the generate phase provides a synthesis of a candidate design model to meet the design objectives and the evaluate phase evaluates the performance of the generated model within its experimental frame to derive useful results. The overall cycle is repeated until we get a satisfactory design.

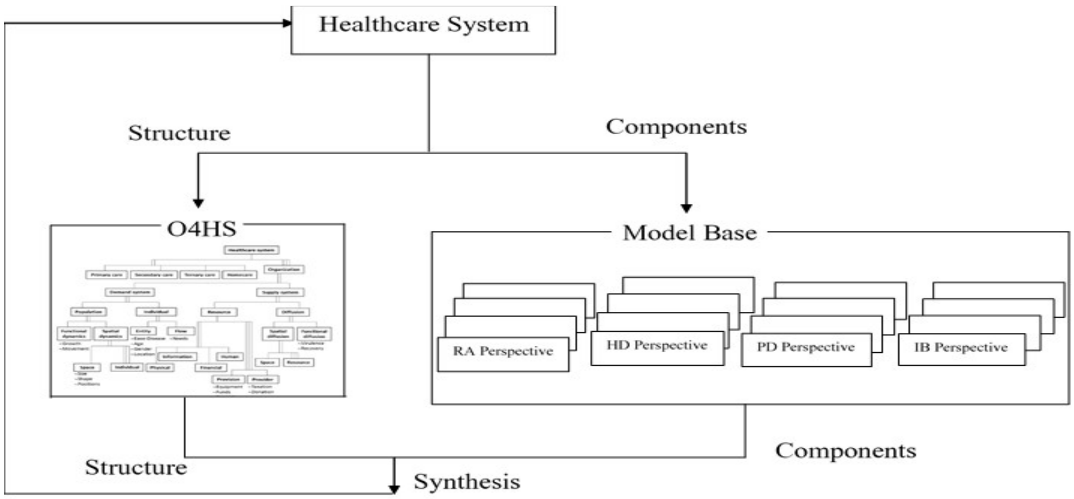


Figure 4.4. SES/MB for HSs Simulation

Figure 4.5 shows the construction of the MB library implemented in a Java written DEVS simulation protocol. More details concerning the pruning mechanism and the resulting DEVS-based parameterized theoretical models will be given in the following chapters.

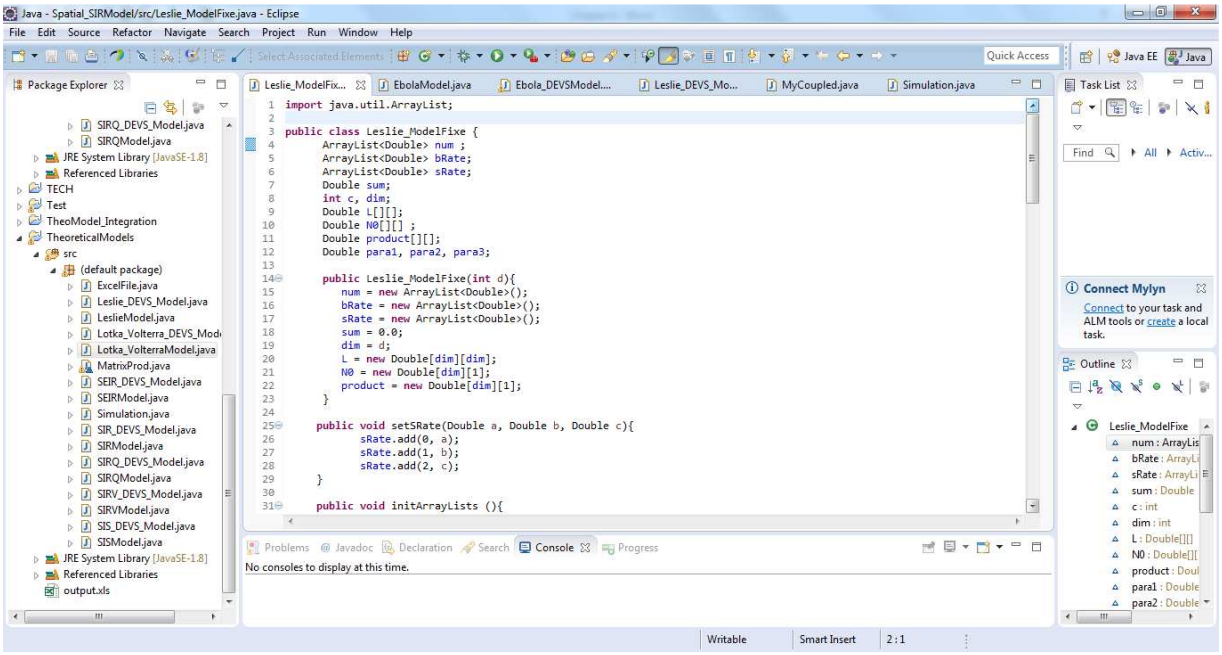


Figure 4.5. Excerpt View of MB

4.5. Conclusion

This chapter proposes a multi-perspective modelling for systematic integration of models of HS that allows live interactions during concurrent simulation. We first lay the basis of our approach with an ontology for HS M&S that is built based on an extensive literature review. The developed ontology captures and shares a common understanding of the knowledge available in the range of healthcare M&S. The novelty of the work is that it reveals the important and subtle intertwinement

of the processes of different HS perspectives, an aspect that is seldom considered in the usual practice of isolated studies of the different perspectives.

The chapter presents a disciplined stratification of major HS problems studied by simulation into four perspectives: resource allocation perspective, health diffusion perspective, population dynamics perspective, and individual behavior perspective. The usual practice is to study problems in each perspective in isolation with some constant parameters representing the influences of other perspectives; we took a slight departure from this approach arguing that, in reality, processes of all perspectives run concurrently and influence one another continuously. The different perspective can be modelled with different formalisms according to the objectives of the modeler and the nature of the system component under consideration. Theses aspects and the formalization of the DEVS-based theoretical models for the integrations of the perspectives will be addressed in the following chapter. It would also be interesting to apply this approach to simulation-based studies of non-healthcare domains like public traffic, defense, emergency evacuations, etc.

Chapter 5
HOLISTIC APPROACH TO HEALTHCARE SYSTEMS MODELLING AND SIMULATION

Modeling complex systems can be tedious not only because of a huge number of hierarchical subcomponents that compose them but also because of the complex processes that govern the relations that exist between them rendering their analysis and design more difficult. More specifically, complex systems like modern healthcare systems are made up of concurrent, fragmented and diverse components that are interrelated with intricate processes. To address the modelling of such systems, one way is to impose on them the separation of concerns while keeping a holistic understanding of the behavioural pattern of the overall system and its interaction with the surrounding environment. The separation of concerns allows analysing and designing properly different subcomponents that are latter integrated together to form a complete whole. Figure 5.1 depicts the idea of holistic modelling with different pieces of subcomponents, subcomponent 1, subcomponent 2, … subcomponent n, representing different concerns that are studied separately and joined together to form the whole system.

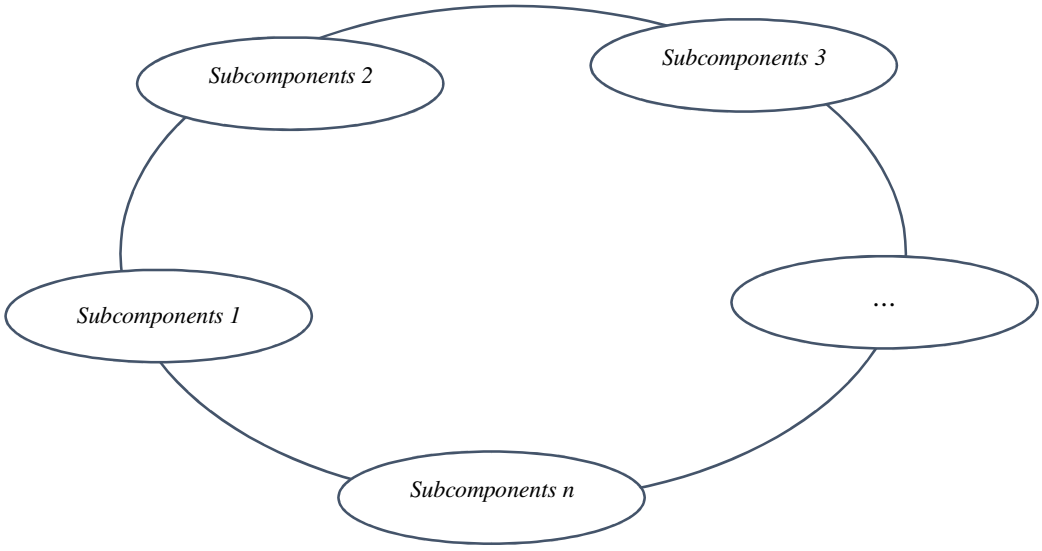


Figure 5.1. Holistic Modeling Approach of Complex Systems

In this chapter, we present an approach for holistic analysis of Healthcare Systems (HSs) based on the multi-perspective view on different aspects presented in chapter 4 and a systematic integration of simulation processes to form a holistic system. A lot of simulation-based research efforts can be found in the literature where HSs are studied with focus on perspectives such as the allocation of scarce health resources (like human resources and infrastructural facilities) to meet the needs of patients, disease spreading within an hypothetical community, and so on. The different perspectives are often studied in isolation with constant parameters as abstractions of the influences that the surrounding environment has on the composing subcomponents. We propose a methodology for a "loosely" integrated simulation where independent simulation processes of disparate concerns in HS exchange live updates of their influences on one another. We believe this approach will take the results obtained closer to the reality of the interactions between health phenomena and help stakeholders to gain a holistic understanding of the whole healthcare system while deriving more realistic decisions.

The rest of the chapter is structured as follows. Section 1 discusses the challenges of modelling healthcare systems followed by section 2 presenting the concept of experimental frame. Section 3 addresses the integration mechanism of the different perspectives then section 4 describes the formalization of the proposed idea. Section 5 concludes the chapter.

5.1. Healthcare Systems Modelling

HSs are complex systems of distributed subcomponents governed by complex health processes, inter-organizational workflow, and various services [Barjis 2011]. Applications of Modeling and Simulation (M&S) to HSs usually target specific aspects of healthcare problems.

Interestingly, simulation processes to address different healthcare problems are often done in isolation. Since in reality, the system under study exists amidst other systems and phenomena that may influence its internal processes, a common approach to model such influences is to represent them as parameters in the model under study to experiment with different hypothetical values of the parameters in separate simulation runs. For instance, in a simulation of the allocation of healthcare resources to tackle the spread of a disease in an environment, the model may include some parameters as abstractions of the levels of infections, awareness, migration, etc. in the community. Then, some hypothetical sets of values of the parameters are used for separate simulation runs to investigate the performance of the resource allocation. In reality, however, some (or all) of these coefficients could change within the period of each simulation run examined, thereby making the modeler's assumption about them obsolete. Conversely, a simulation model of the epidemic itself may contain abstractions mentioned previously including a parameter representing the level of healthcare resource allocations, which are all maintained constant for different simulation runs of the epidemic model.

The contribution of this thesis is to provide a more pragmatic approach that makes the results obtained as close as possible to reality. Therefore, we propose the parallel simulation of independent disparate models under different perspectives, whose outputs may influence one another, and to systematically transmit live updates and feedbacks between them. For instance, we may simulate the epidemic model concurrently with models that feed its parameters, i.e., resource

allocation model, migration model, etc., and allow them to reciprocally update the values of their parameters. This approach will result in more accurate forecasts of the effects of the interactions between the different components of HSs and their responses to issues. We provide more details on the proposal in the following sections.

We use the term "loose" integration between models in different perspectives of HSs to describe our notion of parameter integration and indicate that the simulations models involved are not tightly coupled together as is usually the case in the couplings between the ports of models [Zeigler 1976]. Rather, each model runs independently in its own experimental frame and provides an input and an output interface that change simulation parameters “lively”. While in traditional simulation studies, we are accustomed to maintain the simulation parameters constant throughout the experiment, the current approach considers the influences of such parameters on models from their respective experimental frames leading to change of parameter values but not change in the state variables of a system. The concept of experimental frame and model parameters are discussed in details in the next section.

5.2. The concept of Experimental Frame

The stratification of perspectives in healthcare systems presented in chapter 4 is done according to the objectives of the modeler for the system under study. We recall that each perspective encompasses a family of models that can be developed and coupled together and the resulting top models are respectively coupled with their experimental frame (EF) to derive specific results. We base our argument of the notion of “loosely” coupling between models from different perspectives from the EF point of view. In general, the condition under which a system is studied dictates the values of the simulation parameters and these values are at the core of the EF. For example, let us

assume that patient calls for getting appointment in a clinic for specialized care are based on Poisson distribution. However, due to the fact that appointments for specialized cares are usually tight, patient may end up waiting for more than the required date to be served if no alternative appointment is provided. In worse cases, the number of patient appointment calls can even increase based on the demand registered in the clinic while leading to the change of the arrival rates. Hence, we see that the values assigned to the simulation parameters can change but the current state of the system under study remains the same. Such change of data behavior is acquired through the influence that the environment has on the system through its experimental frame representing the interest of the modeler. We define in the next sub-section what an EF means and how it influences the system of interest.

5.2.1. Experimental Frame

In [Zeigler 1976], it has been highlighted four basic entities including source system, model, simulator, and experimental frame. These entities are held by two fundamental relationships that are the modeling relation and the simulation relation. The modeling relation is concerned with the activity of faithfully representing the source system as a model while the simulation relation is concerned with the activity of separating concerns between design and implementation levels. It is widely acknowledged that a model is known to be valid in M&S practice if it only fits into the purpose and the context for which it has been designed for. Although being useful, it may not answer questions outside the scope of its application. As such, the context of a source system is defined by its experimental frame that specifies the condition of the validity of a model. The source system is the real or virtual environment that is targeted to be modelled.

As introduced by [Zeigler et al. 1976], an EF is defined as a specification of the conditions under which the system is observed or experimented with. That is, the EF represents the operational formulation of the objectives that motivate the study of the modeler. It can also be viewed as the environment that surrounds the system under study. For example, when modelling healthcare units such as outpatient department, one can decide to focus on studying performance factors such as number of patients admitted per day based on beds that are available, human resource utilization like doctors, nurses and technicians, and waiting time. Another objective will rather be concerned to add the arrival rate of patients in the emergency department (ED) and seeks to understand how patients from the ED are sent to outpatient department to be admitted for the rest of care that they need, or how the flow of patient within healthcare units affects the scheduling of health resources. As such, a modeler can formulate many EF for the same system under study and use the same EF to study many systems. This is likely true when many objectives are defined in modelling the same system, or using the same objective in modelling different systems.

Consequently, an EF can be viewed in two different ways. The former is referred to a definition of type of data elements to be stored in a data-base while the latter is referred to a system that interacts with the system under study to obtain the data of interest under specified conditions. From the last point of view, the EF has mainly three system components, including generator, acceptor, and transducer. The generator generates input segments that are to be sent to the system, the acceptor examines conditions under which an experiment is carried to see whether the desired experimental conditions are met or not, and the transducer observes and analyzes the system output segments. Since EF serves to measure the validity of a model and give its full meaning within its context, it requires a sound M&S enterprise to drive its specification as well as the specification

of the source system that is embedded. The specification of a model for a real system and its surroundings is inspired by the current practice in M&S of specifying a model and its simulator [Zeigler et al. 2000]. An advanced concept of EF based on Zeigler's definition is provided by [Traoré and Muzy 2006] to establish the underling duality between a source system and its context. It was argued that describing formally both models and contexts will enable modelers to understand and reason symbolically about the dependencies that exist between them. The context was entirely modeled by EF as described in Figure 5.2.

The formal specification leads to the definition of a frame system as the structure

$FS = < T, I_M, I_E, O_M, O_E, \Omega_M, \Omega_E, \Omega_C, D, \{C_d, d \in D\}, CPIC, EICC, POCC, CEOC, CCC >$, *where*

- T is a time base,
- I_M is the set of input variables from Frame-to-Model,
- I_E is the set of input variables to the frame,
- O_M is the set of Model-to-Frame output variables,
- O_E is the set of Frame output variables,
- Ω_M is the set of admissible input segments for *IM*;
- Ω_E is the set of admissible input segments for *IE*;
- Ω_C is the set of admissible output segments for *OM*;
- D the component names;
- C_d, $d \in D$ the models for each component D;
- *CPIC* Control-to-Plug-in-Input coupling;
- *EICC* External-Input-to-Control coupling;
- *POCC* Plug-in-Output-to-Control coupling;
- *CEOC* Control-to-External-Output coupling;

- *CCC* Control-to-Control coupling.

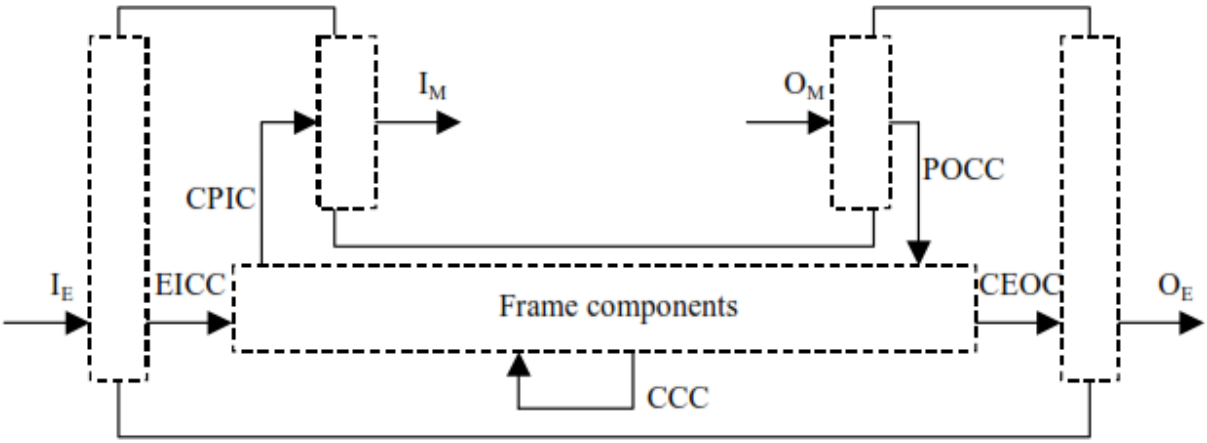


Figure 5.2. Frame System [Traoré and Muzy 2006]

5.2.2. Parameter-based Experimental Frame

Complex systems such as healthcare systems are composed of hierarchical structure and heterogeneous subcomponents at large scale that make challenging their holistic modelling. While it is easy to lose track of the big picture when developing simulation models of a complex system, a holistic modeling approach that combines different aspects such as structural, behavioral, and functional aspects need to be carefully directed at the overall system modelling. For example, modelling approaches such as multiscale modelling [Bonté et al. 2009], Multi-paradigm modeling [Mosterman and Vangheluwe 2004], and domain specific modeling (DSM)-based modeling [Li et al. 2013] have been thoroughly used by academia and industry to investigate complex systems. Using EF concept and Discrete Event System Specification formalism through recursive simulation, [Bonté et al. 2009] developed a multiscale modelling of a single source system modelled at microscopic level and macroscopic level. In their work, the authors considered that processes described in the microscopic model influence some parameters of the macroscopic

model and reversely through EF. This led them to the argument on simulation time bases of the microscopic model and macroscopic model that are reported to be independent from each other, while the concept of EF was defined at two different levels of specification. The definition includes the "experimental frame of transfer" that refers to a set of data and the "experimenter model" that refers to the frame seen as an active observer. The experimenter model (EM) was involved in the core simulation at the macroscopic level and embeds the experimental frame of transfer (EFT) while linking the macroscopic model to the microscopic model by trigging simulations of the microscopic model and updating some parameter values of the macroscopic model.

The EFT is defined at two levels of specification including lowest level and upper level as follows: the lowest level of the EFT is a structure: $< T_1, T_2, I_M, I_E, O_M, O_E >$, where

- T_1 and T_2 are respectively the microscopic and the macroscopic simulations' time bases
- I_M and O_M are respectively sets representing lists of initial conditions and outputs of the microscopic model
- I_E and O_E are respectively sets representing the context given by the macroscopic model and the list of macroscopic level aggregated variables representative of the microscopic behaviors.

The upper level of the EFT is a structure: $<T_1, T_2, I_M, I_E, O_M, O_E, \Omega_E, \Omega_M, \Omega_C, SU>$ where

- $T_1, T_2, I_M, I_E, O_M, O_E,$ are the same as defined at the lowest level,
- Ω_E is the set of Timed possible inputs for the EFT,
- Ω_M is the set of triplets representing the initial conditions, the time segment (initial time, end time) to simulate, and the number of replicas of the same experiment,
- Ω_C is the set of pairs time segments over the cross-product of O_M variables,

- *SU* is the summary mapping of sub-simulation results.

The EM corresponding to the highest level of EFT specification is a structure based on DEVS formalism as follows: $<T, X, Y, S, \delta_{int}, \delta_{ext}, \delta_{conf}, \lambda, ta>$ [Zeigler et al. 2000], where

- T corresponds to the macroscopic simulation time base T_2,
- X corresponds to the frame inputs set I_E and Y is the frame outputs set O_E,
- δ_{int} and δ_{ext} are transition functions defining the experimental design and are composed of four functions Trig (trigger condition function), Gen (generator function), Eval (evaluation function) and Trans (transducer function) used within the EFT structure.

Contrary to the definitions of the EF provided above we propose a different view of the EF to support the idea of models output-to-parameter integration during concurrent simulations. Our aim is to integrate simulation models from different perspectives, developed within their respective EF(s) to form a holistic view of healthcare systems. Since a frame system is made up with a combination of components that are generator, acceptor and transducer, which feedback each other and constitute a coupled network, in this research work, we argue that a simulation model of a given perspective within a given experimental frame has its parameters that are directly fed by the model outputs of another perspective from another EF. The update values of the model parameters are not generated from the model context itself but rather, they are influenced by the outputs of a top model from a different perspective. Every top model is separately developed within its own EF according to the objectives for which it is built. Figure 5.3 depicts the EF of a simulation model A (A is a given name) of a given perspective with its input parameters and respective ports. P1, P2, and Pn represent the simulation parameters, i1 is the input port, and O1, O2, and O3 are output

ports, of the model A. Figure 5.4 gives the overall big picture, where models and their EF are situated in their respective perspectives, while integrated in a holistic simulation scheme.

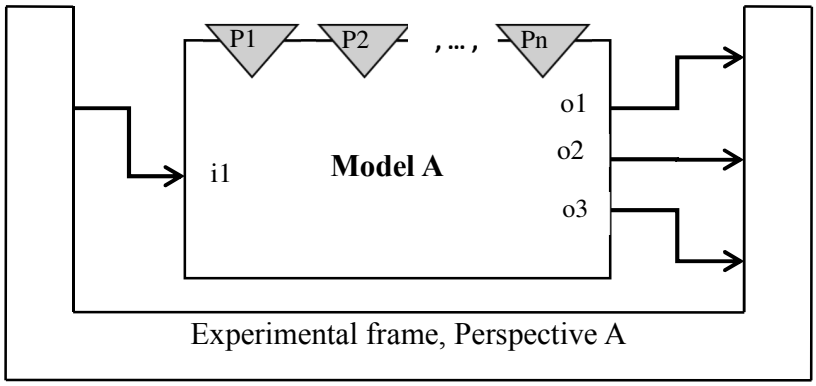


Figure 5.3. Parameterized model within its EF

Considering that each perspective representing a specific aspect of healthcare system problem is represented as a top model in the highest level of hierarchical system specification, that is, a model resulting from the coupling of a family of models. Such a model, encapsulated in its experimental frame, captures a set of modelling questions that motivate the design of the system of interest carried out by the modeller. Hence, model of layers A, B, C and D are embedded in their respective experimental frames EFA, EFB, EFC, and EFD. Let us assume that those layers represent perspectives in HS modelling corresponding to the simulation setup for Healthcare Resources Allocation, Health Diffusion, Population Dynamics, and Individual Behaviour respectively, with their respective experimental frames EFRA, EFHD, EFPD, and EFIB. Each layer is characterized by a set of simulation parameters, p1, p2, …, pn that are in reality abstractions of certain outputs of the simulation models in other layers. While these parameters are usually considered to be constant throughout a simulation run, we argue that, in reality, the

properties (in other layers) represented by any of the parameters can change at runtime thereby making the parameter value outdated in subsequent use.

Given a hypothetical simulation model MRA for the allocation of resources in a healthcare facility as a response to an epidemic in the immediate environment, imagine there is another model MHD of the epidemic itself in the context of the same environment and one of the outputs, y, of MHD is the percentage of the infected population. Assuming MRA has a parameter, x, that denotes the duty over time of a medical doctor; since the number of infected people, y, sent by MHD can increase due to the disease outbreak, the value of x will consequently change as more infected people will arrive at the facility to request for service. Likewise, if we assume MHD has a parameter, α, that denotes the disease attack rate and MRA has one of its outputs, β that denotes the amount of available resources; the allocation of those resources will also affect in return the dynamics of the disease. For example, during the epidemic, a community can be enrolled in awareness campaign through intervention strategies like vaccination or simple social distancing like isolation of infected people, non-handshaking, and school closure, and the results of such interventions alone can significantly reduce the disease propagation rate, α of MHD, while dropping the number of infected people. Hence, we see that in real life, these parameters can change due to some influences from the environment in which the system operates, its experimental frames. Instead of keeping x and α constant for throughout a simulation run, the idea proposed in this thesis is to run the simulations of MRA and MHD concurrently in their respective experimental frames such that, instantaneous outputs, y of MHD and β of MRA are used to update the parameters, x, of MRA and α of MHD at runtime.

Therefore, this chapter proposes an integration mechanism to connect relevant outputs of a model from a given perspective to the parameters of a model of another perspective in a concurrent simulation. This integration mechanism is illustrated by the dashed lines connecting some output ports to parameters in Figure 5.4. For instance, port o1 and o3 of layer A are connected to parameter p2 and pn of layers B, C and D respectively. The purpose of these output port-to-parameter connections is to enable live update of the parameters at runtime whenever there are changes in the values of actual properties they represent. We believe this approach gives a better representation of the influences of the different perspectives of HS on one another and will produce simulation results that are closer to the real behaviours of the actual systems in this context.

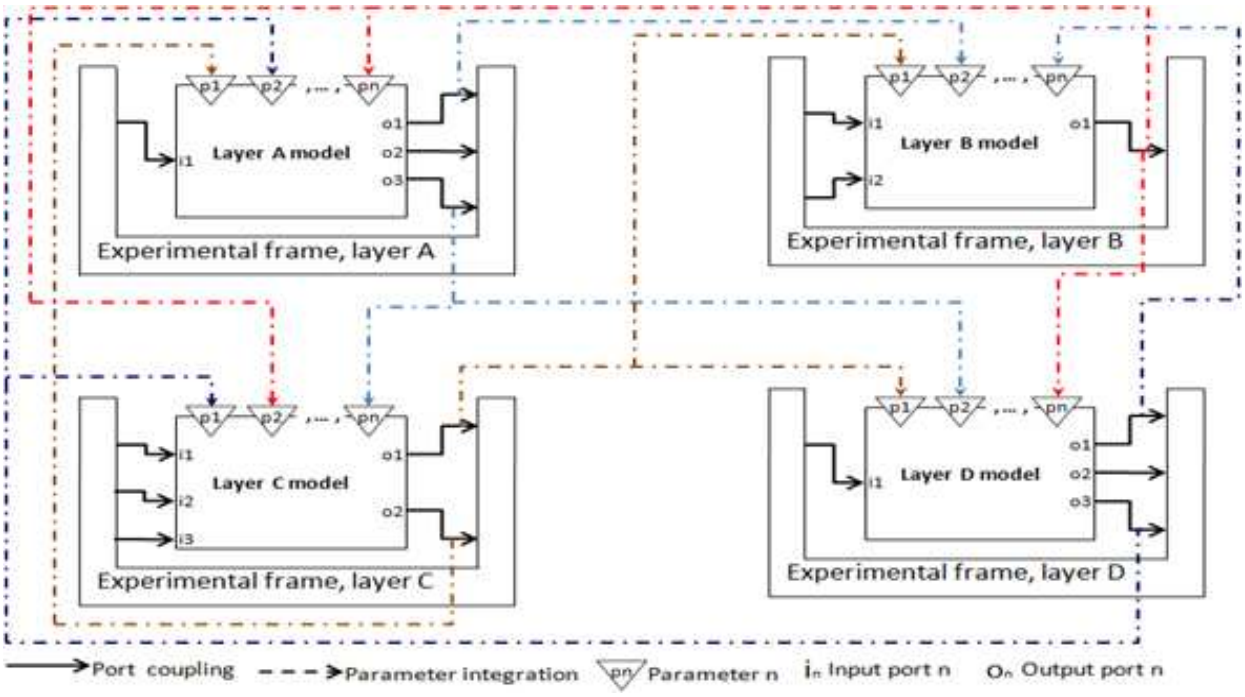


Figure 5.4. Output-to-parameter integration of different perspectives of healthcare system.

5.3. Perspectives Integration

While in practice the isolated perspectives of HS are more often studied separately, we insist that rather simulation processes resulting from those perspectives mutually influence one another in reality. Each perspective holds within itself in a single model a family of HS aspects sharing common modelling objectives. This model is then coupled with its surrounding experimental frame to derive appropriate simulation results. The influences that exist between perspectives result from the complex interactions that already bind them together in the healthcare environment. Such interactions are so tightly strong that the improvement in one measure of performance from one perspective will eventually affect the performance factors of the other perspectives. For example, the reduction in dedicated health resources such as beds capacities or human resource for inpatients (RA perspective) may instead increase cancellation rates for patient treatments or reduce attendance rates for patients screening program (HD perspective). Hence, in order to reflect the influences and translate the mutual dependencies that exist between the isolated HS perspectives, we are proposing an integration mechanism that considers live information exchanges between models from the different perspectives to form a holistic study of the whole HS in a concurrent simulation run.

We would like to emphasize on the difference between the integration mechanism developed in this thesis that links perspectives together and the coupling under closure proposed by DEVS formalism that couples components of a complex model. The former is the connection between model outputs of a given perspective to model parameters of other perspectives while the latter is the connection between components of a complex model such as a model output port is coupled to another model input port, within the same perspective. An attempt of models integration has been introduced in [Seck and Honig, 2012] where the output of a model can feed any other input

of a model regardless of the scope of their definition through an intermediary model called bridging model. An attempt of models integration has been introduced in [Seck and Honig, 2012] based on coupled models defined by DEVS formalism with the subcomponents separated in two distinct models, aspect models and bridge models where the output of a model can feed any other input of a model regardless of the scope of their definition. The bridge models allow connecting the different sub-models through model output to model input interaction. However, in our case, model outputs from different perspective don't feed each other since the modeling questions for which they are built to answer are no longer common outside their respective experimental frames. As such, any simulation process which output is to feed or input is to be fed by other process from a different perspective is an abstraction within the considered perspective. It is hoped that this novel idea will foster the understanding of the mutual effects of simulation processes that are usually hidden in most of the reported studies in the literature.

Our approach is based on HiLLS, a DEVS-based visual language [Aliyu et al., 2016] formalism which provides object-oriented feature for modelling both problems that are specific to different perspectives and their integration in a holistic manner. A HiLLS model enables definition of methods as presented in Chapter 2 which when they are called modify the value of the parameters of that model. It is important to notice that such method call is an activity that the model performs without changing the state variables of the considered model but instead changes its parameter values, contrary to the sending/receiving information through model ports that results in changing the state inside the model. In this very case, model parameters as presented in the example given earlier, such as the rate at which patients arrive in a healthcare facility (resource allocation perspective) or the disease propagation rate (health diffusion perspective) are static data

as regards to the state variable of the models describing these perspectives. However, the parameter values can be used for the required computations to change the state of the model. In order to effectively realize the integration concept of the perspectives, we define additional interface models which are still HiLLS models that we refer to as integrators enabling us to perform method calls while linking those perspectives together and forming an integrated whole model of HS.

Figures 5.5 depicts the underling concept of perspective "integration" contrary to model "coupling. HD model and PD models are respectively coupled to HD2PD integrator and PD2HD integrator while HD2PD integrator and PD2HD integrator integrate PD model with HD model through method calls. By sending model outputs to integrator inputs, we define coupled models under HD perspective and PD perspective respectively. Hence, HD2PD integrator once receives the input value from the disease model, interprets that value and translates it into new value for the parameters of a population dynamics model by calling the required method. Likewise, the same process takes place in the coupling resulting from the population dynamics model with the PD2 HD integrator. PD2HD integrator after receiving the input from population dynamics model performs some activities and calls the method of the disease model and changes the value of the corresponding parameters. Thus, a holistic modelling of the whole healthcare systems is achieved by defining appropriate integrators that will link models that are specific to the different perspectives.

The formalization of the proposed integration concept is done based on DEVS formalism and is called parameterized DEVS that will be discussed in details in the next section.

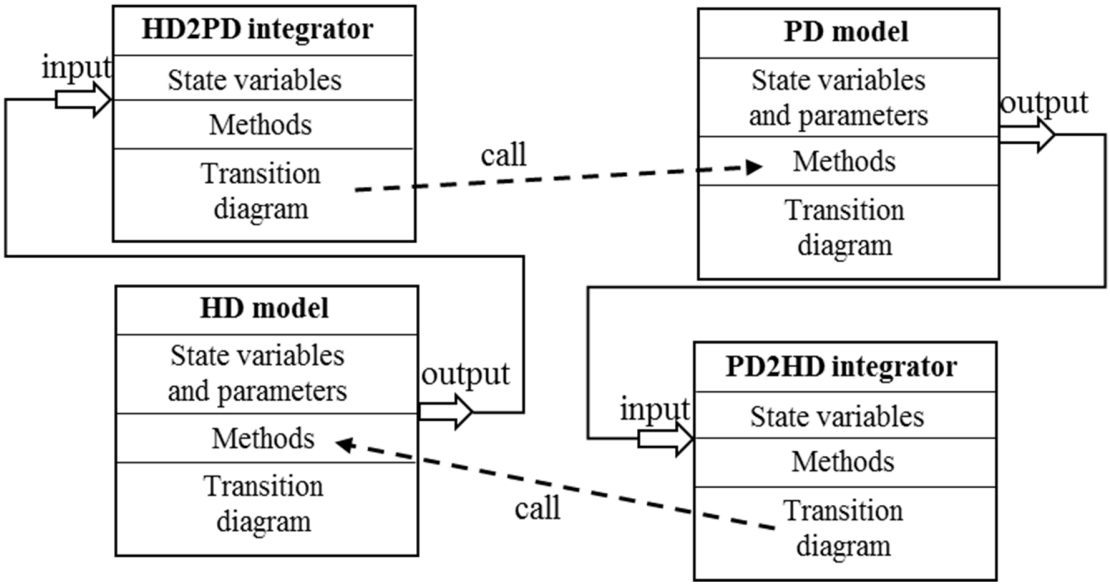


Figure 5.5. Model coupling and integration

5.4. DEVS-Based Formalization

In the previous section we use HiLLS to describe models from the different perspectives and sow how the integration of those perspectives can be done. In this section, we formalize what we did previously with HiLLS in DEVS. In order to realize that formalization we introduce a concept called parameterized model to capture the idea and its specification in DEVS formalism called *parameterized DEVS* at the DEVS atomic and coupled model levels. Hence, the parameterized DEVS is a formal specification of the proposed idea described earlier using HiLLS formalism.

Consequently, we extend the original DEVS formalism by adding an element "*P*", to represent a set of pairs of dynamic parameters. The proposed parameterized DEVS is not another simulation formalism in itself but rather, it maintains DEVS and its simulation protocols and builds on it, a mechanism for realizing live update of parameters in concurrent simulation processes as described in Figure 5.4.

We highlight a major difference that exists between the current approach and the work of [Seck and Honig 2012] in terms of event received by a model through its input port and the resulting effect of that event in parameter modification. In their work, since sub-components are basically defined in DEVS models, be it aspects or bridge models, the semantics of the models suggests that when an event originated from its environment is received by the input port, that event immediately changes the model's states through its governing transition rules such as the external transition function. However, the semantics of parameter modification differs from that work in the sense that not only the event provoking the change is coming from a different environment where the model is built but it also provokes a change of the model's internal rules rather than its state. We provide de semantics of the parameterized DEVS Atomic and coupled models in the next sub-sections.

5.4.1 Parameterized DEVS Atomic Model

While DEVS atomic model defines a set S of state variables that can change and determine the new state of a system at a given time due to state transitions, the values of the set P are not affected by such change during the reconfigurations. The set P of parameters and the set S of state variables of a parameterized DEVS model are disjoint sets. However, the values of P could be used by the governing functions such as transition functions (δ_{int} and δ_{ext}), time advanced function (ta) and output function (λ) to determine new value of the variables. Instead, new values of P are dynamically updated by the influences from models of other perspectives as illustrated earlier in this chapter. Hence, we introduce the set P to reproduce the hidden effect of mutual influence between perspectives that is not taken care of by the DEVS formalism. Since we do not want the system under study to respond to the changes caused by the input received in its ports and the

external transition function, the introduction of *P* is a way out to deal with such undesired response and allow the system to remain in the same state while updating lively the parameters being used. In [Seck and Honig 2012], two models are closed under coupling and an input received by a model in its port triggers the change in state variables of that model lively. We report that this integration mechanism does not suit to the current approach carried out in this work.

As we stated earlier that the proposed idea is not a different formalism from DEVS itself, therefore, it can still be simulated using existing DEVS simulation protocols.

We define a *parameterized atomic DEVS* as a structure $\langle X^P, Y^P, S^P, \delta_{int}^P, \delta_{ext}^P, \delta_{conf}^P, \lambda^P, ta^P\rangle$, where:

- P is the parameters set (each element of P is a vector of values of parameters)
- $\langle X, Y, S, \delta_{intP}, \delta_{extP}, \delta_{confP}, \lambda_P, ta_P\rangle$ is an atomic model whose governing functions depend on P (i.e., they compute their values, using the values of P), called the *strain* model.
- $X^P = X \times P$
- $Y^P = Y$
- $S^P = S \times P \times \Re_0^{+\infty}$
- $ta^P : S^P \rightarrow \Re_0^{+\infty}$

$ta^P(s, p, \sigma) = \sigma$

- $\delta_{int}^P : S^P \rightarrow S^P$

$\delta_{int}^P(s, p, \sigma) = (\delta_{intP}(s), p, ta_P(s))$

- $\lambda^P : S^P \rightarrow Y^P$

$\lambda^P(s, p, \sigma) = \lambda_P(s)$

- $\delta_{ext}^{P} : Q^{P} \times X^{P} \rightarrow S^{Y}$, with $Q^{P} = \{(s,p,\sigma,e) / (s,p,\sigma) \in S^{P}, 0 \leq e < \sigma\}$

$\delta_{ext}^{P}(s, p, \sigma, e, \emptyset, q) = (s, q, \sigma\text{-}e)$

$\delta_{ext}^{P}(s, p, \sigma, e, x, \emptyset) = (\delta_{extP}(s, e, x), p, ta_{P}(\delta_{extP}(s, e, x)))$

$\delta_{ext}^{P}(s, p, \sigma, e, x, q) = (\delta_{extP}(s, e, x), q, ta_{q}(\delta_{extP}(s, e, x)))$

- $\delta_{conf}^{P} : S^{P} \times X^{P} \rightarrow S^{P}$

$\delta_{conf}^{P}(s, p, \sigma, x, \emptyset) = (\delta_{confP}(s, x), p, ta_{P}(\delta_{confP}(s, x)))$

$\delta_{conf}^{P}(s, p, \sigma, x, q) = (\delta_{confP}(s, x), q, ta_{q}(\delta_{confP}(s, x)))$

A parameterized DEVS atomic model is an embedded strain atomic model with two types of input ports: model input port and parameter input port. The former causes change on the model's state while the latter modifies the parameter values. We define a variable (σ) to keep records of the remaining time of the current state of the strain model and determine the time advance function of the parameterized DEVS model. The internal transition of the parameterized model changes the state of the strain model according to its internal transition function, but does not affect the parameters. The output sent at that time is the one computed by the strain model. When only new values for parameters are received by the parameterized model, the state of the strain model is kept unchanged, and only the remaining time is updated. When only input values impacting the strain model's state are received (without input for modification of parameters), the new situation is defined by the strain model's external transition and time advance function. When both input values impacting the strain model's state, and input for modification of parameters are received, the new situation is defined by the strain model's external transition and time advance function; the new state of the strain model is computed based on the current values of parameters, but the lifespan of this new state is computed using the new values of parameters. The same rules apply for confluent transition.

5.4.2. Parameterized DEVS Coupled Model

We similarly define a parameterized coupled model as a coupled DEVS model deriving from a strain coupled model, by $\langle X_{self}^P, Y_{self}^P, D^P, \{M_d^{Pd}\}_{d\in D}, \{I_d^{Pd}\}_{d\in D}, \{Z_{i,j}^P\}_{i\in D\cup\{self\},j\in Ii} \rangle$ where:

- $X_{self}^P = X_{self}\times(\times P_d)_{d\in D}$
- $Y_{self}^P = Y_{self}$
- $D^P = D$
- M_d^{Pd} is a parameterized DEVS model if $P_d \neq\emptyset$ (with $X_d^{Pd} = X_d\times P_d$ as its input set), and a "regular" DEVS model if $P_d= \emptyset$ (with $X_d^{Pd} = X_d$ as its input set)
- I_d^P includes all components models sending input to d, whether for parameter modification or internal state change
- $Z_{self,d}^P : X_{self}^P \rightarrow X_d\times P_d$

$Z_{self,d}^P(x, p) = ((Z_{self,d}(x), p_d)$

- $Z_{d,self}^P = Z_{d,self}$
- $Z_{i\in D,j\in D-\{i\}}^P : Y_i \rightarrow X_j\times P_j$

$Z_{i\in D,j\in D-\{i\}}^P(y) = (x, \emptyset)$ for a "regular" coupling

$Z_{i\in D,j\in D-\{i\}}^P(y) = (\emptyset, p_j)$ for an "integration" (or a bridging)

5.5. Conclusion

We have proposed a holistic approach to healthcare systems modelling and simulation that combines the different perspectives more often developed in isolation in the literature. A common practice is to consider simulation parameters constant throughout the different studies scenarios.

However, we have argued that the values of these parameters can change in concurrent simulation studies. Consequently, we have proposed an integration of the underling perspectives where independent simulation processes of disparate concerns in healthcare systems exchange live updates of their influences on one another to bring results closer to the reality.

Dedicated experimental frames can be designed to answer perspective-specific questions, while a global experimental frame can be used to derive answers from the resulting global model, that couldn't be accurately addressed in any of the perspective taken alone.

Another original and important contribution is that the integration approach proposed by the framework allows to link models that have not been initially designed for this purpose. This is a significant difference with the classic model coupling approach where outputs of existing models are connected to input of other ones, provided the connecting ports were designed to serve that purpose at the time of the construction of these models, and that the ports fit each other. This approach can be generalized beyond the framework to integrate models from other domains in a holistic study.

Furthermore, the developed integration approach that allows linking up the isolated perspectives has been formalized through a concept based upon DEVS formalism called Parameterized DEVS, whereby concurrent simulation processes cause live update through output-to-parameter integration.

Chapter 6
CASE STUDY: HOLISTIC SIMULATION OF NIGERIA HEALTHCARE SYSTEM

This chapter presents an application of the Multi-perspective framework for healthcare Modelling and Simulation with models built and studied in isolation according to each perspective and their simulation results integrated together to form a complete whole. Hence, the obtained results allow us to gain multiple levels of explanation of healthcare phenomena that could not be derived accurately when studying those perspectives separately. We use the outbreak of Ebola in Nigeria in 2014 as a running example to show how the framework is applied.

On July 20, 2014, the contagious Ebola Virus Disease (EVD) was imported into Nigeria from a Liberian traveler who, after contracting the virus in his country, flew to the Lagos International Airport [WHO, 2014]. He died five days later in a Lagos hospital where he was admitted but after having wreaked havoc by infecting healthcare providers at the hospital. Within the first days of Ebola case diagnose, nine healthcare workers were infected and 898 contacts were generated through the country. The urgent need to control the epidemic prompted the Federal Ministry of Health to declare a national Ebola emergency, and the World Health Organization (WHO) declared it a public health emergency of international concern. An intervention plan was swiftly developed, with about USD $11.5 million allocated to establish coordination offices and operation centers, along with massive campaign of awareness of Ebola to the public. Several factors made the control of the pandemic difficult, including the following:

(1) The transmission vectors of the disease include any contact with sweat, saliva, vomit and other bodily fluids of an infected person, even when dead. As a result, care providers,

women and children are among the most vulnerable. The former are in direct contact with patients. The others live in a great promiscuity within rural communities.

(2) With a population of about 14 millions, Lagos, ranked Africa's largest city, is an attractive business area for day laborers, including poor people living in rural areas and slums.

(3) Cultural practices in some places mean that dead people are transported from one place to another to be buried near their ancestors, while putting carriers, gravediggers and neighboring places at high risk of infection.

The rest of the chapter is organized as follows. Section 1 addresses the health diffusion (HD) perspective with a model of the Ebola outbreak and its experimental frame. Section 2 addresses the population dynamics (PD) perspective with a model of migrations between Nigerian states and its experimental frame. Section 3 addresses the individual behavior (IB) perspective with a model of daily workers strategy and its experimental frame. Section 4 addresses the resource allocation (RA) perspective with a model of hospital resource allocation in Lagos and its experimental frame. Section 5 presents the transfer models integrating the different perspectives together. Section 6 discusses the results obtained then we conclude the chapter in section 7.

6.1. Model of Disease Spreading

We model the outbreak of EVD using the compartmental model developed in [Althaus et al. 2015] and presented by the following set of partial differential equations (PDE). The initial model has been extended to take into account the possible infection of individuals by dead people.

$$\frac{dS}{dt} = -\beta SI - \alpha SD \qquad (1)$$

$$\frac{dE}{dt} = \beta SI + \alpha SD - \sigma E \quad (2)$$

$$\frac{dI}{dt} = \sigma E - \gamma I \quad (3)$$

$$\frac{dR}{dt} = (1 - f)\gamma I \quad (4)$$

$$\frac{dD}{dt} = f\gamma I \quad (5)$$

where

- S is the number of susceptible individuals in the population
- E is the number of exposed individuals (susceptible individuals become exposed before being infected)
- I is the number of infectious individuals
- R is the number of recovered individuals
- D is the number of dead individuals
- β is the transmission rate with infected individuals
- α is the transmission rate with dead individuals
- σ is the incubation rate
- γ is the "recovery or death" rate
- f is the case fatality rate

This PDE model (which can also be seen as a Systems Dynamics model) is given from the HD perspective of our framework. It is translated to its DEVS counterpart by defining an atomic model with S, E, I, R and D as state variables, which applies equations (1) to (5) during each of its internal transitions to get the values of the state variables in the new state, and which time advance is always equal to 1 day. A specific DEVS-based experimental frame is built to experiment with the model and answer questions such as the distribution of health statuses in the population over a

period of time, and the sensitivity of the disease spread to variations of parameters. The specification of the model (as explained in chapter 5) is described as follows:

$$M_{EbolaSpread} = \langle X^P, Y^P, S^P, {\delta_{int}}^P, {\delta_{ext}}^P, {\delta_{conf}}^P, \lambda^P, ta^P \rangle, \text{ where:}$$

- $P = (\alpha \in \mathbb{R}_0^{+\infty}, \beta \in \mathbb{R}_0^{+\infty}, \gamma \in \mathbb{R}_0^{+\infty}, \sigma \in \mathbb{R}_0^{+\infty}, f \in \mathbb{R}_0^{+\infty})$
- $X^P = \{(p, v), p \in \{set\alpha, set\beta, set\gamma, set\sigma, setf\}, v \in \mathbb{R}_0^{+\infty}\}$
- $Y^P = \{(p, v), p \in \{\#S, \#E, \#I, \#R, \#D\},\ v \in \mathbb{R}_0^{+\infty}\}$
- $S^P = \{current\} \times (\mathbb{R}_0^{+\infty} \times \mathbb{R}_0^{+\infty} \times \mathbb{R}_0^{+\infty} \times \mathbb{R}_0^{+\infty} \times \mathbb{R}_0^{+\infty}) \times \mathbb{R}_0^{+\infty}$
- $ta^P: S^P \longrightarrow \mathbb{R}_0^{+\infty}$

  $ta^P(current, p, phase) = phase$
- ${\delta_{int}}^P: S^P \longrightarrow S^P$

  ${\delta_{int}}^P(current, \alpha, \beta, \gamma, \sigma, f, phase) = (\text{current}, \alpha, \beta, \gamma, \sigma, \text{f}, \text{1day})$
- $\lambda^P: S^P \longrightarrow Y^P$

  $\lambda^P(current, \alpha, \beta, \gamma, \sigma, f, phase) = \{(\#S, S), (\#E, E), (\#I, I), (\#R, R), (\#D, D)\}$
- ${\delta_{ext}}^P: Q^P \times X^P \longrightarrow S^Y$ with $Q^P = \{(s, p, sigma, e) | (s, p, sigma) \in S^P, 0 \leq e < sigma\}$

  ${\delta_{ext}}^P\big(current, \alpha, \beta, \gamma, \sigma, f, sigma, e, (set\alpha, v)\big) = (current, v, \beta, \gamma, \sigma, f, sigma - e)$

  ${\delta_{ext}}^P\big(current, \alpha, \beta, \gamma, \sigma, f, sigma, e, (set\beta, v)\big) = (current, \alpha, v, \gamma, \sigma, f, sigma - e)$

  ${\delta_{ext}}^P\big(current, \alpha, \beta, \gamma, \sigma, f, sigma, e, (set\gamma, v)\big) = (current, \alpha, \beta, v, \sigma, f, sigma - e)$

  ${\delta_{ext}}^P\big(current, \alpha, \beta, \gamma, \sigma, f, sigma, e, (set\sigma, v)\big) = (current, \alpha, \beta, \gamma, v, f, sigma - e)$

  ${\delta_{ext}}^P\big(current, \alpha, \beta, \gamma, \sigma, f, sigma, e, (setf, v)\big) = (current, \alpha, \beta, \gamma, \sigma, v, sigma - e)$

Figure 6.1 shows how the respective numbers of susceptible, exposed, infected, recovered and dead evolve over a period of 100 days. Initial conditions are: 1,000,000 susceptible individuals, only 1 infected person, and no exposed, recovered or dead individual. Parameters β, α, σ, γ and f

are respectively set to 1.22e-06, 0, 0.33, 0.71 and 0.42, as calibrated in [Althaus et al. 2015], which model of spreading without control measures coincides with our for α=0.

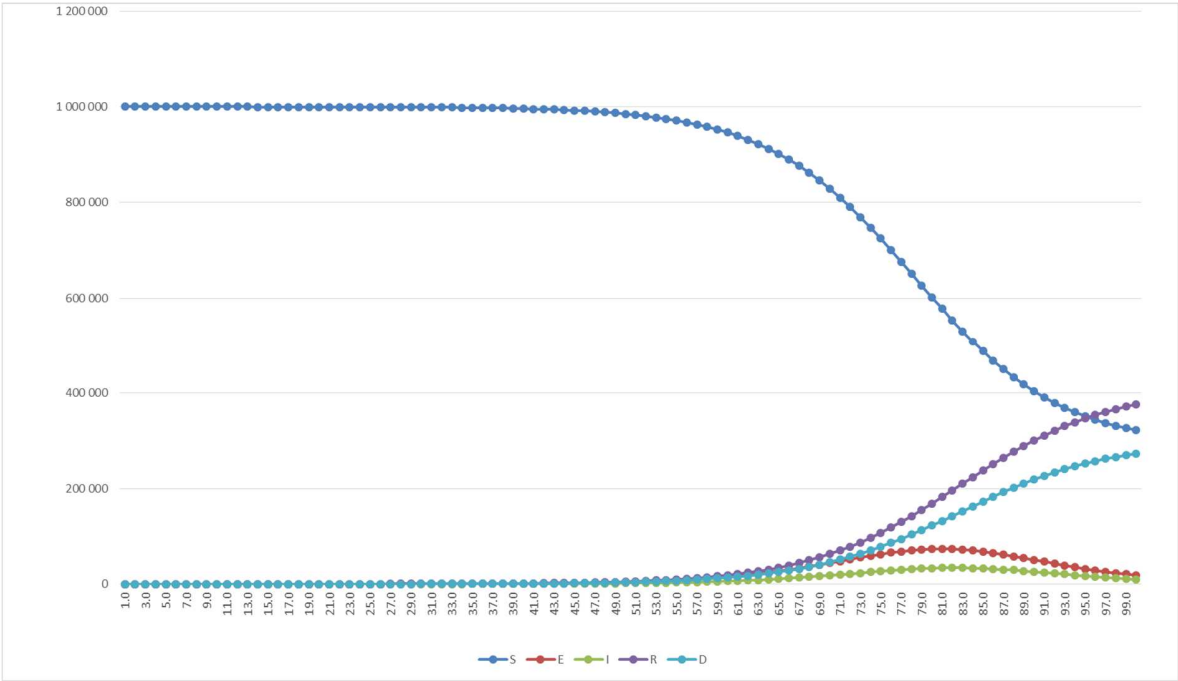


Figure 6.1. Ebola spreading in a period of 100 days, with calibrated parameters

Because of the scarcity of reliable data in the Nigerian healthcare management system, validation is a major issue (e.g., a good estimate of the population size of Nigerian states or cities is frequently disputed by national agencies). However, understanding the dynamics of the disease diffusion as regards to the variation of parameters is paramount to getting the exact figures for each health status at a given time.

Figure 6.2 shows such an exploration, with a focus on the level of disease penetration at one hand (variation of I/S, the ratio between initial numbers of infected and susceptible individuals), and at the other hand, the impact of some socio-cultural dimension (variation of α).

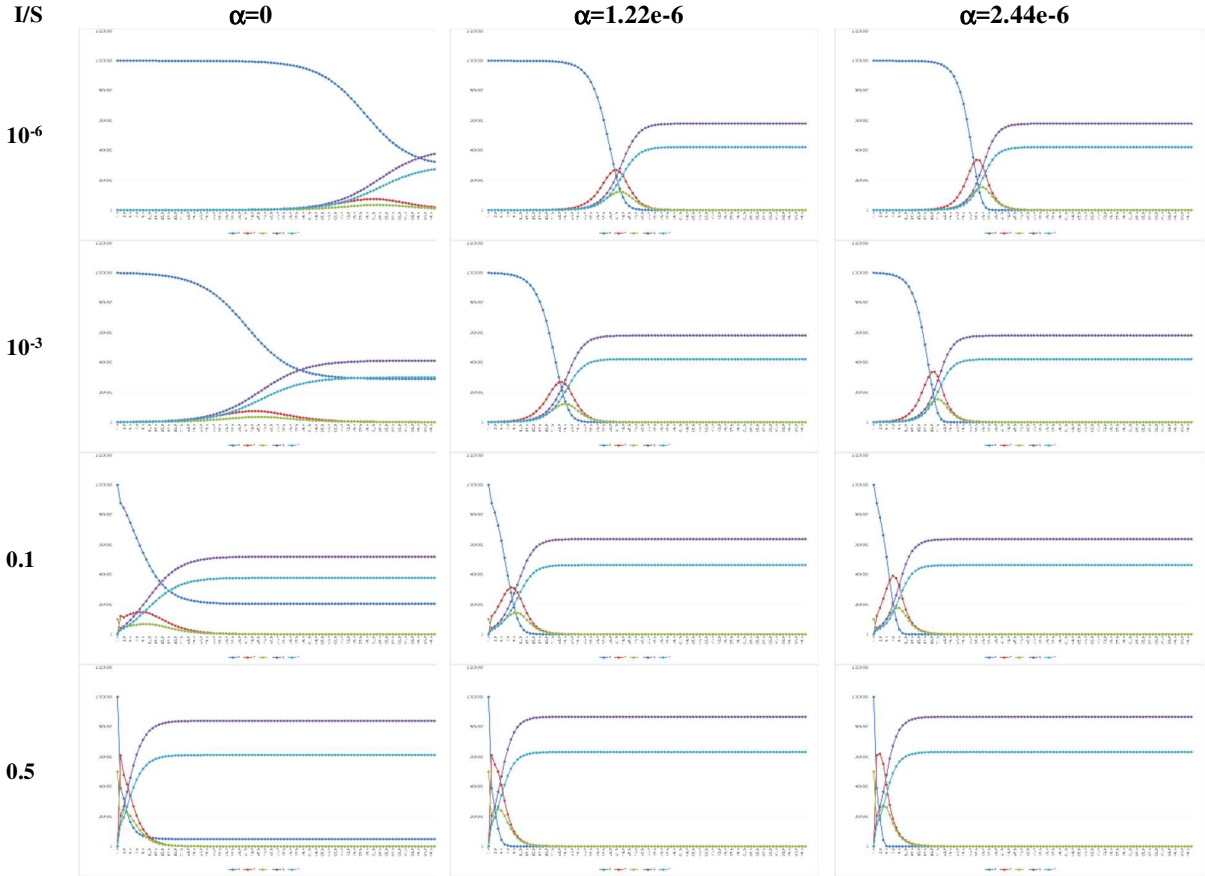


Figure 6.2. Sensitivity of the Ebola spreading to variations of parameters

We considered four levels of infectious situations: disease appearance stage (i.e., only one infection over a million of individuals, something comparable to what happened in big and medium cities in Nigeria, but also in Liberia, Guinea and Sierra Leone), state of emergency level (i.e., a thousand infections over a million of individuals, a level at which countries often activate very special measures), catastrophe level (i.e., 10% of the population infected), and chaos level (i.e., 50% of the population infected). We also considered three levels of social interaction: safe burial level (i.e., dead persons are buried with the maximum of caution, not allowing any direct contact with any living individuals), classic burial level (i.e., burial ceremonies are making interactions with dead persons as intensive as with living persons), and feasting burial (i.e., burial ceremonies

take many days and go at many places, with direct contacts between dead and living individuals). The top-down reading of Figure 6.2 shows that there is a drastic change of trajectories when burial-based socio-cultural interactions come into play compared to safe burial situations, but their intensity does not have a very significant impact above a certain limit. The left-to-right reading of the same figure shows that above a threshold, the infection penetration is out of control, regardless of variations in the socio-cultural interactions. These are two simple conclusions derived, where much more can be explored to get a full level of explanation of this HD perspective-oriented issue.

6.2. Model of migrations

The dynamics of a population play a key role in its healthcare system. Numerous theoretical models exist to represent population dynamics, emblematic examples are [Volterra, 1931], [Rogers, 1975], [Allen, 1976] and [Sikdar and Karmeshu, 1982]. We developed a model inspired by [Sheppard, 1985], but with the following specificities:

- We consider the Nigerian population at states level. Nigeria is a federal country with 36 states (each having its capital city) and a Federal Capital Territory (FCT).
- A cellular automata (CA) is used for modeling interstate migration flows. The neighborhood of a cell includes all other cells of the CA. Each cell is defined by a reference (0 for FCT, and 1 to 36 for the states) and is assigned a geographical position (i.e., latitude and longitude of its capital city). The state of a cell at a given time is the population of the corresponding federal state at that time.

The general rule of the CA is expressed by the following equation:

$$n_i(t+1) = g_i n_i(t) + \sum_{i \neq j} (\alpha_i - \alpha_j) \left| n_i - n_j \right| e^{-\tau d_{ij}} \qquad (6)$$

where

- $n_i(t)$ is the population of state i at time t
- g_i is the net growth rate (i.e., $birth - death \pm migrations$ from/towards outside the country) of state i
- α_i is the relative attractivity of state i (i.e., the GDP per capita of state i over the GDP per capita of the country)
- d_{ij} is the distance between capital cities of states i and j
- τ is a constant positive number

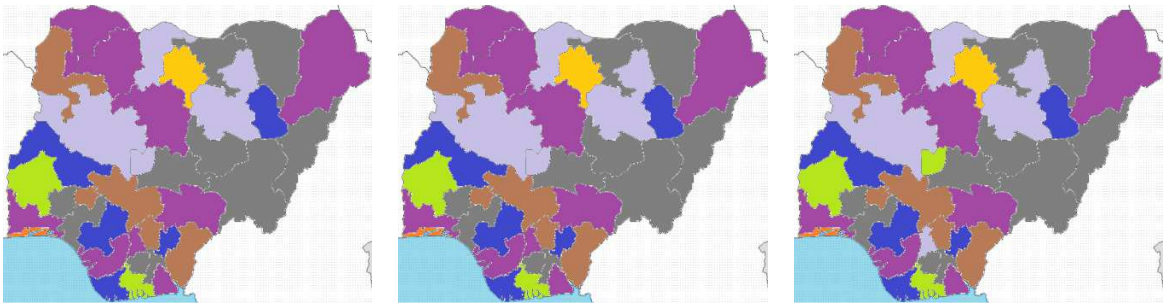
Equation (6) is inspired by [Sheppard, 1985] in that the rate of migration between any pair of federal states depends on the population distribution. But, while [Sheppard, 1985] considers the attractivity of a place grows with its size, and eventually declines as it approaches its capacity, we address this aspect in a different way, as follows: The interstate migrations for each federal state are addressed in the second member of equation (6) by its second term.

- $\alpha_i - \alpha_j$ expresses that between any pair of federal states, the more attractive one "wins". One can notice that the number of migrants leaving a source state ($\alpha_i - \alpha_j < 0$) is the same entering the target state ($\alpha_i - \alpha_j > 0$).
- $|n_i - n_j|$ expresses that states with nearly the same size have few attraction to each other. The greater the difference of size is, higher is the attraction (in favor of the more attractive one).
- $e^{-\tau d_{ij}}$ expresses that attractivity between any pair of states is amplified or reduced by the distance between them. Closer states have more attractivity to each other (the extreme case

is $d_{ij} = 0$, which gives $e^{-\tau d_{ij}} = 1$), very distant states have a low attractivity to each other (the extreme case is $d_{ij} = +\infty$, which gives $e^{-\tau d_{ij}} = 0$).

This CA model is given from the PD perspective of our framework. Its DEVS counterpart is an atomic model which has the CA grid as its state variable, and which applies the CA rules during each of its internal transitions. Time advance is always equal to 1 day. A specific DEVS-based experimental frame is built to experiment with the model and answer questions such as the distribution of population in the Nigerian states over a period of time.

Figure 6.3 shows how the respective states evolve over a period of 1460 days (i.e., 4 years period). Calibrating data are taken from the annual report of the National Bureau of Statistics [NBS, 2012]. The initial distribution of population considers the figures from the 2006 census. Net growth rates are calculated for the period of time from 2006 to 2010. Attractivity rates are calculated for year 2010. We use the Euclidian distance and τ =0.01. The experimental frame for the study displays each state by coloring it according to the range in which falls the daily growth of the state's population. Figure 6.3 displays snapshots at respective times 1, 183, 364, 545, 726, 907, 1088, 1261 and 1442 (top-down and left-to-right), i.e., every semester approximatively.



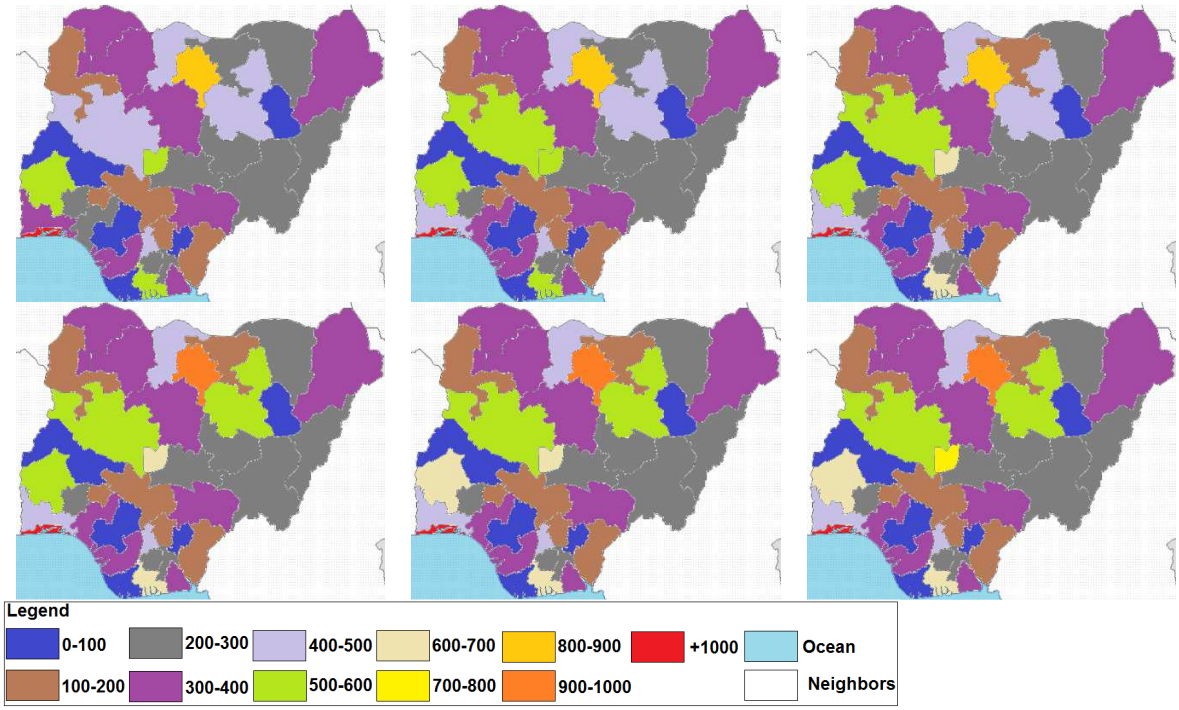


Figure 6.3. Snapshots of population dynamics simulation (daily growth) in Nigerian states

We compared the evolution curves obtained from the CA simulation, with data available for the period from 2008 to 2011. Figure 6.4 shows (on top) how cumulative real data present for all states (horizontal axis) and for 4 years (vertical axis cumulating annual rates). It also shows (at bottom) how cumulative simulation results present, using the same layout. Differences are in the interval of confidence of 95% for all states, except Gombe state and Kwara state which have lesser annual growth rates with simulation than in reality. We have no explanation for this difference.

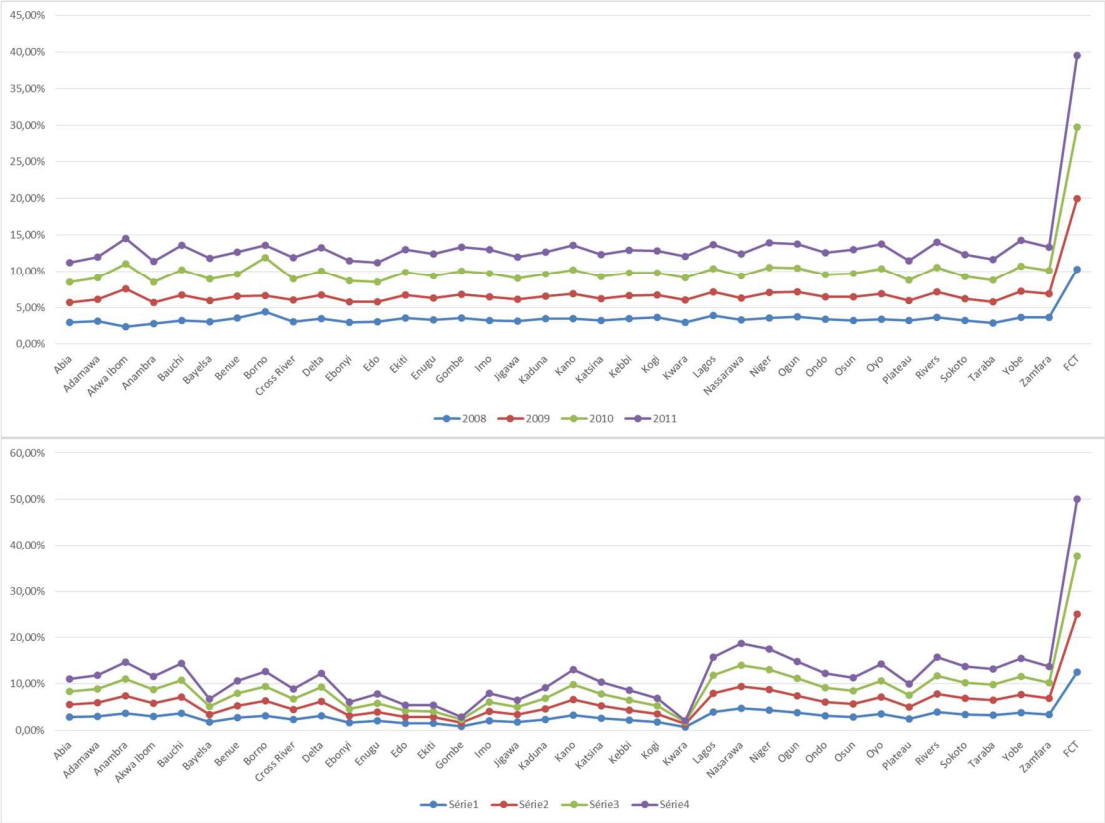


Figure 6.4. Real data vs. simulation results (cumulative population growth rate per state)

6.3. Model of daily worker

Models form the IB perspective of our framework capture the micro level of explanation (i.e., at individual level) of phenomena that are often described at the macro level (i.e., at population level) in healthcare systems simulation. For the running example of this paper, let us focus on the agent-based model of daily workers in the Nigerian population. They constitute a very significant part of intrastate and interstate migration flows. The objective of this agent-based model is to simulate the impact of a simple social strategy in the working condition of a daily worker. The model generates the result of scenarios depicting decisions by a daily worker to move from a working area to another one, based on the situation of the local labor market and the consequential effect on his working rate (i.e., the average number of worked days, hence the worker's earning).

In this study, local labor market refers to a combination of labor parameters such as the probability r for a primo entering to get a job daily, the probability p for a worker to keep the same job for the next day, and the probability q for a jobless to find a new job. These parameters affect the behavior of the daily worker in a way described by Figure 6.5. Arriving in a new place as a primo entering, it takes 3 days to establish and understand how the local market works. This time represents for the daily worker the cost of moving from one area to another, since the corresponding days are lost in terms of earnings. The transition diagram of Figure 6.5 shows that the primo entering individual gets a job with probability r, and is jobless with probability 1-r. A job is kept with probability p and lost with probability 1-p. A jobless individual will daily seek for a new opportunity, with a level of patience of x days. If he doesn't get any new job after this deadline, he will move to another working area (a counter n is used to know at each time the number of jobless days). We assume he won't go back to a place he formerly visited, and that the national labor market is uniform (therefore, probabilities don't change from one local labor market to another one). This may look contradictory, since the daily worker would probably move to a new place with higher probabilities. However, in reality, daily workers randomly change their areas of research since they don't have a clear visibility of the labor markets map. Their strategy relies solely on the choice of the value of x. Indeed, r being greater than q, any new relocation increases the potential for a jobless to get a new job, at the cost of the time lost in relocating.

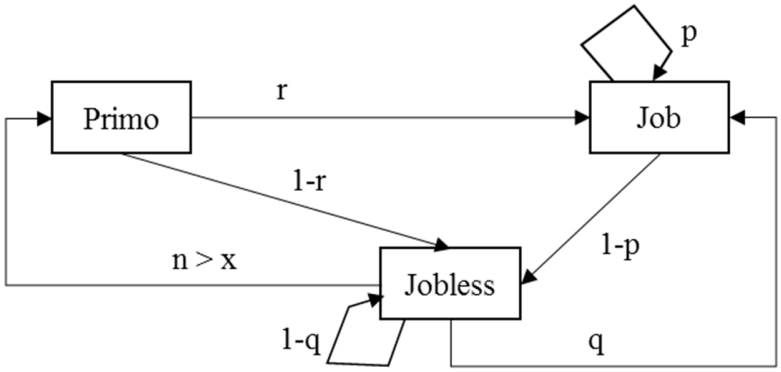
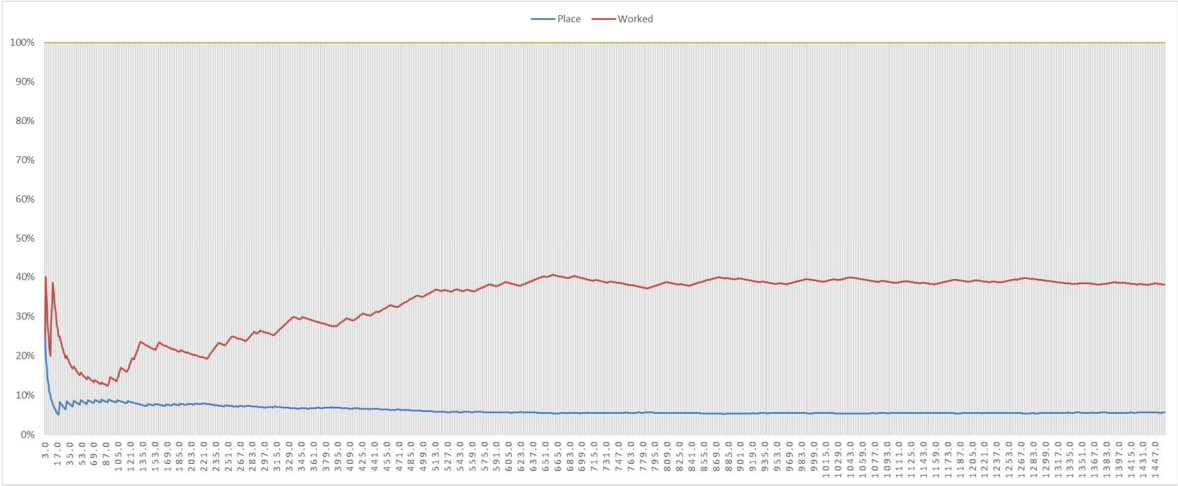


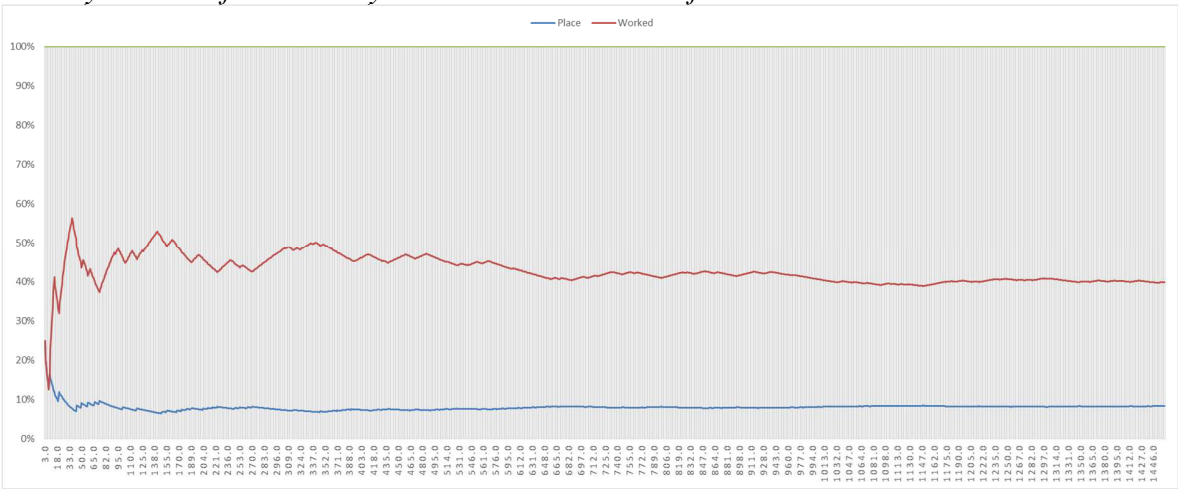
Figure 6.5. Individual behavior model of a daily worker

This agent-based model is easily described by a DEVS atomic model. Each node of the transition diagram given in Figure 6.5 is a state of the DEVS model. Transitions are all internal transitions in the DEVS model. Time advance is 1 day for JOB and JOBLESS states, while it is 3 days for PRIMO state. Internal transitions are triggered depending on probabilities, except for the case of the worker moving to a new place. The perspective-specific DEVS-based experimental frame built to experiment with the model, explores for various values of x the trajectories of two variables: (1) the percentage of worked days, and (2) the frequency of moves. For each value of x, 1000 experiments are run, each for 1460 days (4 years). Figure 6.6 shows the impact of the workers decision (frequency of relocations) on his job performances (percentage of worked days), respectively for x=6, x=3 and x=1 (top-down). Values of r, p and q are respectively 0.45, 0.85 and 0.05. The strategy of highest mobility, although showing high uncertainty of performances at the beginning, is the most rewarding for the daily worker (highest average number of worked days). This result echoes the reality on ground of day labor (low segment of the labor market) and its resulting migration flows.

x=6 days # of worked days =500.5±13.43 # of relocations =85.5±0.70



x=3 days # of worked days =570.5±10.60 # of relocations =119.5±2.12



x=1 day # of worked days =665.5±2.12 # of relocations =156.5±0.70

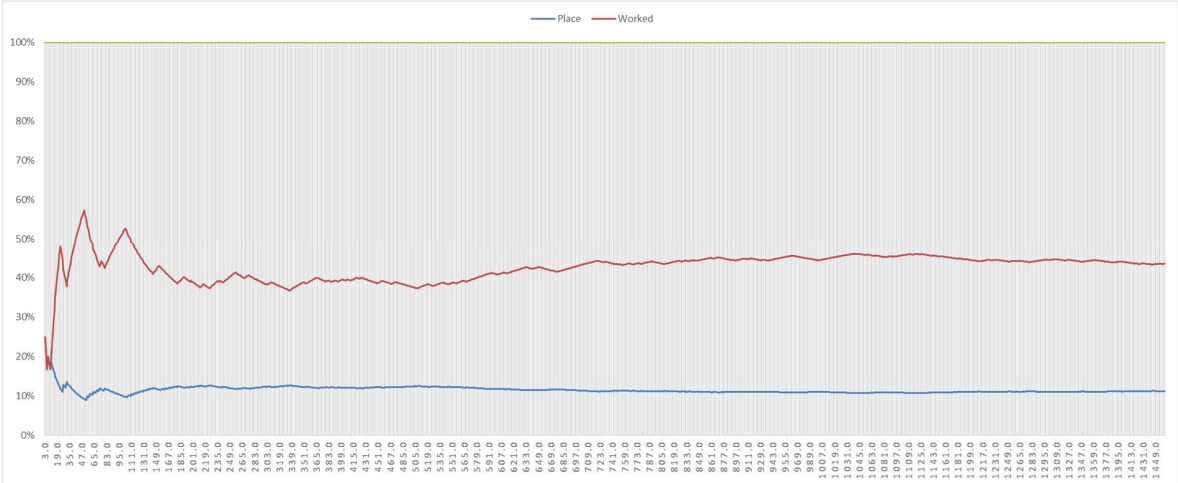


Figure 6.6. Relocations frequency (blue) versus job performances (red)

6.4. Model of hospital resource allocation

Healthcare affordability is a topic of immense interest to both individuals and national policymakers. An accurate depiction of healthcare affordability requires adequate consideration of the way resources can be allocated to meet the healthcare demand. As identified in the ontology presented in chapter 4, such resources can be human (doctors, nurses, etc.), physical (beds, rooms, vaccines, drugs, etc.), financial (funds, taxes, out-of-pocket payments, etc.), or information (health records, training, adverts, etc.). The model developed in this section, using Forrester's system dynamics, is meant to help policy-makers understand and anticipate on beds acquisition and management in a Lagos hospital. System dynamics is a popular modeling approach in healthcare systems M&S. A general survey of system dynamics in healthcare systems studies can be found in [Homer and Hirsch, 2006].

The system dynamics-based model is presented in Figure 6.7. The demand for hospital services is modeled by the admission stock, which derives from an admission rate applied to the population stock. The population demographics change dynamically due to births, mortality and migration. The mortality rate is disaggregated in the model into external death rate (i.e., deaths caused independently from the hospital intervention) and failure rate (i.e., deaths caused within the hospital). The net migration rate aggregates inflow and outflow migrants. While the admission rate subtracts quantities from population, the success rate reinjects into the population those hospitalized patients who do not die at the hospital. Also, non-hospitalized patients return to the population stock. The bed occupancy rate (i.e., the ratio of beds daily occupied by patients over the number of beds available) controls the bed occupation stock, the latter being an indicator of resource need for policy-makers.

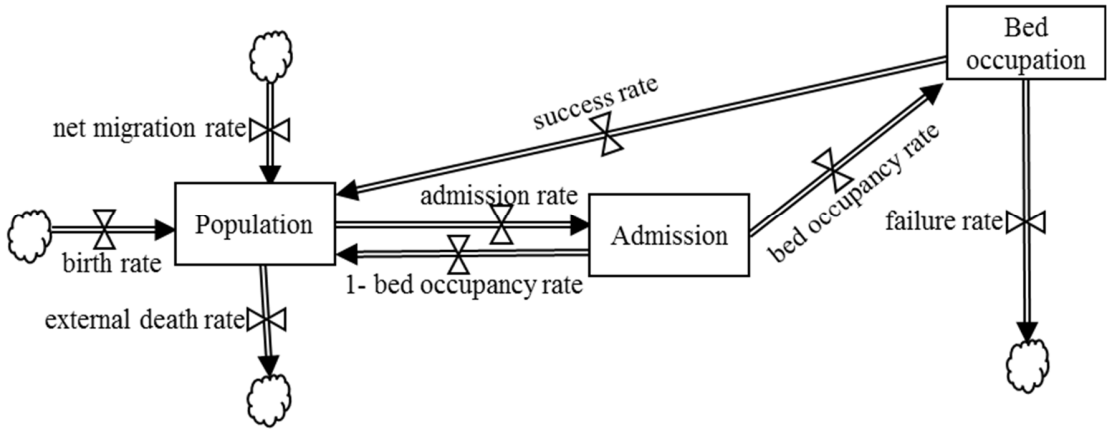


Figure 6.7. Model of demand for hospital services

This model is given from the RA perspective of our framework. Its DEVS counterpart is an atomic model which defines a state variable to represent each stock of the system dynamics model, and which internal transitions modify the values of these variables according to the rates given as parameters. The time advance is always equal to 1 day. The DEVS-based experimental frame specifically built to study the behavior of this displays the results shown by Figure 6.8. On top of the figure is shown the daily evolution over 1460 days (i.e., 4 years) of respectively the number of admissions (red) and the number of beds occupied. At the bottom of the figure is shown the ratio of bed occupancy in proportion of the population. The model has been calibrated using 2010 data from the NBS records (hospital-specific data are averaged over major hospitals and health centers of Lagos): birth rate = 19.854 per thousand annually, net migration rate = -0.40 per thousand annually, external death rate = 7.95 per thousand annually, admission rate = 0.45 annually, bed occupancy rate = 0.73 annually, success rate = 850 per thousand annually, failure rate = 150 per thousand annually.

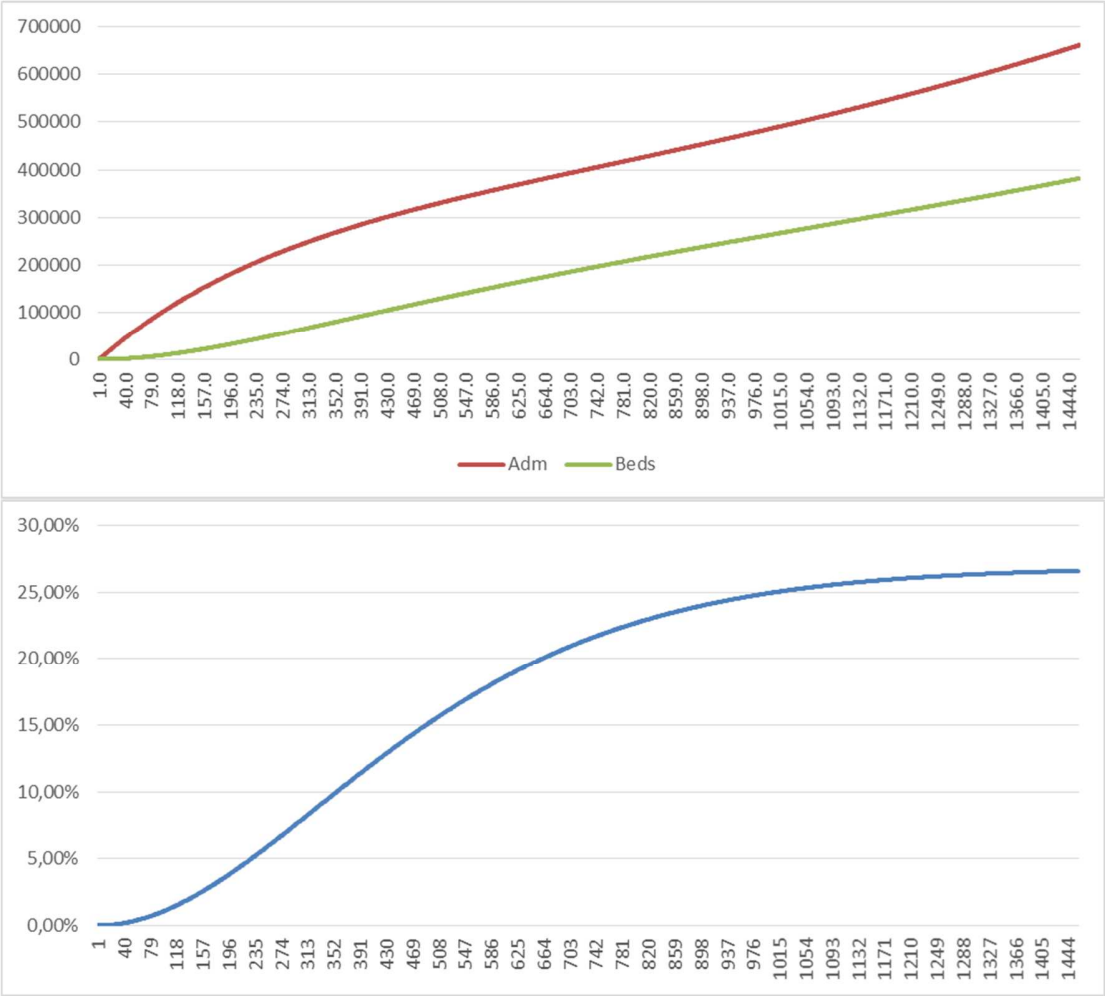


Figure 6.8. Evolution of health demand and supply indicators

6.5. Transfer models

Transfer models describe how the outputs of some of the models we've described affect the parameters of others as explained by the models integration mechanism described in chapter 5. These models, each described as a DEVS atomic model, allow to integrate together all the models given in the different perspectives of our framework. The DEVS atomic model, in each case, has only two states: a waiting state, which time advance is +∞, and a generating state, which time advance is 0. Only an external transition is possible from the waiting state to the generating state

(which corresponds to the receipt of new outputs from the feeding model). In the generating state, the transfer model computes new values for parameters of its target model, then calls the target model to change the values of its parameters, and then executes an internal transition to go back to its waiting state.

If the healthcare system to study is taken at the scale of a hospital located in a popular area of Lagos, the flow of patients will depend on what is going on in the direct environment. Therefore, the individual behavior of the majority of inhabitants (i.e., day workers), as well as the population dynamics of the federal state and the impact of the outbreak of Ebola would greatly influence the admission rate and the bed occupancy rate as well. On contrary, performances of the hospital (i.e., cure and death frequencies) would impact on the relative attractivity of the area as well as the spreading of the disease. A causal loop diagram is shown in Figure 6.9 that illustrates key influences between outputs (in blue) and parameters (in red) of models developed in this paper (the four vertical layers that are apparent in the figure correspond respectively to the RA, HD, PD and IB models). Outputs are influencing variables and parameters are influenced ones. A positive feedback (e.g., from number of infectious individual to admission rate) indicates that an increase (respectively a decrease) of the influencing variable results in an increase (respectively a decrease) of the influenced variable. A negative feedback indicates that both variables evolve in the opposite direction.

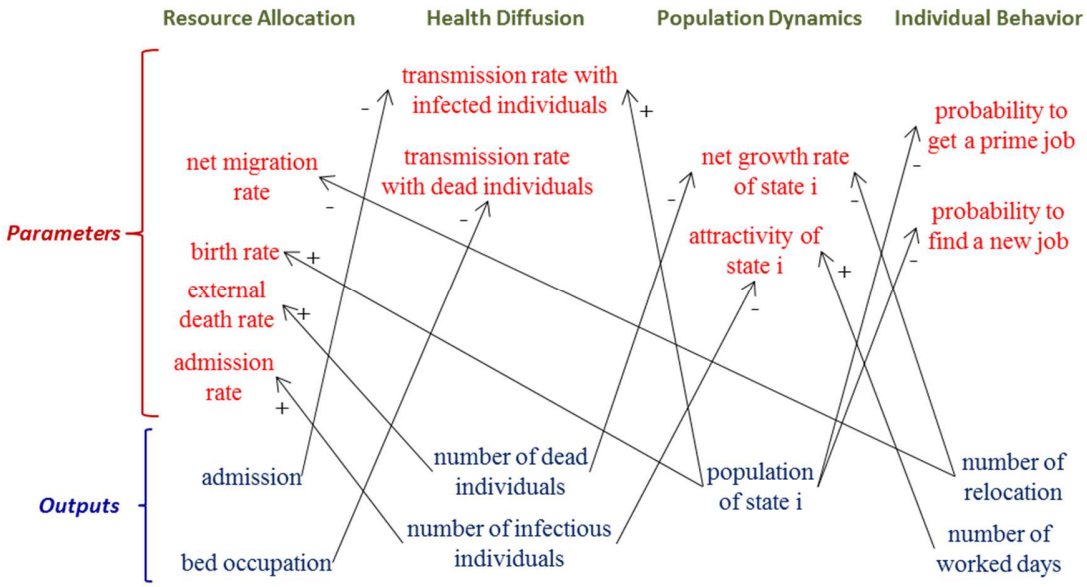
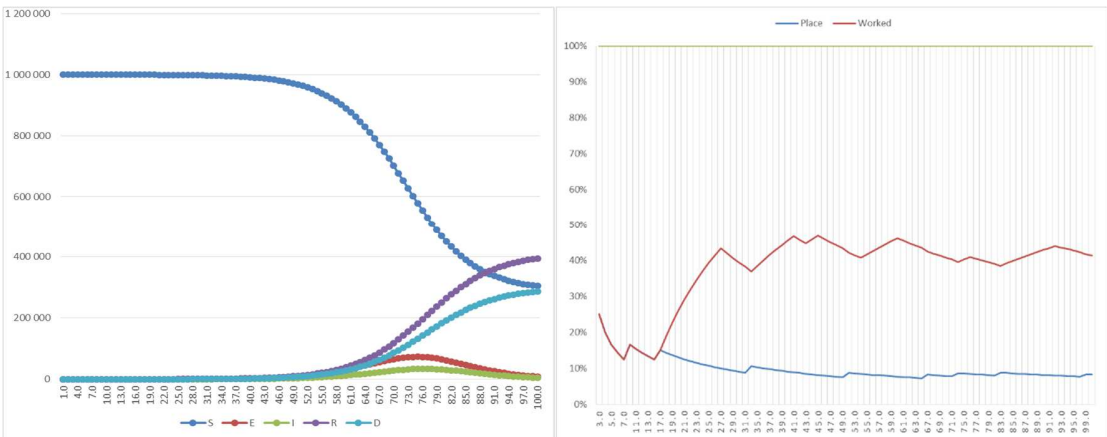


Figure 6.9. Causal loop diagram between outputs and parameters

The experimental frame built to experiment with the resulting holistic model allows to see how all models impact on each other simultaneously, and in various scenarios of influence. Figure 6.10 shows results for the case a linear influence has been defined for each output-to-parameter integration.



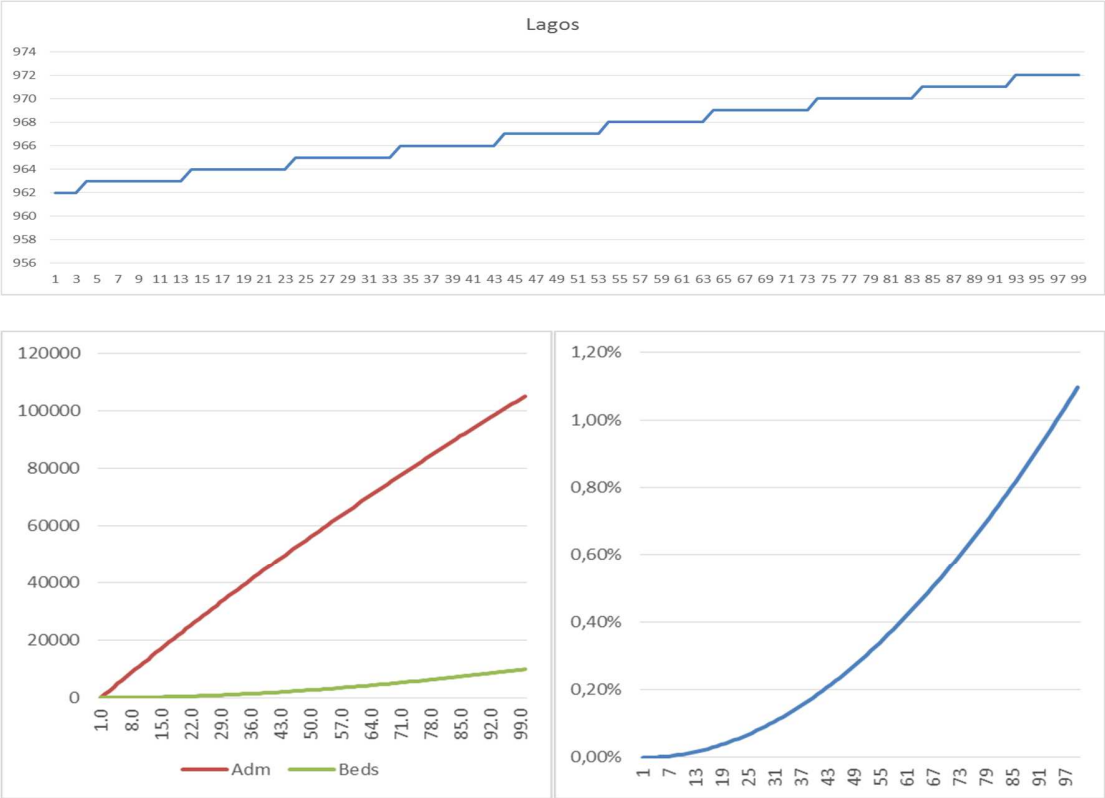


Figure 6.10. Holistic simulation results

Experiments are run for 100 days and each model is initialized to coincide with the outbreak of the EBV period. On top of Figure 6.10 are the new evolutions of respectively the disease-related variables (as the ones shown in Figure 6.1) and job performances of daily workers in relation to the frequency of relocations. At the middle of the figure is the daily evolution of the population in Lagos state. At the bottom of the figure are evolutions of respectively the number of admissions and beds occupied (red and green curves), and bed occupancy in proportion of the population (blue curve). The key interest of this holistic simulation is less to forecast actual future values of the system than to learn about the relative impacts of alternative assumptions and interventions.

6.6. Discussion

The running example has illustrated how the framework can address multiple levels of explanation. Experimental frames from the different perspectives focus on perspective-related questions. Models being abstractions and approximations by essence, a model developed within any perspective will necessarily use parameters to represent the aggregated dynamics of all influencing factors from other perspectives, ceteris paribus. The disaggregation of parameters binds representations from different perspectives to each other. Therefore, models in each perspective are sources of explanation of the hidden influencing processes of models in the other perspectives. That's why the resulting global model allows deriving results that couldn't be accurately addressed in any of the perspectives taken alone.

The key issue is how to relate outputs of some models to parameters of others. In other words, how do we model the disaggregation of parameters for any given model, using information provided by others? How do we validate such model? Two approaches can be considered:

- In static integration approach, a model's parameters remain constant during a simulation. Each variation of parameter implies running new experiments on the model. Therefore, a significant effort is needed to run many simulations, collect quantities of data, and statistically establish a correlation (linear, quadratic, polynomial, etc.) between outputs of some models and parameters of others.
- In dynamic integration approach (i.e., the one we adopted) parameters of a model are modified during the simulation, by the outputs of others. This is possible only if an a priori knowledge of such correlation exist (which may come from an interpolation built, using the static approach). Therefore, a transfer model is nothing more than the description of a correlation knowledge in the form of a discrete event system.

If the healthcare system we studied was taken at the scale of the country, each cell of the population dynamics model (i.e., each federal state) would have been associated to a disease spreading model, many hospital models (as much as the number of health centers of the state) and many individual behavior models (for categories of workers). Such a fine-grained holistic model, though computationally more expensive than simple models, provide a more accurate understanding of the national healthcare system. This is of tremendous interest for decision-makers and has a huge impact on cost, access and affordability concerns.

6.7. Conclusion

We have successfully applied our holistic framework to study the Nigerian healthcare system where problems related to different aspects are studied in isolation then integrated together to form a whole system. A running example of the recent Ebola in Nigeria in 2014 is used to illustrate the multi-perspective modelling approach adopted in this thesis. We are able to elaborate the relationships that exist between the hidden simulation processes of the diverse subcomponents that are most often studied separately and better understand their interactions through a concurrent simulation that brings the results closer to the reality.

A library of theoretical models was developed based on a concept built on DEVS formalism called parameterized DEVS to faithfully describe perspective-specific problems within their respective experimental frame. From this library, the models that are built include model of health diffusion perspective, model of resource allocation perspective, model of individual behavior perspective, and model of population dynamics perspective. A transfer model was constructed

showing how the integration mechanism between models of different perspectives takes place, i.e., how the outputs of some of the models affect the parameters of others.

The simulation results provide multiple levels of explanation in modeling and simulating the Nigerian healthcare system. Hence, it is hoped that healthcare managers and decision makers can get a holistic understanding of the overall healthcare system while accurately designing and analyzing their problems by taking useful decisions.

Chapter 7
RELATED WORK

While considerable efforts have been made to investigate the domain of healthcare using Modelling and Simulation these last decades, few research works if not none have considered studied healthcare systems in a holistic manner using multi-formalism as presented in this thesis. We present in this chapter some research works that have integrated some perspectives together to study healthcare problems as presented in our work. We argue that the contribution of this thesis is original in the sense that it offers a systematic way of identifying, addressing and simulating concurrently the four perspectives of the developed framework to form an integrated whole healthcare system.

The rest of the chapter is organized as follows. Section 1 presents works that are related to one or more perspectives of our framework. Section 2 presents research efforts that use one or more formalisms while section 3 reports on multi-perspective modelling of complex systems as we see healthcare system as one of them then section 4 discusses on the model driven engineering approach. Section 5 concludes the chapter.

7.1. Perspectives specific work

The problem of resource allocation in emergency medical services has been addressed by [Aboueljinane et al. 2013] where the authors highlighted key characteristics of EMS operations as follows: operations - processes describing central and external operations-, decisions regarding EMS operations - long term decisions, mid-term decisions, and short term decisions-, and performance measures associated with EMS operations such as timeliness, survival rate and costs.

A modeling framework that considers three major components including entities, resources, and processes has been proposed by [Mes and Bruens 2012] to study emergency departments (ED). The flow of patients denoted by care pathway were captured by entities, the moving parts of the ED, while resources that were considered include medical staff, operating rooms, hospital beds, and medical equipment. Processes represent services required by the entities. Sequence of activities through which patient undergo start from arrival processes and ends with treatment processes in the emergency room.

[Verma and Gupta 2013] conducted a study on doctors' utilization in outpatient department based on time factor in an outdoor patient department, one of the most congested department in the hospital. The authors investigated on doctors' activities times including arrival time, time spent to examine admitted patients, break time, and time taken by doctors to treat patients depending on illness.

[Ozcan et al. 2011] studied clinical pathway across surgery department at a public hospital and identified critical activities and scarce resources that represent process bottlenecks both from patients and facility point of view. The authors considered patients going through surgery department activities while competing against common resources such as personnel, ambulatory time, beds, and operating theatres.

The problem of physicians' reimbursement schemes has been studied by [Einzinger et al. 2013] to analyze its influence on physicians' treatment decisions. The authors considered patients

and medical providers with main attributes such as epidemiology, service need, and provider utilization.

[Davis et al. 2013] conducted a study on kidney transplantation challenges for improving policy allocation that gives more survival chance and quality of life to patients. Such challenges include high cost of services, donation shortage, and geographic disparities that more often result in considerable amount of waiting time and cause thousands of transplant patients to die each year. Three system performances were considered including average waiting time, probability of death, and probability of transplant.

[Lee et al. 2013] studied supportive care problem to allow individuals to remain in their homes or communities while receiving services. Demand for long-term care in the United States has witnessed rapid increase causing home care industry to face with shortage of home caregivers. The authors argued that the suggested study has great potential to solve a large scale scheduling problem in a short time.

[Charfeddine et al. 2007] discussed on generic aspects of healthcare simulation including population and healthcare delivery systems. The authors argued that simulation studies focusing on population and demand aspects are comprised of economic, epidemiologic and clinical modeling while simulation studies focusing on healthcare delivery networks are directed towards modeling care processes, patient flows and available resources within healthcare supply chains and facilities such as hospitals, clinics and care units.

[Khurma et al. 2013] studied a planning for discharging patients within a reasonable time by reducing their length of stay (LOS) in critical healthcare units. The authors reported that more people could stay in the hospital for lesser time and this will result into considerable savings (in dollar values). The developed planning is referred to as a requirement to address nonmedical reasons for delayed discharges known as one of the causes of system obstacle that result in disrupted flow, blocked beds, frustrated patients and distressed unit staff.

[Zeng et al. 2012] investigated on how to improve quality of care at an emergency department (ED). The authors studied the daily challenges faced by ED such as increase of patient visits, nursing workforce shortage, and long delays experienced by patients during their medical journeys. The model was used to carry out analyses on patient throughput, waiting times, length of stay, and staff and equipment utilizations.

[Vanhoucke and Maenhout 2009] worked on nurse scheduling problem (NSP) instances based on four classes of performance indicators including problem size, preference distribution measures, coverage requirements of the schedule, and incorporated time related constraints. Such effort is hoped to improve the performance and quality of health systems that ultimately depend on the motivation of health human resources such as healthcare managers.

[Fletcher and Worthington 2009] conducted a study on key issues affecting patients flow in A&E (Accident and Emergency) department in a hospital and causing significant patient delay. Such issues include waits for bed, waits for diagnostics, waits for a decision to admit, and variability in demand and process by time of day and day of week. The authors concluded that the

natural level of performance of the A&E department under study may be around 89% based on performance factors such as process time, resource constraints, variability and time of day and day of week, and demand.

[Bountourelis et al 2011] worked on challenges associated with hospital bed allocation within different departments like medicine, surgery, neurology, cardiology and critical care. The focus of the study was on patient blocking referred to as a patient that is medically able to leave a critical healthcare unit like Intensive Care Unit but might experience a prolonged stay due to unavailable beds downstream.

[Cote 1999] addressed challenges related to patient flow and examining room capacity with focus on physician's activities in an outpatient clinic that has four general outpatient services, three examining rooms, and 14 physicians working according to a shift with a nurse aide that has been allocated to each of them. The study was conducted based on the assumption that each patient can select only one primary care physician while a choice of variables such as examining room capacity and arrival rate of the patients were independently considered.

The challenge of surgeon's allocation was addressed by [Sobolev et al. 2008] based on their activities like diagnostic, pre-operative, operative, and postoperative stages at the British Columbia hospital, Canada. The authors considered three care paths of patients including elective patient, inpatient, and emergency patient with coronary artery disease. Performance factors such as the availability of surgeons for consultations, scheduled operations, and on-call duties according to the rotation and vacation schedules in the service were considered.

[Viana et al. 2012] addressed the problem of age-related macular degeneration (AMD) management that lead patients to interact with the eye clinic via appointment scheduling processes. The authors explored different scenarios from which new individuals are weekly added to initial individuals within a period of one year.

[Ramirez-Nafarrate et al. 2013] worked on child obesity which is a public health concern for several countries leading to risk of diabetes, hypertension, sleep apnea, liver disease, stroke and some types of cancer. The authors argued that an estimate of 25% higher health expenditure is associated to an obese person than a person with a healthy weight while leading to 5% and 10% of the overall health expenditures in the United States. Excess caloric intake was reported as a main cause of child obesity.

[Harper 2002] discussed on performance factors related to hospital resources such as hospital admission and discharge dates, time of arrival, length of stay, emergency or elective status, and operation time of patients were considered. The study reports on hospital beds, operating theatres, use of human resources like nurses, doctors and anesthetists.

[Topaloglu 2006] worked on emergency medicine residents (EMRs) scheduling problem while considering both hard and soft constraints in assigning day and night shifts to the residents over a monthly planning horizon. Scheduling EMRs is known as one of the most difficult tasks among other groups of healthcare personnel. The authors claim that the research study is able to

generate a successful and high-quality monthly schedules in reasonable time considering all the constraints in the scheduling environment.

[Gavirneni et al. 2013] addressed the challenge of decision making in Concierge Medicine, an alternative to traditional medical practices that provides better care services to registered patients in a timely manner. Concierge medicine practice facilitates a limited number of 600 patients to register per doctor with some guaranteed revenue streams.

[Morrice et al. 2013] developed a patient-centered surgical home (PCSH) model for coordination of outpatient surgery process at the acute care facility for University Health System (UHS), Texas. The study was concerned with a systems-level process analysis for the Anesthesia Preoperative Clinic (APC) which is the key clinic for system-wide coordination in outpatient surgery. Thus, patients with more complicated medical conditions are referred to the APC for a pre-operative assessment prior to their day of surgery.

[Weng et al. 2011] conducted an operational efficiency based study that finds adequate formula to provide a right number of health resources including physicians, nurses and beds in the healthcare facilities such as resuscitation rooms, triage station, observation unit to maximize the efficiency of the ED. The ED department is equipped with beds distributed into the different sub-units. Patients are modeled from their arrival at the ED till when they are either released from the ED or admitted into the hospital inpatient department for further treatment.

[Price et al. 2013] worked on health service cost reduction at the Maryland proton treatment center by examining facility layouts and scheduling plans to minimize idle equipment and maximize total patient throughput. The study aims at improving patient access to proton therapy, a highly expensive treatment. The treatment center is designed with each imaging and gantry rom servicing only one patient at a time with one cyclotron that provides protons for all different gantry rooms based on first come first served.

[Ahmed and Alkhamis 2009] conducted a research study of an emergency department (ED) unit at a governmental hospital in Kuwait with focus on resource utilization. The study aims at maximizing the utilization of the available resources subject to constrains such as high demands for service, high costs, and limited budget. The designed decision support tool is hoped to help decision makers at the hospital to either evaluate different situations of staffing distribution or optimize the system for optimal staffing distribution at the ED unit.

[Yeh and Lin 2007] addressed specifically nurses' schedule problems at the emergency department (ED) of Show-Chwan Memorial Hospital in Central Taiwan. The ED under study faces serious challenges such as, high patient acuity, hospital bed shortage, high ED patient volume, radiology and lab delays, and insufficient ED space leading to overcrowding and staff availability.

[Person and Person 2009] conducted a medical and economic based study that integrates both patient flow and resource constraint for surgery management decisions. The study considers performance factors such as patient arrival, operating room scheduling, and resource allocation. The scheduling of surgeries was done based on medical priority, time spent in the queue by patients

and available resources like operating rooms, surgeons, and post-operative beds while two types of costs were considered including patient related costs - out-sourcing costs, rescheduling and cancellation costs-, and surgery costs - extra bed costs and overtime costs.

[Choi et al. 2013] addressed the problem of patients waiting time and staff scheduling in an outpatient department, one of the most congested departments in a hospital. The authors reported that patients have longer waiting times while the outpatient have 21 clinics, each operated by a consultant, a team of interns, residents, and nurses.

[Ma et al. 2012] conducted a capacity planning based study to match patient demands and supplied resources. The study was directed both to patient volumes that can be taken care of at a hospital and the resource management. The authors argued that decisions regarding patient flows is based on the annual number of patients that can be treated per pathology group while decisions regarding resources consist of the capacity requirement of each specialty within the hospital.

[Bigus et al. 2011] proposed a general framework for studying the impact of incentives on healthcare that allows to control costs of health services and improve health by healthcare government and employers. The proposed framework considers healthcare main components such as decision-makers, regulations and reimbursement mechanisms.

[Brailsford et al. 2011] conducted a study that considers major factors affecting supply and demand targeting the UK health and social care system. The authors reported that demand for health is a function of need influenced by factors such as disability and disease, new technologies,

changes in levels of income and wealth while supply for health is influenced by factors like demographic trends, economy, and policy environment.

[Paleshi et al. 2011] investigated on intervention strategies for handling disease spread within a generic US metropolitan area. The authors based their study on factors such as population structure, disease characteristics within human body, and disease transmission between people. Population structure includes age groups: less than or equal to 4 years old, 5 to 18 years old, 19 to 64 years old, and 65 years old or older.

Similarly, [Zhang et. al 2012] proposed a contact network-based study that incorporates different intervention strategies to assist policy makers to make decisions for containing the spread of infectious diseases. The authors examined major health interventions including public health interventions that are comprised of pharmaceutical interventions like antiviral treatment and vaccination and non-pharmaceutical interventions such as social distancing, hand wash, and face mask.

[Kasaie et al. 2013] addressed unanswered questions on tuberculosis (TB) transmission dynamics and the role of various contact networks. The authors defined three layers contact network comprised of close contact, casual contact, and random contact capturing social relationships of each individual with the rest of the population. Close contacts represent contacts among household members, casual contacts are social relationships among friends in places such as bar, store, and school, and random contacts represent encounters of people at places such as bus stops and museums.

Population projection is related to public health issues, political decision-making, or urban planning. [Bohk et al. 2009] developed a probabilistic population projection model (PPPM) allowing detailed projections of a population. The proposed PPPM was based on macro-level projection model and integrated two variants: open type and limited type.

Surveys in healthcare M&S showing the different perspectives include the following research efforts. [Roberts 2011] presented a taxonomy of healthcare simulation that considers the following aspects: bed allocation and planning, admission control, room sizing and planning, patient flow, physician and healthcare staff scheduling, materials handling, and logistics. The underlying aspects are concerned with healthcare management challenges including outpatient scheduling, inpatient scheduling and admissions, and emergency department and specialist clinics, hospital departments like laboratory, radiology, surgery and recovery, pharmacy, and supply and support.

[Barjiis 2011] presented healthcare simulation along four axes including clinical simulation - used for studying and analyzing the behavior of certain diseases-, operational simulation -used for capturing and studying healthcare activities such as service delivery, healthcare operation, scheduling, and patient flow-, managerial simulation –used as decision support tool for managerial purposes, strategic planning and policy implementation-, and educational simulation - used for training and educational purposes.

[Brailsford 2007] presented a review of applications of simulation in healthcare into three levels. Level 1 models refer to models at the cellular, organ or system level of the human body, or

disease models and are used to study clinical effectiveness of healthcare interventions. Level 2 models are used to study activities of health unit – hospital department, clinic or emergency room at operational or tactical level. Level 3 models also called strategic models are used for studying long-term problems.

[Onggo 2012] presented a review on simulation modeling for the provision of social care services. Main components of social care services that were considered include demand, supply, delivery methods and finance. The authors argued that health demand is generated by care users and its planning is linked to population projection that is partly influenced by healthcare system.

[Gunal and Pidd 2010] presented a review of performance modeling in healthcare simulation that considers models according to the objectives of the studies. The models address simulation aspects such as scheduling and patient flow, sizing and planning of beds, rooms, and staff. The authors highlighted that healthcare simulation based studies are unit specific, that is, their focus is on specific problems in individual units of healthcare systems. Additional surveys can be found in [Thorwarth and Arisha, 2009], [Katsaliaki and Mustafee, 2011], [Almagooshi, 2015], and [Powell and Mustafee, 2016] among others.

While many research works concentrate on only one of our four perspectives, some combine two or three of them as summarized in a representative sample in Table 7.1 as follows.

Table 7.2. A benchmark of integrated healthcare M&S frameworks

Integrated Healthcare M&S Frameworks	*Resource Allocation*	*Health Diffusion*	*Population Dynamics*	*Individual Behavior*
[Augusto and Xie 2014]	✓			✓
[Viana et al. 2012]	✓	✓		✓
[Zulkepli et al. 2012]	✓			✓
[Bisset et al. 2012]		✓	✓	
[Macal et al. 2012]		✓		✓
[Harper, 2002]	✓			✓
[Okhmatovskaia et al. 2012]		✓	✓	
[Ferranti & Freitas Filho 2011]		✓		✓
[Fletcher and Worthington 2009]	✓			✓
[Bountourelis et al. 2011]	✓			✓
[Bohk et al. 2009]			✓	
[Cote, 1999]	✓			✓
[Brailsford and Schmidt 2003]			✓	✓
[Ahmed and Alkhamis 2009]	✓			✓
[Weng et al. 2011]				
[Jeffers, 2014]	✓	✓	✓	
[Andradóttir et al. 2010]	✓	✓		
[Barhak et al. 2010]		✓	✓	
[Aboueljinane et al. 2013]	✓			✓
[Djanatliev et al. 2012]	✓	✓	✓	

[Brailsford et al. 2011]	✓	✓		
[Carr and Roberts 2010]		✓	✓	
[Charfeddine and Montreuil 2010]	✓	✓	✓	
[Chow et al. 2008]	✓			✓
[Yeh and Lin 2007]	✓			✓
[Crooks and Hailegiorgis 2014]		✓		✓
[Davis et al. 2013]		✓		✓
[Dibble 2010]				
[Ma et al. 2012]	✓			✓
[Lee et al. 2013]	✓			✓
[Ma and Demeulemeester 2013]	✓			
[Ng et al. 2011]	✓			
[Ozcan et al. 2011]	✓			✓
[Perez et al. 2010]	✓			
[Price et al. 2013]	✓			✓
[Ramirez-Nafarrate and Gutierrez-Garcia 2013]		✓		✓
[Shin et al. 2013]	✓			✓
[Sobolev et al. 2008]	✓	✓		✓
[Topaloglu 2006]	✓			✓
[Choi et al. 2013]	✓			✓
[White et al. 2009]		✓		

[Person and Person 2009]	✓	✓		✓
[Morrice et al. 2013]	✓			✓
[Bigus et al. 2011]	✓	✓		✓
[Althaus et al. 2015]		✓		
[Salimifard et al. 2013]	✓			✓
[Kasaie et al. 2013]		✓	✓	
[Einzinger et al. 2013]	✓			✓
[Gavirneni et al. 2013]	✓			✓
[Paleshi et al. 2011]		✓	✓	✓
[Zhang et. al 2012]	✓	✓		

The closest work to our contribution is (Jeffers, 2014), in which a similar integration approach is proposed, with all models developed in Forrester's System Dynamics. This work, though not proposing a generic framework, is a perfect illustration of a possible application of our framework, where models have been developed in 3 perspectives and the outputs of some used to feed the parameters of others. This integration approach is not used by the works presented in Table 7.1.

7.2. Formalism specific works

A considerable number of research works based on single or multiple-formalism has been dedicated to study problems fallen into the perspectives formulated by our framework. Such efforts include the work of [Ng et al. 2011] based on system dynamics modeling to study healthcare affordability problem in Singapore by investigating on different scenarios that evaluate the effectiveness and sustainability of policies over time.

[Djanatliev et al. 2012] integrates system dynamics and agent-based models to investigate the effects of implementing new technologies in healthcare systems. Major modules such as population dynamics, disease dynamics, health care and health care financing were considered for the study. After using different use case scenarios, the authors concluded that the research effort has achieved an overall credibility from all domain expects including doctors, health economics, medical informatics, and knowledge management experts.

In a similar way, [Viana et al. 2012] combined agent-based modeling (ABM) with system dynamics (SD) for the management of age-related macular degeneration (AMD) problem. Individuals were modeled as agents in the population developing AMD that lead them to interact with the eye clinic via appointment scheduling processes. SD was used to model progressive sight loss from AMD which affects agent eyes. The authors reported that the integration ABM and SD in a health care context is rare in the sense that the main conceptual challenges lie in designing those sub-components and achieving their interactions.

[Einzinger et al. 2013] developed an agent-based model to study reimbursement schemes, a factor that influences physicians' treatment decisions in the Austrian healthcare sector. The authors defined two types of agents including patients and medical providers. They argue that the model facilitates comparisons of different reimbursement system in outpatient care while it is useful for testing assumptions.

[Topaloglu 2006] developed a goal programming (GP) model to deal with emergency medicine residents (EMRs) scheduling problem that considers both hard and soft constraints in

assigning day and night shifts to residents over a monthly planning horizon. The author asserted that the developed GP model was capable of generating high-quality monthly schedules in reasonable time.

[Yeh and Lin 2007] developed a genetic algorithm (GA) to address nurses' schedule problems at the emergency department (ED) of Show-Chwan Memorial Hospital in Central Taiwan. The concerned ED is faced with management challenges of high patient acuity, hospital bed shortage, and radiology and lab delays that lead to overcrowding and staff unavailability. The authors considered ED processes such as triage, insurance procedures, recovery rooms, and diagnostic and respiratory therapy in their approach.

[Ferranti and Freitas Filho 2011] developed a system dynamics model to study risk factors for age-related cardiac diseases. The model considered key parameters such as growth rate, reserve rate, and aging rate. The authors report the results of the study have shown that maintaining good blood pressure and participating in physical activities have an impact on a person's lifespan and delaying mortality in the population while claiming that sex is related to a person's lifespan, thus anticipating mortality in the male population.

[Sobolev et al. 2008] used Statecharts, a system of graphical specification, to address perioperative processes of cardiac surgical care department. Statecharts specification paradigm was chosen because it extends the formalism of finite-state machines through notions of hierarchy, parallelism, and event broadcasting, for representing reactive systems. The authors modeled surgical activities such as diagnostic, pre-operative, operative, and postoperative stages while

concluding that Statecharts enables the representation of surgical care features in a rigorous manner.

[Paleshi et al. 2011] developed an agent-based simulation model of a pandemic within a generic US metropolitan area in order to study how the disease spreads and to prepare for handling the consequences by implementing intervention strategies. The proposed model consists of three main subroutines including the structure of the population, disease characteristics, and transmission of the disease between people. The population was structured into four age groups: less than or equal to 4 years old, 5 to 18 years old, 19 to 64 years old, and 65 years old or older..

[Bigus et al. 2011] used multi-agent modelling to study the impact of alternative healthcare incentives. The simulation model considered four components that are: disease model, patient, medical intervention and provider components. Based on 'state abstraction' from the perspective of a Markov disease model, relevant disease states and the estimation of transition probabilities between disease states were automatically extracted. Statistical estimation of certain patterns of intervention was used for characterizing provider's behavioral model.

[Kasaie et al. 2013] developed an agent-based simulation (ABS) model to study tuberculosis (TB) transmission dynamics and the role of various contact networks. People in the population were represented as agents in the model. The population was structured into different groups including households, neighborhoods and communities. TB natural history was modeled at the individual level using five main TB health states including susceptible, early latent TB, late latent TB, active TB, and recovered states. The authors defined a three-layer contact network referred to

as close, casual, and random contacts representing the social relationships of any individual with the rest of the population.

[Ramirez-Nafarrate et al. 2013] presented an agent-based simulation (ABS) framework that can help policy-makers to design meal menus and physical activity programs for school-age children that reduce the prevalence of obesity during childhood. The authors argued on the proposed modeling framework that ABS models are used because they allow analyzing a complex system with autonomous agents. Children were represented with eight attributes including age, gender, weight, height, body mass index (BMI), weight status category, daily caloric intake, and energy expenditure.

[Charfeddine and Montreuil 2010] presented a conceptual framework for healthcare delivery systems with focus on two major components: population generating the demand for healthcare services, and healthcare delivery network representing the organization of the healthcare system in order to satisfy the population demand. Population demand for healthcare services is expressed as the probability distribution through the stochastic modeling of the health state evolution of each person (represented as an agent) while the model of healthcare delivery network was based on a strategic mapping framework and agent oriented modeling methodology.

[Brailsford et al. 2011] presented an integrated model of supply and demand of both health and social care of the UK health and social care system. UK society was modeled with Statistical models using theories from social models of disability. An agent-based model of the demographics of aging and social care was constructed to investigate the effects of individual-level behaviors. A

high-level system dynamics simulation model was developed to study health and social care at the institutional level. The authors reported that these three approaches are linked to build a suite of models which represents UK health and social care at multiple levels: population, individual and institutional.

7.3. Multi-perspective Modelling

The problem of modeling complex system has already been addressed in various manners. Some authors argued that it is not sufficient to model system components in isolation and capture the behavioral properties of the overall system. Complex systems are defined as ones made up with a large number of subcomponents that interact in a non-simple way [Simon 1962]. Hence, to understand complex systems one of the common ways is to impose on them a hierarchical design by separating the subcomponent parts and defining relations between them [Seck and Honig 2012]. The idea of viewing complex systems as they are hierarchically structured was introduced by [Simon 1962] and he defined a hierarchical system as one composed of interrelated subsystems, each being hierarchical and so on until some lowest level of elementary subsystem. Consequently, current modelling and simulation approaches such as DEVS formalism [Zeigler et al. 2000] rooted in system hierarchy specification formalism, represents systems as atomic and coupled models.

System of systems approach is another way used to study complex system. As such, in a systematic view of healthcare, [Zeigler et al. 2012] presented an illustrative general framework for systems of system level modelling to support design of coordinated care architectures while linking up hospitals and physicians through networked information systems. According to the authors, today's healthcare system is fragmented with uncoordinated assemblage of component systems

that are loosely coupled. However, an ideal healthcare delivery system will require methods to model large loosely coupled distributed system of systems that target the optimization at the macro level (the entire system itself) instead of the micro (component system) level. The proposed approach integrates models of human behaviour limitations for predicting quality versus cost metrics. The concept of system of systems applied to healthcare was motivated by the ability to provide the right information to the right people in real time.

Modelling complex system within a single model where different aspects of the system are captured by different views has been reported as difficult, if not impossible by [Reineke and Tripakis 2014]. In order to overcome this challenge, multi-perspective modelling approach has been successfully adopted by a lot of research work where distinct models are constructed to model the same system and each model focuses on the particular aspects of the system.

[Seck and Honig 2012] proposed a multi-perspective modelling approach (Figure 7.1) to overcome the limitations of a single-perspective hierarchy approach based on aspect models integrated with bridge models. They adopted the idea of modelling relation as introduced by Rosen (2000), and Mikulecky (2001) that defines a bridge between two worlds as the natural world in which we live and the mental world referred to as formal system that represents our perceptions of the former. The bridge from the natural system to formal system is done through encoding while the inverse is done through decoding. Based on this idea, they argued that when trying to model a complex system, it can be described as a collection of perspectives where each perspective represents a unique formal system having a unique decomposition. Hence, one could model a complex system in a richer way by having multiple non-isomorphic decompositions that may

influence each other and capture its complexity resulting from the observation through different perspectives.

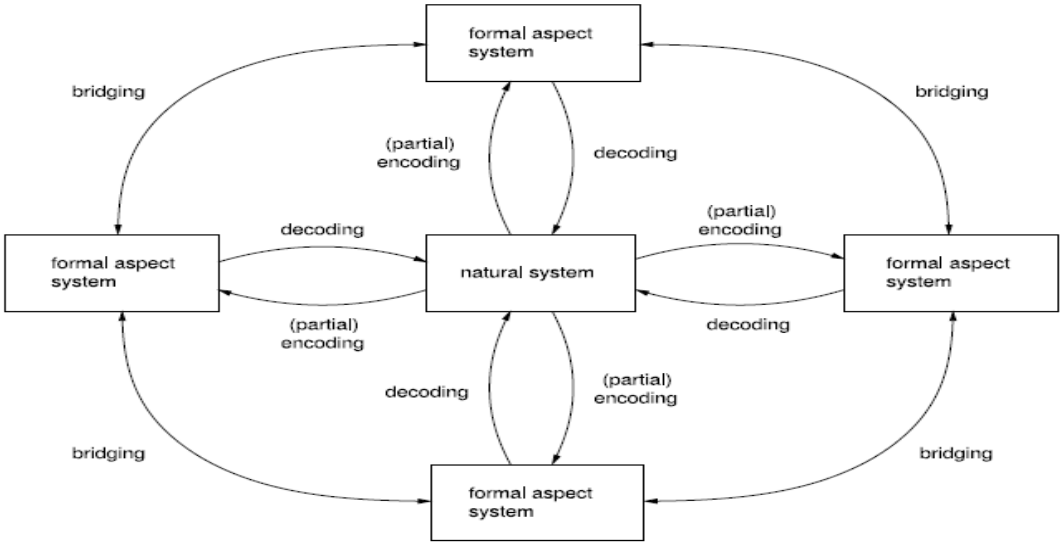


Figure 7.1. Modelling complex phenomena via multiple perspectives [Seck and Honig 2012]

[Tekinay et al. 2010] introduced a context-based "view" concept as an enabler to support multi-perspective modelling in multi-actor environments using an example of quay crane system. The authors claimed that the proposed "view" concept is able to provide extensibility and adaptability that are not addressed in the Multi-resolution Entity design scheme.

[Braun and Esswein 2015] argued that structuring the different views of an information system through multi-perspective modelling is more relevant to improve the understanding of its complexity. As such, the modeller can either provide the description of the entire information system through view building or focus on specific aspects of the system to support the understanding of a particular domain. The different aspects are then linked by integrative model

elements. As a result, one can establish process-oriented, document-oriented and goal-oriented perspectives within a BPMN (Business Process Management) model.

Multi-perspective modelling has also been used by [Kingston 2001] in ontology to represent knowledge from the viewpoints of "who", what", "where" and "how" for the purpose of knowledge valuation. The argument was based on a widely acknowledge concern which states that the principle of multi-perspective modelling is that for any "knowledge asset" to be represented adequately, it's necessary to represent a number of different perspectives on its knowledge and, possibly, to represent the asset at multiple different levels of decomposition.

[Vangheluwe 2000] showed that when modeling complex systems, due to their nature of being composed of a large number of subcomponents that are diverse and interrelated by complex interactions, it is necessary to answer questions about the overall system through multi-formalism modeling. The different models of the subcomponents expressed in different formalisms according to criteria such as application domain, the goals and the available computational resources can then be transformed in a common formalism making semantics of models explicit and meaningfully integrated using closure under coupling.

In software engineering systems are often modelled using different multiple models of different types.

[Salay 2007] proposed a formal framework for multimodeling in software engineering to underline the reasons for that: i) different views of the system are best captured using an appropriate modeling language corresponding to that view, ii) the complexity of a system demands

that it be decomposed into smaller parts according to different levels of abstraction, iii) through "separation of concerns" different objectives are met by different models. The author introduced a multimodeling formalism based on sorted first order logic with transitive closure to describe multimodels as a set of models hierarchically interrelated through relations type of different orders. This led Salay (2007) to argue that a multimodel can be seen as a macromodel.

More closely related to this, [Fishwick 2007] defined multimodeling as a "process of engineering a model by combining different model types to form an abstraction network or hierarchy". As such, multimodels can be seen as models being composed of other models that can be heterogeneous or homogeneous being coupled together.

Yet another way of dealing with complex systems is through model composability of sub-systems to develop a whole model. [Sarjoughian and Huang 2005] presented a multi-formalism modeling composability framework with a new concept called KIB (Knowledge Interchange Broker) to compose disparate modeling formalisms such as DEVS formalism and Reactive Action Planning (RAP) formalism while the resultant composed models have a well-defined structure and behavior. The composition of the two formalisms is defined as the composition specification with its corresponding executor which includes DEVS simulator and RAP interpreter.

As complex systems are increasingly becoming heterogeneous due to various implementation technologies involved in their design, [Mosterman and Vangheluwe 2004] introduced a computer automated multi-paradigm modeling (CAMPaM) a domain-independent framework as enabler of complex system design that aims to address this issue through integration of three orthogonal

directions of research including model abstraction, multiformalism modeling, and meta-modeling. Using a power window system as an illustration, the authors explore the combination of these three dimensions of research to facilitate the use of high-level modeling languages in designing complex systems.

7.4. Model Driven Engineering (MDE) approach

Another dimension of our work is the use of a Model Driven Engineering (MDE) approach to allow multi-formalism modeling on top of our framework. In recent decades, M&S practitioners have been adopting MDE techniques to facilitate M&S processes. Prominent among such approaches is the development of model-driven environments that provide tooling supports for specific simulation formalisms by offering high-level notations, which are graphical in most cases, for model editing. Such high-level models serve as the basis for systematic and progressive synthesis of executable codes for the targeted simulation platforms.

[Wu et al. 2007] presented an extended Model Driven Architecture (MDA) method based on robustness analysis and UML models for user interface modeling and transformation that considers four levels modeling including Computation Independent Model (CIM), Platform Independent Model (PIM), and Platform Specific Model (PSM) and JSP code. User requirements are modeled using use case diagram and activity diagram that is being mapped unto robustness diagram at the CIM level. At the PIM level, behavioral aspect and structural aspects were modeled using sequence diagram for the former and class diagram for the later. The PSM model is obtained from the PIM model which was transformed unto widget class diagram based on MVC (model view controller) architecture. The resulting PSM model is then used to generate the JSP code.

[Song et al. 2015] proposed a model driven simulation approach to guide and support the design of healthcare information system from point of system engineering with some key technologies such as SMP2 (simulation model portability), and HL7 HDF (healthcare information system development methodology). The transformation of the model is realized from HDF design model to SMP2 simulation model.

[Mishra and Upadhyay 2014] used MDA approach in designing healthcare database system in order to improve portability, resilience, and maintainability in software engineering. The CIM model of the healthcare information system reflects all entities related to a patient and healthcare and it is presented using UML Class Diagram. The PIM model represented using ER Diagram captures database information system independently from the implementation and business process model. The transformation from PIM model to PSM model was done through revolution specification.

Seeking to improve information systems (IS) engineering [Fazziki et al. 2010] proposed an IS development based on model driven architecture integrated with Meta modeling and multi-agent systems. The adoption of multi-agent systems is motivated by the need to have adaptive components that deals with the regular change that happens from one project to another with the application of modeling approach. The authors separated three layers including domain layer, the agent oriented layer and the implementation platform layer corresponding to three kinds of Meta models.

[Jones et al. 2007] proposed a methodology for the development of m-health (mobile health) systems based on Body Area Networks (BANs) using model driven architecture (MDA) approach combined with formal validation and verification as a support for the correctness of the transformation of models. The authors used two different formalisms including UML diagrams and a linear discrete mathematics notation to describe the modeling of the health BAN at PIM level while models are developed according to each selected device to form the Epilepsy BAN PSM.

[Kriouile et al. 2013] presented a critical review of the methods used in MDA literature for modeling and transforming CIM models to PIM models. According to the authors the general evaluation criteria for CIM coverage must satisfy business objects model (static view), business process model (behavioral view) and requirements model (functional view) while the focus of PIM models is more on the structural aspect and the behavioral aspect of the system.

Examples of environments, using MDE which are based on discrete event simulation formalisms, have been reported in [Kofman et al. 2003], [Mittal and Martín 2013], [Bonaventura et al. 2013], [Ighoroje et al. 2012], [Zeigler and Sarjoughian 2013], [Mittal and Douglass 2012], and [Risco-Martín et al. 2009]. Comparative surveys of the relative strengths of some of these environments have been done independently by [Franceschini et al. 2014] and [Aliyu et al. 2016].

7.5. Conclusion

We present research efforts that are related to the work developed in this thesis. Many papers in the literature have addressed problems peculiar to healthcare domain suing M&S based on

different perspectives similar to the ones proposed in our framework. Such perspectives specific research works have been thoroughly discussed as well as the formalisms used to address them. Furthermore, we report on the methodologies used for investigating overall complex system difficulties.

Chapter 8
CONCLUSION

The thesis presents the study of healthcare systems (HS) using Modeling and Simulation (M&S) as a potential tool. This study is a response to the problems associated with the holistic understanding of HS behavior characterized by a large number of composing components that are associated with complex processes. In today's complex world, studying HS can be a difficult task, specially saying where a HS starts and ends because there is a wide variety of healthcare systems around the world and every country has its own health system that reflects its own history, its own politics, and its own economy and national values that all vary to some degree. Coupled to these problems, the domain of healthcare is facing a wave of challenges due to an ever increasing financial pressure, unlimited demands for healthcare services caused by aging population of the world, degrading quality of health delivery, and limited access of healthcare services. However, the competing goals including access, quality and cost, are bond together in an "iron triangle" such that any attempt of achieving anyone of them would significantly deteriorate the others. As a result, the work of healthcare managers becomes very challenging while trying to provide efficient management of health resources and patient-centered services. Such services include duties like developing strategic visions, hiring, training, assigning schedules and tasks, handling finances - creating budgets, calculating and issuing patient bills, negotiating insurance claims-, organizing and maintain patient records. Therefore, the issue of healthcare efficiency - the need to produce more with less, despite the scarcity of resources- has been widely acknowledged among policy-makers and healthcare managers.

We investigate the different aspects of healthcare domain and the relationships that exist between them and the interaction they have with the environment in which they were modelled. This work is intended to assist healthcare managers and decision makers to take decisions that are closer to the reality while designing and analyzing healthcare systems that significantly improve performance factors. While this work focuses on healthcare systems study, it is hoped that its application could be extended to the study of other complex areas like public traffic, defense, emergency evacuations, etc.

The rest of the chapter is structured as follows. We present in section 1 the conclusions of the different parts of the work done in this thesis followed by section 2 highlighting the perspectives of the work to be carried out in the future.

8.1. Conclusions

To address the problems related to healthcare complexity modelling, we adopted a methodological approach following a series of activities towards achieving the objectives of the thesis. First, we lay the basis of our approach by building an ontology for healthcare systems M&S based on extensive literature review. We then investigate HSs through multi-perspective modeling and simulation where different aspects of healthcare are captured by different views within a single model. The perspectives we developed are: *resource allocation perspective (RA)*, *health diffusion perspective (HD), population dynamics perspective (PD)*, and *individual behavior perspective (IB)*. Consequently, the top single model within each of the perspectives is coupled with its experimental frame to run simulations and derive results. Perspectives are identified by the categories of questions that the corresponding experimental frames can allow to answer. Hence, modelling HSs is made more practical and richer with deep insights.

Additionally, we propose an approach for holistic analysis of Healthcare Systems (HSs) based on the multi-perspective modeling framework and a systematic integration of simulation processes to form a holistic system. A lot of simulation-based research efforts are found in the literature where HSs are studied with focus on specific problems that are often studied in isolation with constant parameters. However, we argue that the values of these parameters can change in concurrent simulation studies. To bridge this gap, we propose a methodology for a "loosely" integrated simulation where independent simulation processes of disparate concerns in HS exchange live updates of their influences on one another while obtaining a holistic understanding of the whole healthcare system and deriving more realistic decisions. The proposed integration approach is one of the major contributions of the thesis and can be generalized beyond the framework to integrate models from other domains in a holistic study. Furthermore, we formalize the integration approach that allows linking up the isolated perspectives through a concept based upon Discrete Event Systems Specification (DEVS) formalism called Parameterized DEVS, whereby concurrent simulation processes cause live update through output-to-parameter integration. We implement a large library of DEVS-based parameterized theoretical models, organized along the stratification of abstractions proposed in our framework. The library includes the SIR model and its derived SEIR, SIRQ, MSEIR… models for the HD perspective, Prey-Predator and cohort-component models for the PD perspective, Queueing theory models for the RA perspective, and agent-based models for the IB perspective.

Finally, we apply our framework to build models in isolation according to each perspective and integrate their simulation results together to form a complete whole. The outbreak of Ebola

in Nigeria in 2014 was used as a running example to show how the framework is applied. The obtained results allow us to gain multiple levels of explanation of healthcare phenomena that could not be derived accurately when studying those perspectives separately. A transfer model was successfully constructed showing how the integration mechanism between models of different perspectives takes place, i.e., how the outputs of some of the models affect the parameters of others. We are able to understand the interactions that exist between the hidden simulation processes of the different perspectives through concurrent simulation studies and got results that are closer to the reality.

8.2. Future Work

Modelling and Simulation of healthcare system remains an open challenge problem due to the mounting pressure of healthcare cost, the ever increasing demand for care services and its multiple extensions such as various healthcare specialties, and external laboratories that are intertwined with intricate processes. The research effort presented in this thesis is a step forwards to understanding the holistic behavior of the overall healthcare systems. However, this current work opens doors to additional questions that can be easily addressed into future research directions.

We are projecting to use a multi-formalism modeling approach to effectively capture the different concerns embedded into the multi-perspective framework presented in this thesis. Such effort will definitely accommodate the diverse familiarities of the experts with modeling formalisms, reuse of existing models, easiness to reproduce realities using specific formalism for specific perspectives accordingly. To realize that, we place the multi-formalism modeling feature at the top layer of the proposed framework and support it with the Model Driven Engineering

(MDE) approach through which a co-simulation or a formalism transformation can be carried out. A co-simulation approach promotes the simulations of the disparate models based on their respective formalisms with a mechanism for data exchange, while a formalism transformation involves the translation of the disparate models into a formalism upon which the simulation will be based. We intend to use formalism transformation, such that users can model the different perspectives in their preferred formalisms then translate all those models to DEVS for simulation. MDE is a software development approach which considers models as central artefacts, being used throughout all engineering disciplines while raising the level of abstraction through models usage in program specification. MDE also allows increasing automation in program development. Hence, models at higher level of abstractions in our framework using formalisms such as Petri Net, System Dynamics, Cellular Automata, or Queuing Networks will be transformed unto models at lower level of abstractions until code generation. Therefore, the proposed MDE-based framework for holistic M&S of healthcare systems will make the modeling easier and systematically allow generating the final DEVS-based simulation model.

Figure 8.1 presents the overall framework to be implemented at conceptual level. The topmost layer contains the metamodels of prospective formalisms for modeling the different perspectives of healthcare systems. Note that the list in the figure is not exhaustive. Hence, each of the perspective models in the third layer must conform to the metamodel of the formalism chosen to create it. We will use the ATL (Atlas Transformation Language) technology [Jouault et al. 2006] to transform the disparate perspective models into SimStudio implementations of DEVS simulation models [Traoré, 2008] at the bottom layer.

We also intend to develop a software environment support that will serve as a domain specific modelling language to help healthcare managers and decision makers to design and analyze their daily tasks. It is hoped that such tool will assist addressing healthcare problems through what if scenarios that could not be accurately achieved whiteout simulation means while saving cost and time.

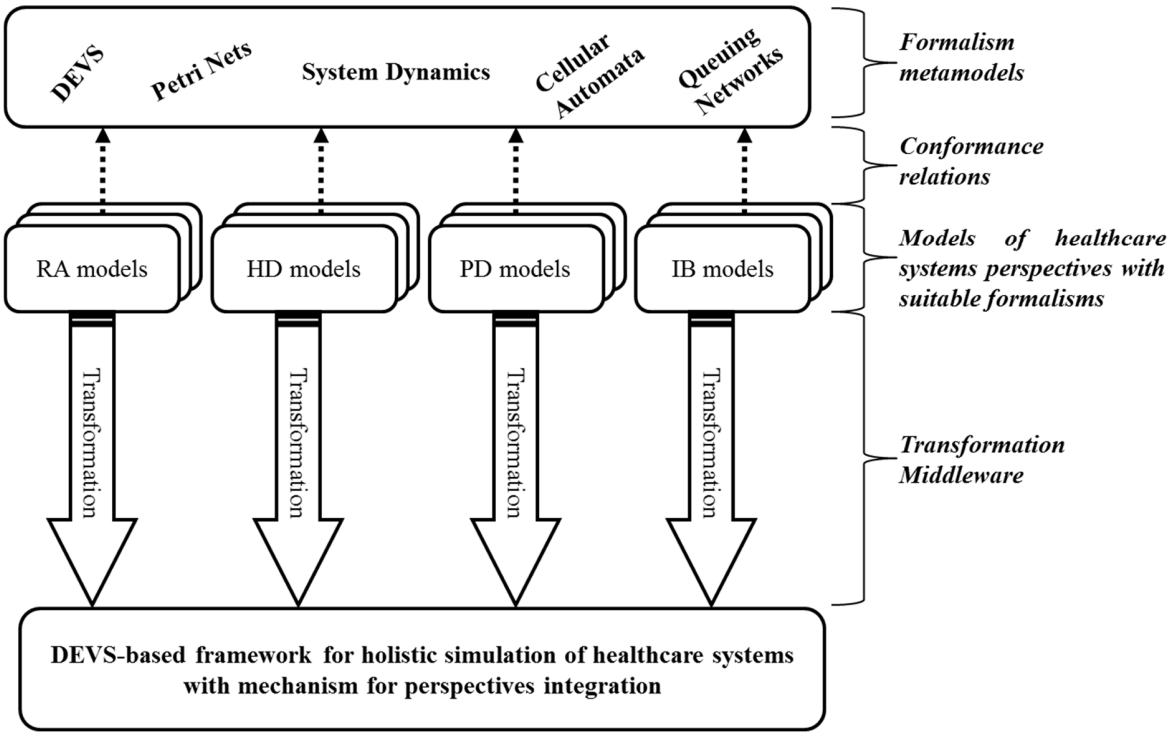


Figure 8.1. MDE-based framework for holistic M&S of healthcare systems

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