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A model-driven framework for multi-paradigm modeling and holistic simulation of healthcare systems

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Abstract

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. Most often, the diverse perspectives of healthcare systems are studied in isolation and using specific formalisms. 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 this article, we propose a framework for multi-paradigm modeling and holistic simulation of healthcare systems. We present a modeling methodology with a plethora of formalisms to allow the modeler to choose an appropriate formalism at a given level of abstraction while model transformation relates the different formalisms. Furthermore, we develop an integrative approach for the interactions between models of different perspectives through dynamic update of model output-to-parameter integration during concurrent simulations. Such an approach provides multiple levels of explanation for the same system, while offering, at the same time, an integrated view of the whole. The framework has successfully been applied to study part of the Nigerian healthcare system.

Keywords

Healthcare systems, Modeling and Simulation, multi-paradigm modeling, holistic simulation, model-driven engineering

1. Introduction

Modeling and Simulation (M&S) is becoming a considerable means of studying healthcare systems. However, capturing all significant processes involved in the behavior of such systems is not obvious. This is due to the fact that healthcare systems are composed of distributed components interrelated with intricate processes that can be revealed only from various perspectives. Consequently, research efforts interested by only one perspective use parameters to approximate all the hidden processes resulting from the ignored perspectives. However, simulations from isolated perspectives are not sufficient for a comprehensive study of a healthcare system. Rather, a holistic framework, such as the one proposed in this paper, is needed to allow multiple levels of explanation as well as to derive results that could not be accurately addressed in any of the perspectives taken alone. The outbreak of Ebola in Nigeria in 2014 will be used as a running example to introduce the framework proposed and show how it applies.

On 20 July 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 Lagos International Airport.[1] 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 diagnosis, nine healthcare workers were infected and 898 contacts were generated throughout 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

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centers, along with a 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, or 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.

We argue that studying in isolation the Ebola outbreak, without integrating characteristics of the Nigerian healthcare system that can be seen from other perspectives, may fail to provide all the necessary levels of explanation for policymakers to design efficient decisions. This includes the allocation of scarce health resources, the vibrant population dynamics, and socio-cultural behavior of individuals. The EVD spreading can be modeled by a compartmental model.[2] Taken alone, this perspective provides a level of explanation for the epidemiological understanding of the disease outbreak (as detailed in section 4), where the influence of all other possible perspectives is approximated by parameters. For example, population dynamics, as well as cultural behavior, are all considered together and assumed to lead to transmission rates, without distinction between urban/rural areas or between health workers and the remaining part of the population. It would be interesting to have a platform that allows us to study how the problems in one perspective evolve with respect to those in the others. For example, how do the dynamics of the population and/or the resource allocation strategy deployed by the government affect the evolution of the disease, and vice versa? While the simulation from one perspective abstracts all realities concerning the rest of the perspectives, connecting different perspectives simultaneously takes into consideration all realities.

This paper presents a multi-paradigm modeling (MPM) methodology to support a holistic simulation of healthcare systems through a stratification of the levels of abstraction into multiple perspectives and their integration in a common model-driven engineering (MDE) framework. 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. The rest of this paper is organized as follows. Section 2 gives the technical background of this work. Section 3 presents the framework proposed. Results of its application are shown and discussed in Section 4. Section 5 compares our contribution to related works in the literature. Section 6 concludes the paper and gives perspectives for future efforts.

2. Background

In this section, we briefly introduce the terminology with respect to the work reported. Interested readers may refer to Vangheluwe et al.,[3] Cellier,[4] Praehofer,[5] Mosterman,[6] and Fishwick[7] for elaborate discussions of the terms used. MPM was introduced by Vangheluwe et al.[3] as integrating three dimensions: (a) model abstraction; (b) multi-formalism modeling; and (c) meta-modeling. While the first dimension is concerned with the relationship between models at different levels of abstraction, the second one concerns the coupling of models described in different formalisms, and the last one with formalism specification. This paper addresses the first dimension in Section 3.2, while the second and the third dimensions are addressed in Section 3.5.

2.1. Abstraction: single perspective versus multiple perspectives

In the M&S study of problems in the healthcare domain, we refer to the scope of an approach as the extent to which it covers the different perspectives of the domain. In this context, a single-perspective simulation approach (which is most of the cases in literature) refers to a simulation study within an isolated view of healthcare issues (e.g., resource allocation, or disease spreading). A multi-perspective approach refers to the concurrent studies of problems within two or more perspectives as well as their inter-perspective interactions (e.g., combined impact of resource allocation strategy and disease spreading in an area). The contributions of the present paper are specifically in the multi-perspective approach. 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.

2.2. Multi-formalism: discrete, continuous, or hybrid simulation

As the names imply, multi-formalism modeling refers to the use of a mixture of appropriate formalisms (e.g., Petri Nets, Differential Equations, Discrete Event System Specification (DEVS)…) to model the different components of a system. As argued by Fishwick,[7] one formalism

Table 1. Modeling versus simulation paradigms.

	Discrete simulation	*Continuous simulation*	*Hybrid simulation*
Mono-formalism modeling	Petri Nets DEVS Cellular automata	Bond graph System 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

DEVS: Discrete Event Systems Specification; DESS: Differential Equation Systems Specification; DAE: Differential Algebraic Equation.

cannot effectively model all aspects of a complex system, considering the diversity of the variables of interest as well as the mechanisms of the evolutions of such variables. While the concept of formalism refers to the modeling paradigm, it has an underlying simulation paradigm, which refers to the approach used to generate the behavior of the system represented. Simulation paradigms fall into discrete simulation, continuous simulation, and hybrid simulation. The latter is a combination of the formers.[4–6] Table 1 shows examples pertaining to each modeling/simulation paradigm.

2.3. *Meta-modeling: toward model-driven engineering*

While multi-formalism enables the use of suitable formalisms to model different perspectives of a system, generating the overall simulation code can be challenging. To achieve this goal, each of the formalism-specific components can be simulated with its corresponding formalism-specific simulator, and interactions due to coupling are resolved at the trajectory level. This approach, known as co-simulation, discards a variety of useful information[3] and involves speed and numerical accuracy problems.[8] Another approach (which is adopted in this paper) is to transform all the different formalism-specific components into one single target formalism (therefore reducing multi-formalism to mono-formalism), from which the final simulation code is derived.[3] To automate these successive transformations, all formalisms involved need to be represented by their meta-models (a meta-model is a model of a formalism), and rules need to be defined to map meta-models onto each other. In that way, for any component specified in formalism A, its counterpart specification in formalism B is obtained by applying the rules that map the meta-model of A onto the one of B. MDE provides the methodology to capture these concepts and organize the systematic application of model transformation. The state-of-practice in the domain-specific applications of MDE-based M&S can be in one of the following forms:

(a) to use suitable formalisms to create high-level models with which to drive the (semi-)automated syntheses of the executable simulation codes;
(b) to define a Domain-specific Language (DSL) based on some established simulation formalisms but with the notations of the beneficiary domain (e.g., healthcare) providing the concrete syntax;
(c) to define a mapping of the concepts of an existing DSL of the beneficiary domain to the concepts captured in an existing simulation tool and automate mapping using model transformation technologies.

Considering the complexity of healthcare systems and the diversity of their various components, it would be difficult to make a one-fits-all selection from the existing approaches for a comprehensive MDE-based M&S of healthcare systems. This paper proposes an approach that supports (a) and (b). As depicted by Figure 4 in Section 3.5, the idea is to enable analysts to use the most suitable formalisms to model the different perspectives of healthcare systems, and systematically generate the final simulation code from the disparate models through a DEVS-based M&S framework. To achieve this goal, we have specified a dedicated model transformation from each of the possible modeling formalisms to the target framework in the transformation middleware shown in Figure 2. Thus, we add legacy and modeling tools to the overall framework by adding suitable transformations to the middleware. Details of the underlying framework for holistic M&S of healthcare systems are discussed in the next section.

3. Holistic approach to healthcare Modeling and Simulation

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, the top 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 one to answer. Thirdly, we build a library of theoretical models that are categorized along this multi-perspective approach, in which model components can be selected to build the model of an overall healthcare system. Lastly, we propose to integrate models from various perspectives, linking outputs of some to parameters of the others. These steps are detailed in the next sections.

The principles of our holistic approach stand, regardless of the formalism used to express models. However, we choose DEVS as the reference formalism for the two following reasons: (a) DEVS is a universal discrete event simulation formalism that can serve as a common denominator,[9] including when hybrid simulation is needed[10]; and (b) supporting tools for DEVS simulation are readily available.[11] Section 3.4 of this section shows how we extend the framework to allow multi-formalism modeling to DEVS simulation.

3.1. Ontological view

Based on an extensive literature review, we have built an ontology to capture and share a common understanding of the 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,[12] Günal and Pidd,[13] and Roberts,[14] and we used the System Entity Structure Model Base (SES/MB) framework[15] to formally express it. Figure 1 presents the SES hierarchy of the ontology. SES/MB provides an ontological framework for knowledge representation of decomposition, taxonomy, and coupling of systems. The SES/MB representation of a system is a directed and labeled tree composed of Entity nodes connected by Aspect, Specialization, and Multi-aspect edges. An Entity (represented by a box) is a system component of interest, and variables (mentioned below the box) can be attached to it. An Aspect (represented by a vertical line) denotes the decomposition relationship of an entity, while a Specialization (represented by vertical double lines) represents its taxonomy (i.e., derived entities in the sense of object-oriented modeling). A Multiple-aspect (represented by three vertical lines) specifies that the parent entity is a composition of multiple entities of the same type. SES/MB axioms include uniformity, strict hierarchy, the alternation mode, and valid brothers. The first axiom ensures that any two nodes with the same labels have isomorphic subtrees. The second axiom ensures that no label appears more than once down any path of the tree. The third axiom ensures that if a node is Entity, then the successor is Aspect, Multi-aspect, or Specialization, and vice versa. The fourth axiom ensures that no two brothers can have the same label.

3.2. Stratification of abstractions

Along with the SES-based ontology, we have identified the categories of healthcare problems studied in the literature. They fall into four perspectives (as presented in Figure 2), each encompassing a family of questions that can be formulated through experimental frames[15] with which models are coupled to derive answers. They are as follows.

1. The Resource Allocation (RA) perspective. This encompasses all scheduling and planning problems, mostly in the context of limited resource provisions (such as beds, rooms, medical records, doctors, nurses, funds…) to meet the healthcare demand.
2. The Health Diffusion (HD) perspective. This covers simulation studies of contagion spreading, whether positive (such as information or vaccination) or negative (such as disease or panic).
3. Population Dynamics (PD) perspective. This comprises all studies of the dynamics in the population of a community (immigration, emigration, birth, death…).
4. Individual Behavior (IB) perspective. This covers 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 2 shows that we place this stratification of abstractions in the context of the hierarchy of systems specification introduced by Zeigler.[16] 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 (MB) introduced in the next section (or in deriving new ones from existing models).

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 as described in Figure 2. While the dashed boxes depict concurrent simulations in the different perspectives, the double arrows represent the live exchanges of information between them. The idea is to allow for the transmissions of the outputs of the simulations in one perspective to provide live feedbacks to the simulation parameters in other perspectives where required. Section 3.4 provides more details on this integration.

3.3. Model Base

SES/MB introduces two mechanisms to allow interactive or automatic generation of an executable simulation

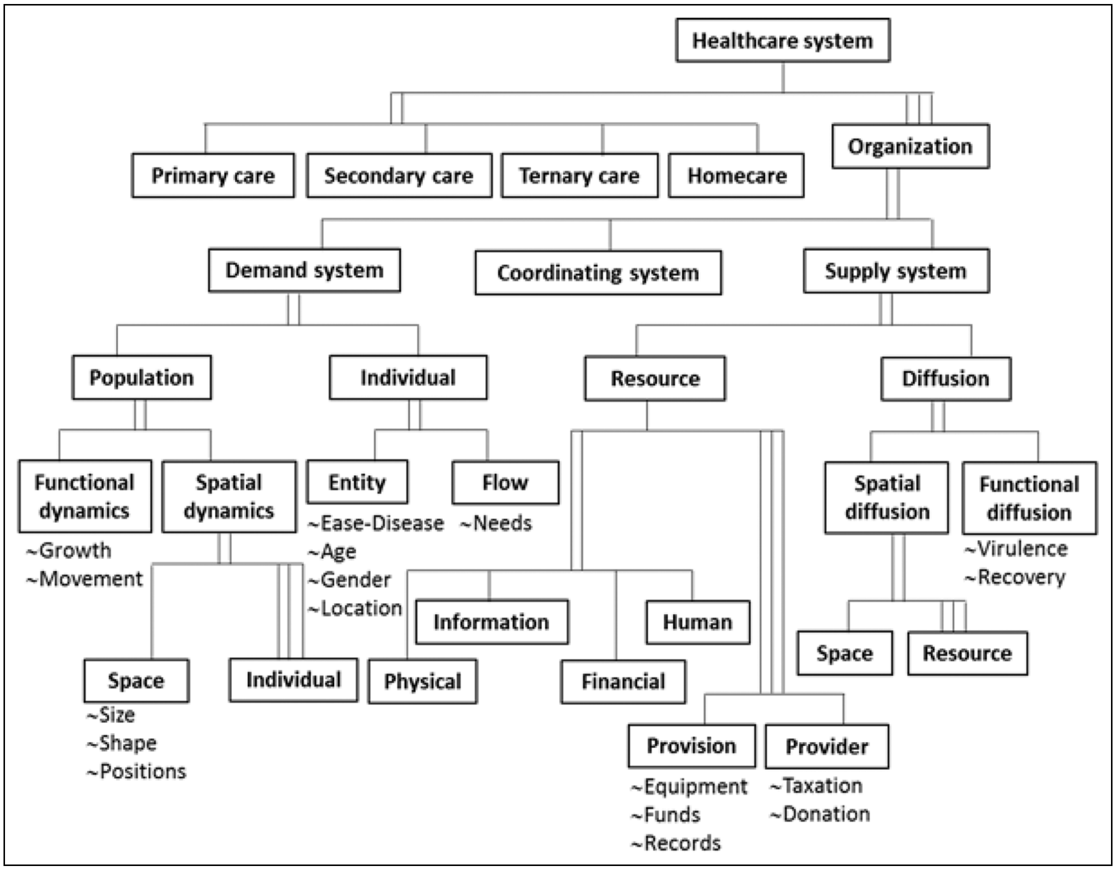

Figure 1. Ontology for healthcare system Modeling and Simulation.

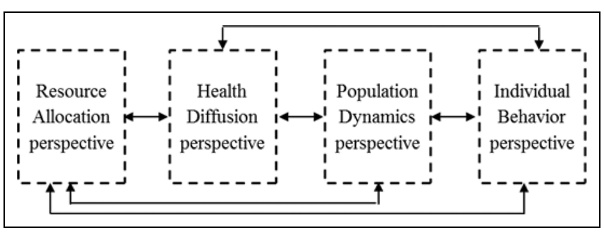

Figure 2. Multi-perspective framework for holistic Modeling and Simulation of healthcare systems.

model: the MB and the pruning process. The MB is a repository where basic models (i.e., entities of the SES tree) with a predefined input/output interface are organized. 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[17] and its derived SEIR, SIRQ, MSEIR… models[18] for the HD perspective, Prey-Predator[19] and cohort-component models[20] for the PD perspective, queuing theory models[21] for the RA perspective, and agent-based models[22] for the IB perspective.

3.4. *Integration approach*

In practice, M&S processes in each of the identified perspectives are often executed in isolation, that is, without recourse to the processes from other perspectives. In reality, however, processes usually have mutual influences. For instance, when there is an epidemic in a community (HD perspective), it will naturally affect the provisions and allocations of the human and infrastructural healthcare resources in the health centers within the community (RA perspective) and the migrations of people into and out of the community (PD perspective). To allow a holistic simulation, which encompasses isolated perspective-specific simulations and their mutual influences, we suggest an integration mechanism to enable live exchanges of information between models from the different perspectives.

At this point, it is important to identify the difference between perspective integration in the context of this paper and the concept of coupling between components of a complex model as formalized by DEVS. While ‘‘coupling’’ refers to the connections between the ports of the components of a coupled model within the same perspective, ‘‘integration’’ refers to logical connections between the output ports of the model in one perspective and the parameters of the models in some other perspectives.

We use HiLLS, a DEVS-based visual language,[23] to effectively realize this ‘‘integration’’ concept. Indeed, HiLLS provides an object-oriented feature allowing defining methods for a model. A model method is a set of activities that the model can instantaneously perform on call without affecting its state. Such activities must not change the value of the model's state variables, but can modify the value of its parameters. Parameters (such as a transmission rate in a disease-spreading model) are static information that does not pertain to the state information of a model. Rather, they are used for the computations required when the model changes state. Consequently, calling a model's method results in reading/modifying the value of some of its parameters, while sending of a message to a port of the model results in a change of state within the model. Readers can refer to the Appendix for details on HiLLS representation of DEVS models.

Figure 3 schematizes the technical difference between ‘‘coupling’’ and ‘‘integration’’ in the context of this work. By coupling the output of a disease-spreading model to the input of an integrator, we create a coupled model under the HD perspective. The role of this integrator is to interpret the outputs received from the disease model and translate it into new values for the parameters of a population dynamics model. The integrator will then call the method of the population dynamics model to modify its parameters. Similarly, the population dynamics model is coupled to an integrator that translates its output to values for the parameters of the disease-spreading model. A holistic model of the healthcare system is obtained by introducing appropriate integrators between perspective-specific models.

3.5. Multi-formalism modeling capabilities

Considering the diversity of the constituent variables of the models in the different perspectives, a multi-formalism modeling approach is needed to effectively capture the concerns of the various stakeholders. This is necessary to accommodate the diverse familiarities of experts with modeling formalisms, reuse of existing models, easiness to capture some realities in some specific formalisms, and other realities in other formalisms. Hence, we suggest a multi-formalism modeling approach at the top layer of the proposed framework for holistic M&S of healthcare systems. As mentioned previously, in practice, multi-formalism M&S can be achieved with either co-simulation or formalism transformation. While the former promotes the simulations of the disparate models based on their respective formalisms with a mechanism for data exchange, the latter involves the translation of the disparate models into a formalism upon which the simulation will be based. In this work, we choose to use formalism transformation such that users can model the different perspectives in their preferred formalisms while we translate

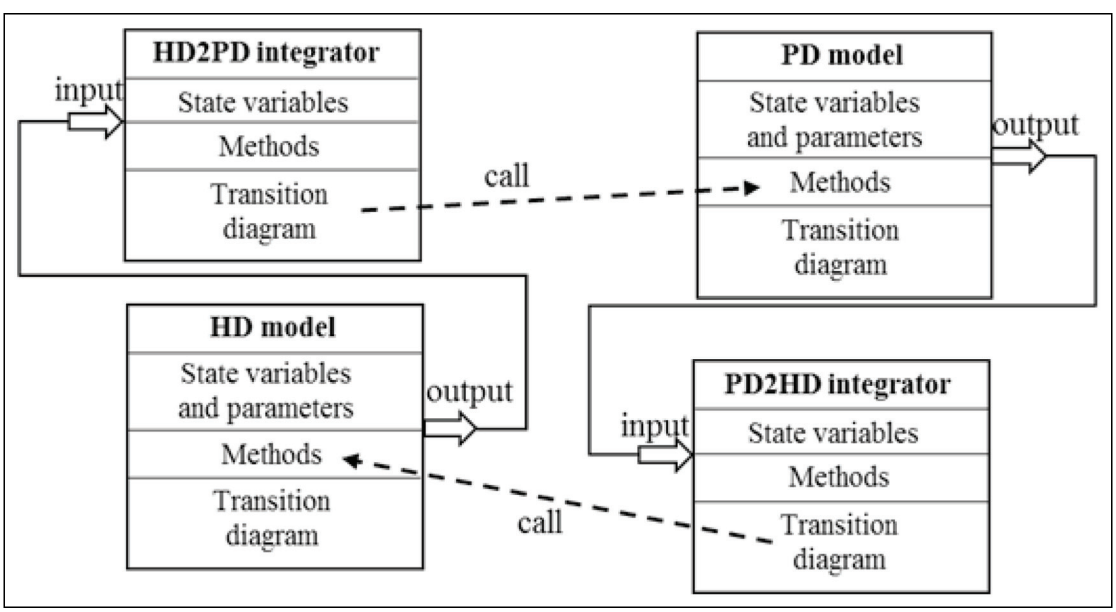

Figure 3. Model coupling and integration. HD: Health Diffusion; PD: Population Dynamics.

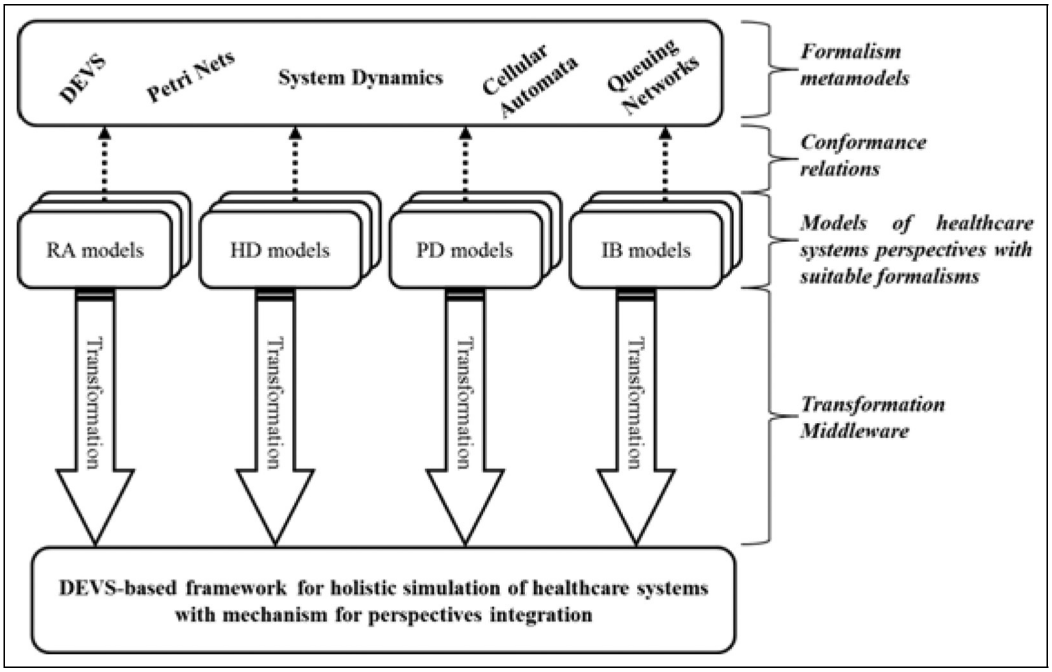

Figure 4. Model-driven Engineering-based framework for holistic Modeling and Simulation of healthcare systems. DEVS: Discrete Event System Specification; RA: Resource Allocation; HD: Health Diffusion; PD: Population Dynamics; IB: Individual Behavior.

all models to DEVS for simulation. Therefore, the proposed MDE-based framework for holistic M&S of healthcare systems will remove the constraint on the choice of modeling formalism, thereby making the modeling easier, while we use model transformation technologies to systematically generate the final DEVS-based simulation model.

Figure 4 presents the overall framework at the conceptual level. The topmost layer contains the meta-models 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 meta-model of the formalism chosen to create it. We use the ATL (Atlas Transformation Language) technology[24] to transform the disparate perspective models into SimStudio implementations of DEVS simulation models[25] at the bottom layer.

4. Application and results

In order to study the Nigerian healthcare system in a holistic way and in the context of the Ebola outbreak, we applied our framework and built models in each of the perspectives identified, that is:

- a model of the Ebola outbreak and its experimental frame;
- a model of migrations between Nigerian states and its experimental frame;
- a model of daily workers strategy and its experimental frame; and
- a model of hospital resource allocation in Lagos and its experimental frame.

We studied each model in isolation and derived some results, and then integrated all the models together to produce a holistic view of the situation. The subsequent sections present each of the perspective-specific models developed, as well as the integrators needed to integrate them together.

4.1. Model of disease spreading

The EVD spreading can be modeled by the following compartmental model, which extends the work presented by Althaus et al.[2] to take into account of the possibility of infection by dead individuals:

$$\frac{dS}{dt} = -\beta SI - \alpha SD \tag{1}$$

$$\frac{dE}{dt} = SI + SD - E \tag{2}$$

$$\frac{dI}{dt} = E - I \tag{3}$$

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

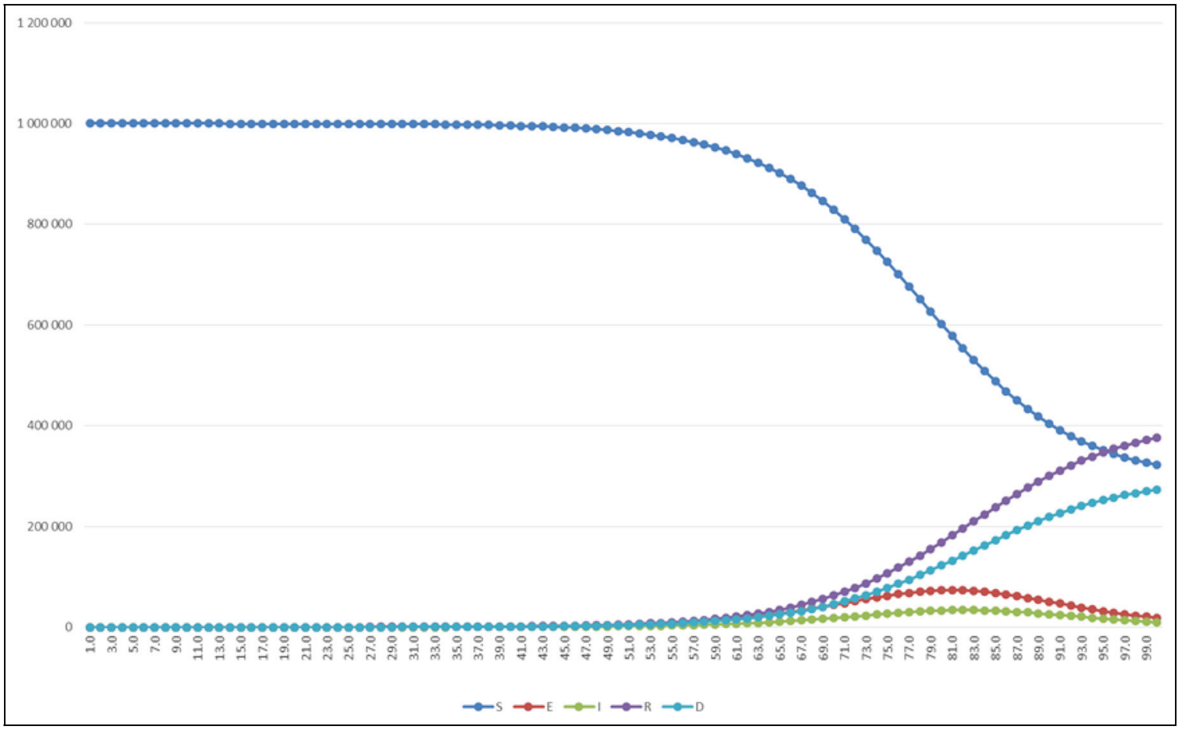

Figure 5. Ebola spreading in a period of 100 days, with calibrated parameters.

$$\frac{dD}{dt} = fI \tag{5}$$

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 (Partial Differential Equation) model (which can also be seen as a System Dynamics model) is given from the HD perspective of our framework. Its HiLLS representation is shown in Appendix. Following the rules described, the DEVS counterpart is an atomic model with S, E, I, R, and D as state variables, which applies Equations (1)–(5) during each of its internal transitions to get the values of the state variables in the new state, and for 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.

Figure 5 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 one, 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 by Althaus et al.,[2] whose model of spreading without control measures coincides with our model for $\alpha = 0$.

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 shows such an exploration, with a focus on the level of disease penetration on the one hand (variation of I/S, the ratio between initial numbers of infected and susceptible individuals), and on the other hand, the impact of some socio-cultural dimension (variation of α). We considered four levels of infectious situations: the disease appearance stage (i.e., only one infection over a million of individuals, something comparable to what happened in

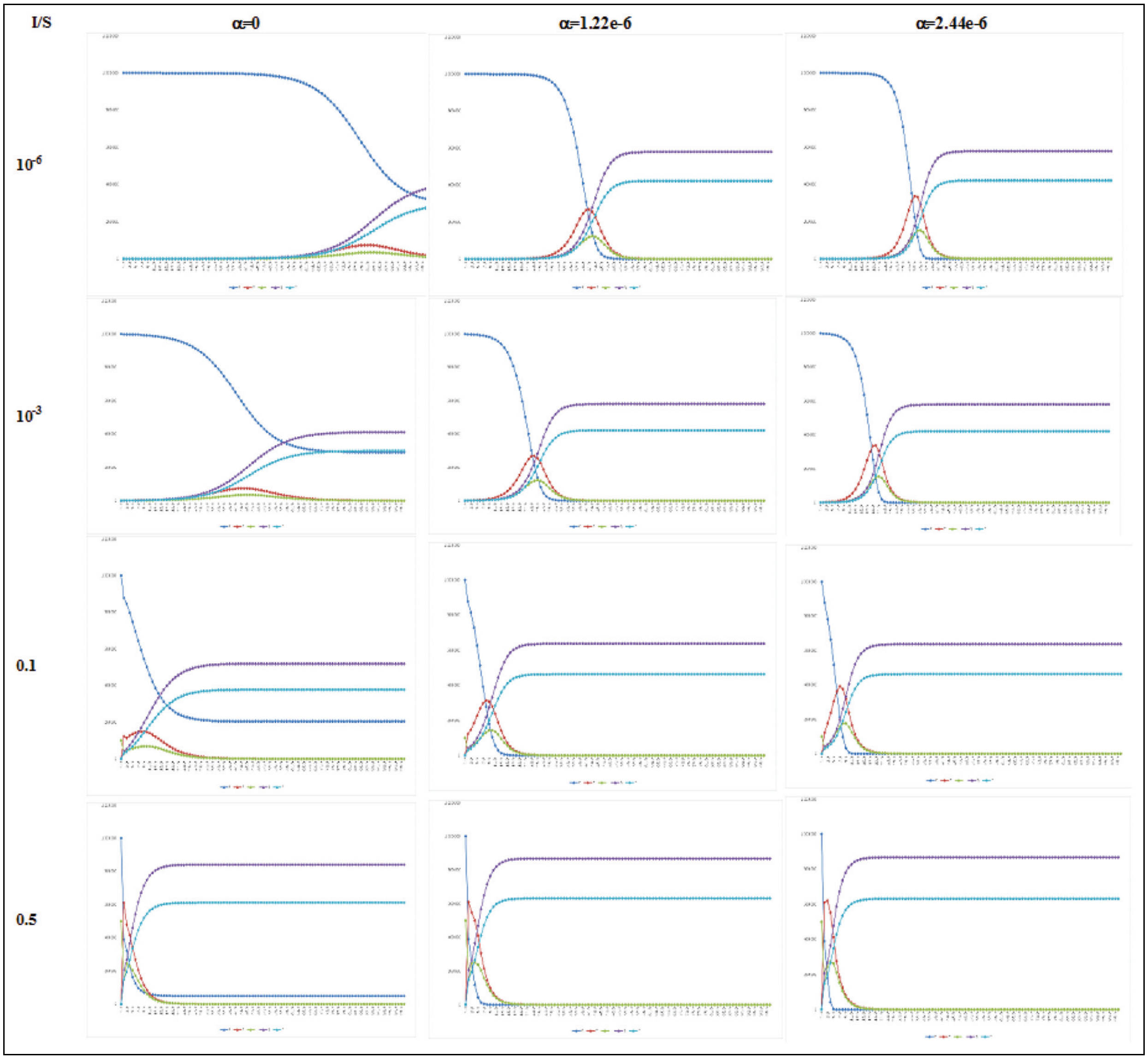

Figure 6. Sensitivity of the Ebola spreading to variations of parameters.

large and medium cities in Nigeria, but also in Liberia, Guinea, and Sierra Leone); state of emergency level (i.e., 1000 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 to many places, with direct contact between dead and living individuals).

The top-down reading of Figure 6 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 certain 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.

4.2. *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,[19] Rogers,[26] Allen,[27] and Sikdar and Karmeshu.[28]

We developed a model inspired by Sheppard,[29] but with the following specificities.

- We consider the Nigerian population at state levels. Nigeria is a federal country with 36 states (each having its capital city) and a Federal Capital Territory (FCT).
- Cellular automata (CA) are 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 1–36 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:

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

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/toward outside the country) of state i;
- α_i is the relative attractivity of state i (i.e., the gross domestic product (GDP) per capita of state i over the GDP per capita of the country);
- d_{ij} is the distance between the capital cities of states i and j;
- τ is a constant positive number.

Equation (6) is inspired by Sheppard[29] in that the rate of migration between any pair of federal states depends on the population distribution. However, while Sheppard[29] 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.
- Here $\alpha_i - \alpha_j$ 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 as that entering the target state ($\alpha_i - \alpha_j > 0$).
- Here $\left|n_i - n_j\right|$ expresses that states with nearly the same size have few attractions to each other. The greater the difference of size is, the higher is the attraction (in favor of the more attractive one).
- Here $e^{-\tau d_{ij}}$ 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 $e^{-\tau d_{ij}} = 1$), while 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 that has the CA grid as its state variable, and that 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 7 shows how the respective states evolve over a period of 1460 days (i.e., four-year period). Calibrating data are taken from the annual report of the National Bureau of Statistics (NBS).[30] 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 $\tau = 0.01$. The experimental frame for the study displays each state by coloring it according to the range in which the daily growth of the state's population falls. Figure 7 displays snapshots at respective times 1, 183, 364, 545, 726, 907, 1088, 1261, and 1442 (top-down and left-to-right), that is, every semester approximatively.

We compared the evolution curves obtained from the CA simulation, with data available for the period from 2008 to 2011. Figure 8(a) shows how cumulative real data evolve for all states (horizontal axis) and for four years (vertical axis cumulating annual rates). Figure 8(b) how cumulative simulation results evolve, 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.

4.3. Model of a daily worker

Models form the IB perspective of our framework capture the micro level of explanation (i.e., at the 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

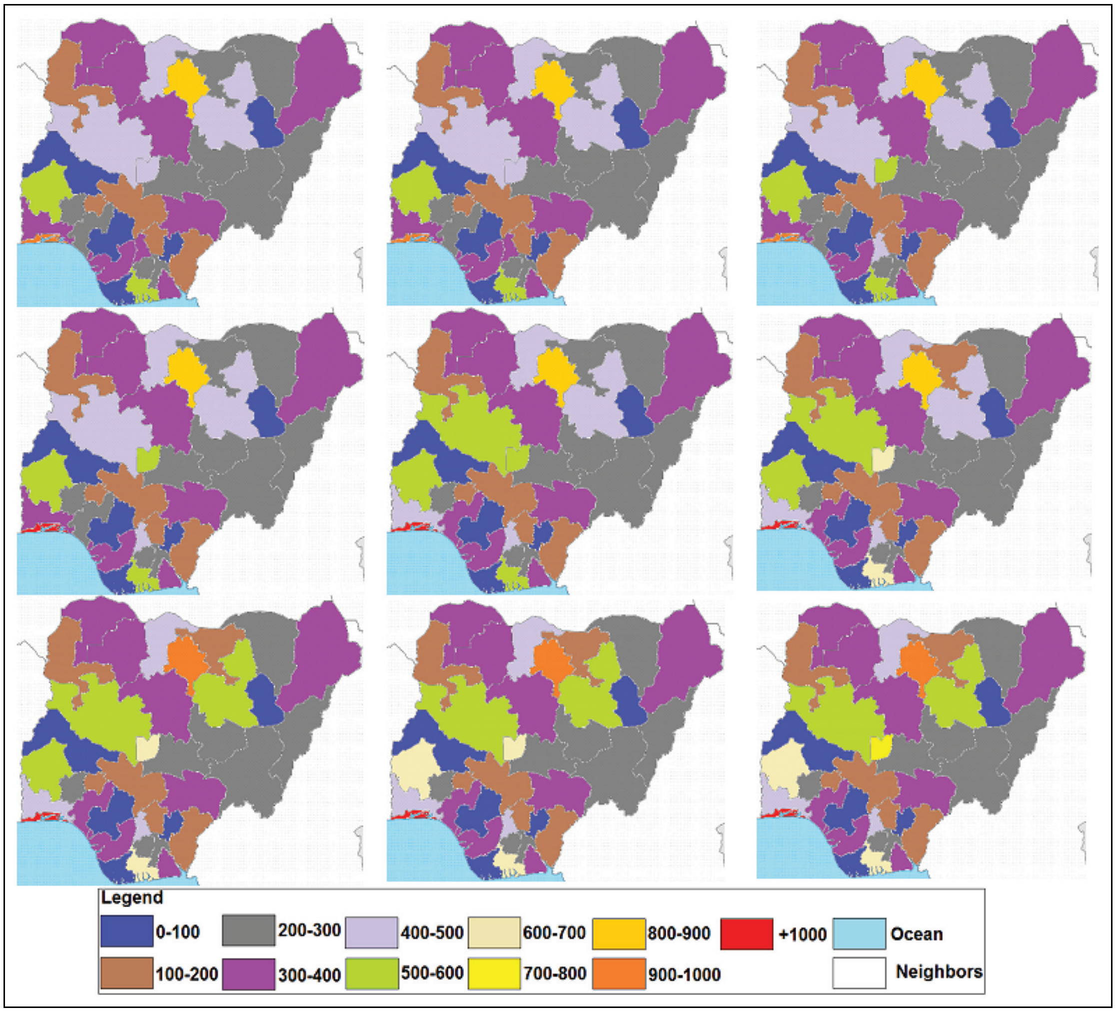

Figure 7. Snapshots of population dynamics simulation (daily growth) in Nigerian states.

the consequential effect on his working rate (i.e., the average number of worked days, hence the worker's earnings).

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 person to find a new job. These parameters affect the behavior of the daily worker in the way described by Figure 9.

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 9 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 does not get any new job after this deadline, he will move to another working area (a counter n is used to find at each time the number of jobless days). We assume he will not go back to a place he formerly visited, and that the national labor market is uniform (therefore, probabilities do not 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 do not have a clear visibility of the labor market 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 person to get a new job, at the cost of the time lost in relocating.

This agent-based model is easily described by a DEVS atomic model. Each node of the transition diagram given in Figure 9 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

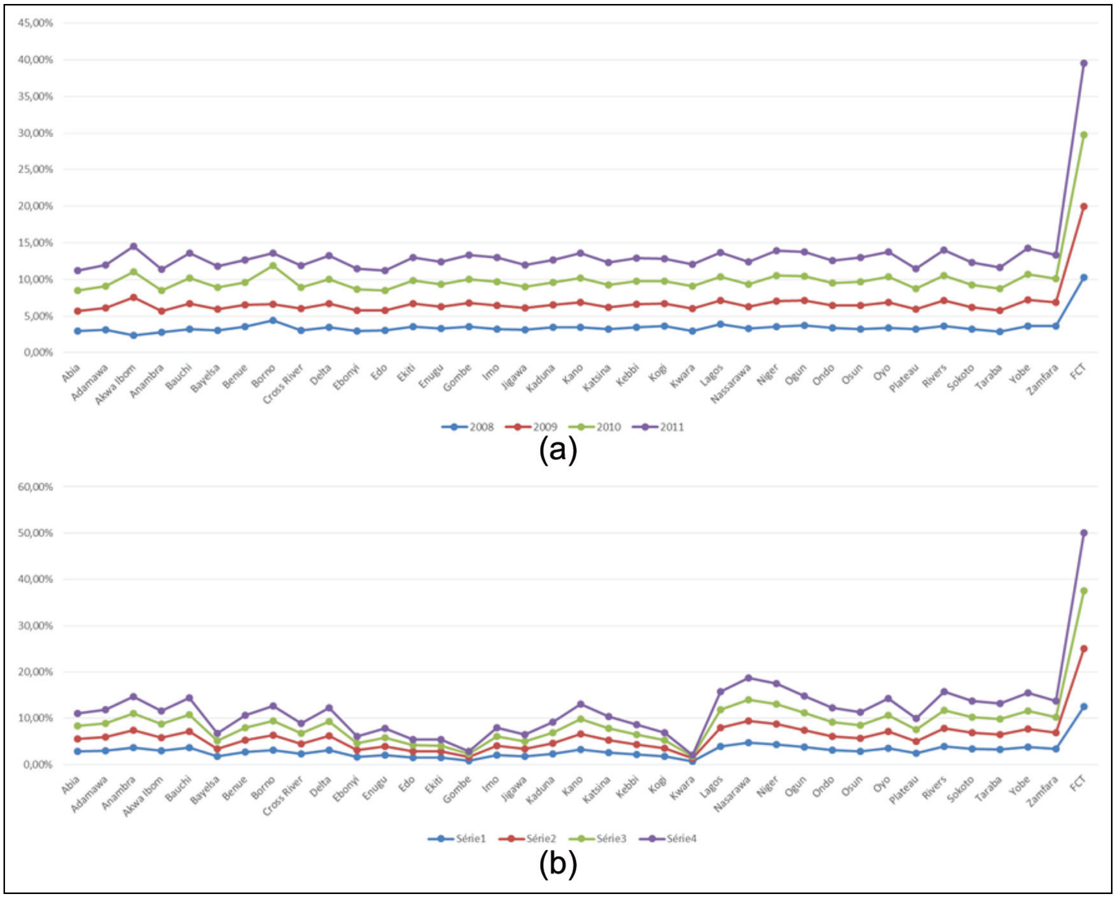

Figure 8. Real data versus simulation results (cumulative population growth rate per state).

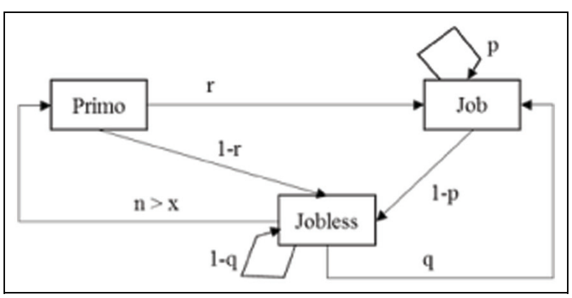

Figure 9. Individual behavior model of a daily worker.

for the 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: (a) the percentage of worked days; and (b) the frequency of moves. For each value of x, 1000 experiments are run, each for 1460 days (4 years). Figure 10 shows the impact of the worker's decision (frequency of relocations) on his job performances (percentage of worked days), respectively for $x = 6$, $x = 3$, and $x = 1$ ((a)–(c)). 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 the grounds of day labor (low segment of the labor market) and its resulting migration flows.

4.4. 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 Figure 1, 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 policymakers understand and anticipate bed acquisition and management in a Lagos hospital. System dynamics is a popular modeling approach in

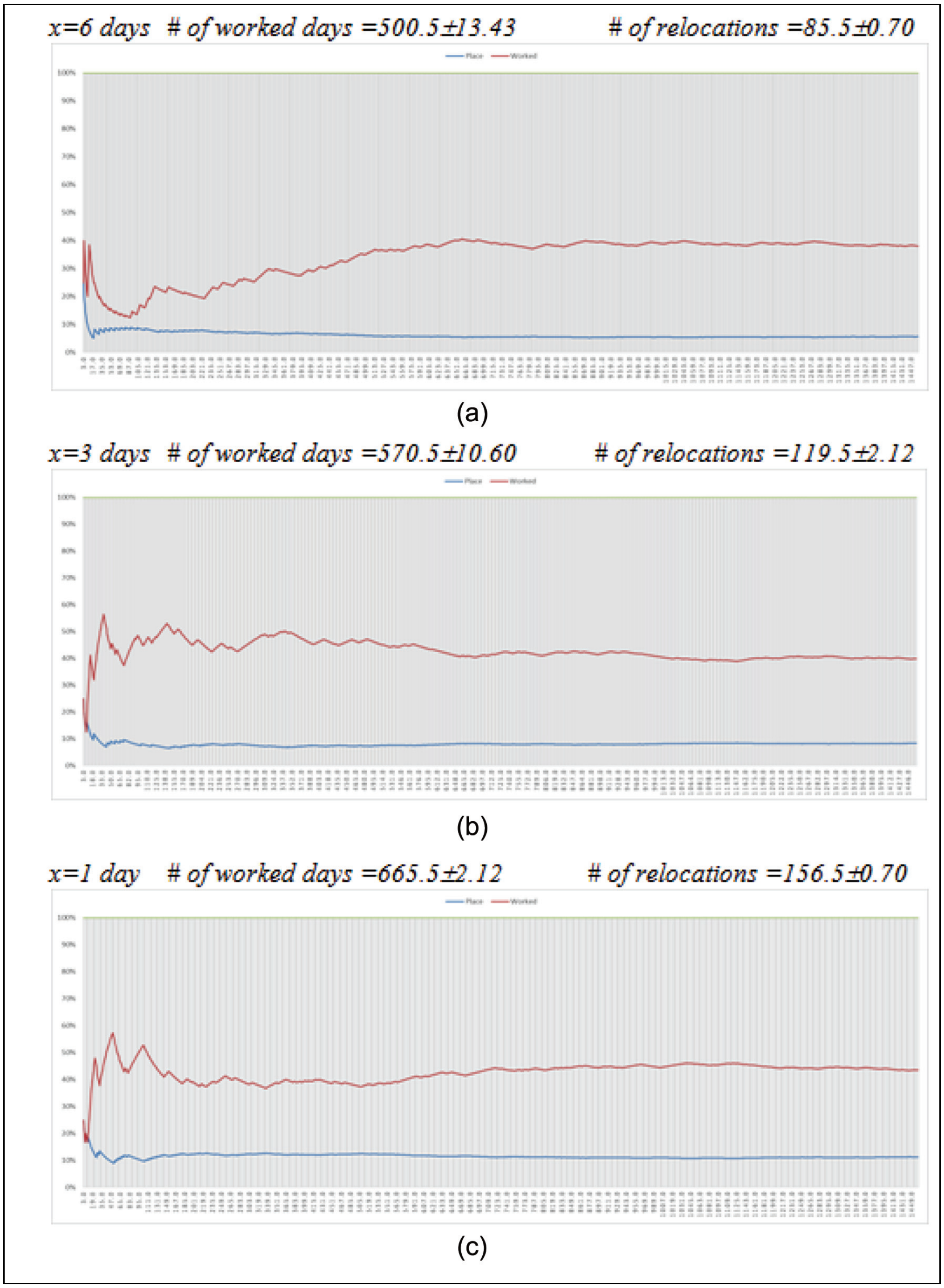

Figure 10. Relocations frequency (upper curve) versus job performances (lower curve) in three different scenarios ((a)-(c)).

healthcare systems M&S. A general survey of system dynamics in healthcare systems studies can be found in Homer and Hirsch.[31]

The system dynamics-based model is presented in Figure 11. 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 the external death rate (i.e., deaths caused independently from the hospital intervention) and the 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 re-injects into the population those hospitalized patients who do not die at the hospital. Also, non-

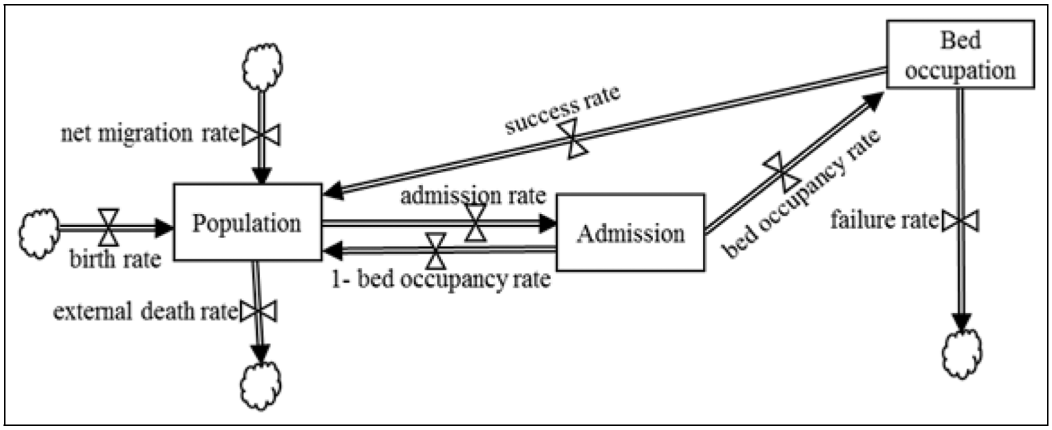

Figure 11. Model of demand for hospital services.

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 policymakers.

This model is given from the RA perspective of our framework. Its DEVS counterpart is an atomic model that defines a state variable to represent each stock of the system dynamics model, and internal transitions of which 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 model displays the results shown in Figure 12. Figure 12(a) shows the daily evolution over 1460 days (i.e., four years) of respectively the number of admissions (upper curve) and the number of beds occupied. Figure 12(b) shows 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.

4.5. Integrators

Transfer models describe how the outputs of some of the models we have described affect the parameters of others (as previously explained in Figure 3). These models, each described as a DEVS atomic model, allow one 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, for which time advance is $+\infty$, and a generating state, for 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. In contrast, 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 13 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 individuals 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.

The experimental frame built to experiment with the resulting holistic model allows one to see how all models impact on each other simultaneously, and in various scenarios of influence. Figure 14 shows results for the case where a linear influence has been defined for each output-to-parameter integration.

Experiments are run for 100 days and each model is initialized to coincide with the outbreak of the EBV period. On top of Figure 14 are the new evolutions of

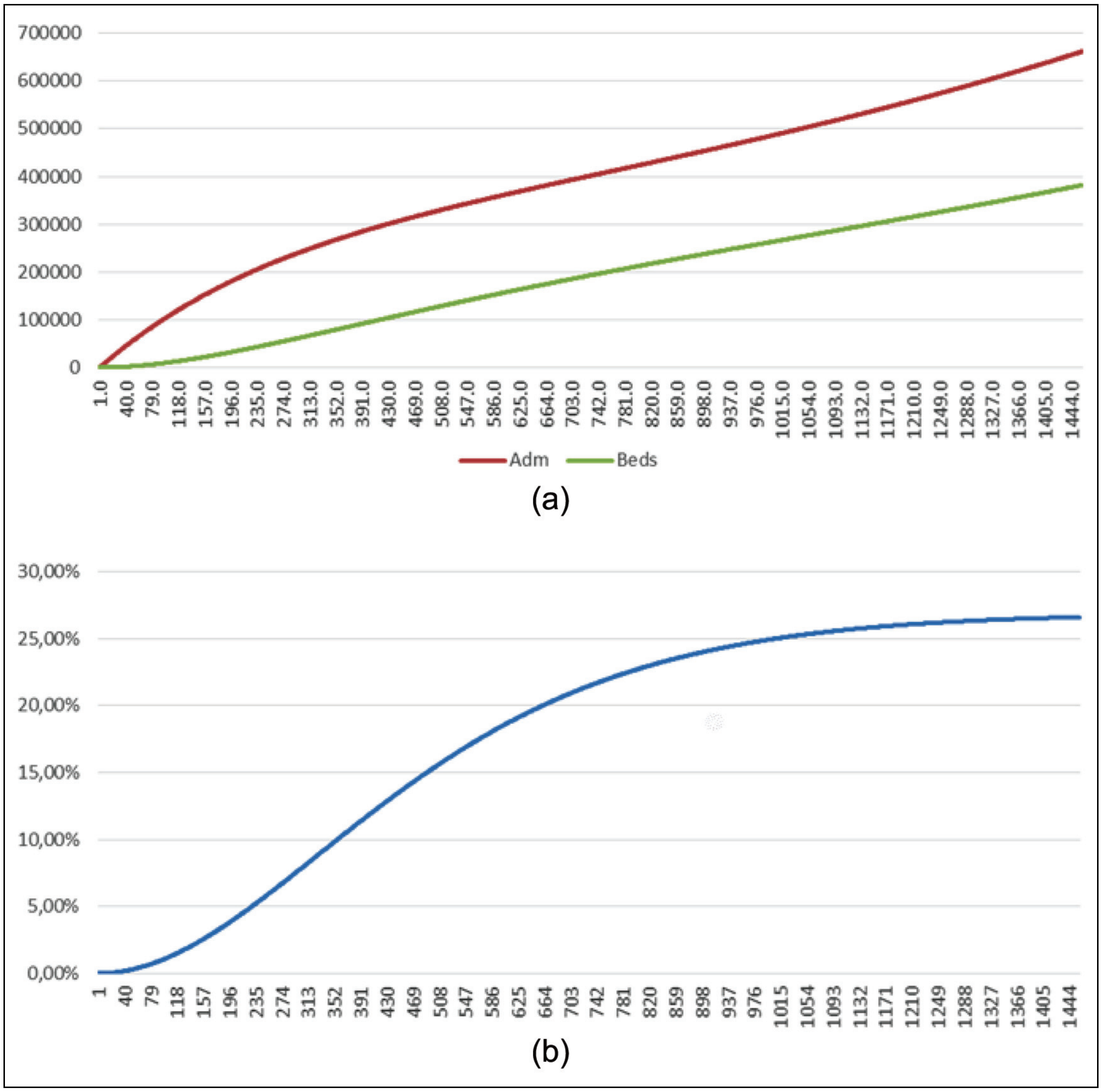

Figure 12. Evolution of health demand and supply indicators.

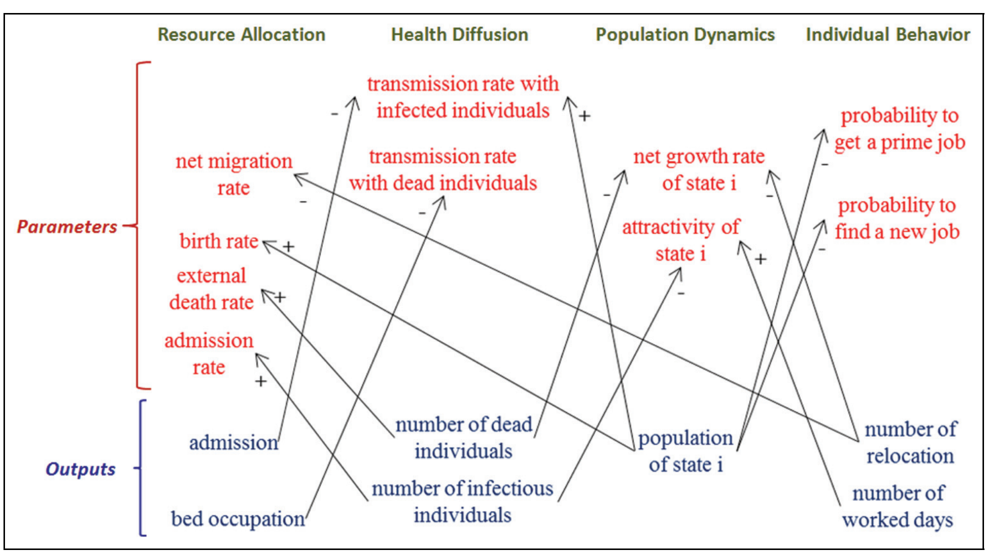

Figure 13. Causal loop diagram between outputs and parameters. (Color online only.)

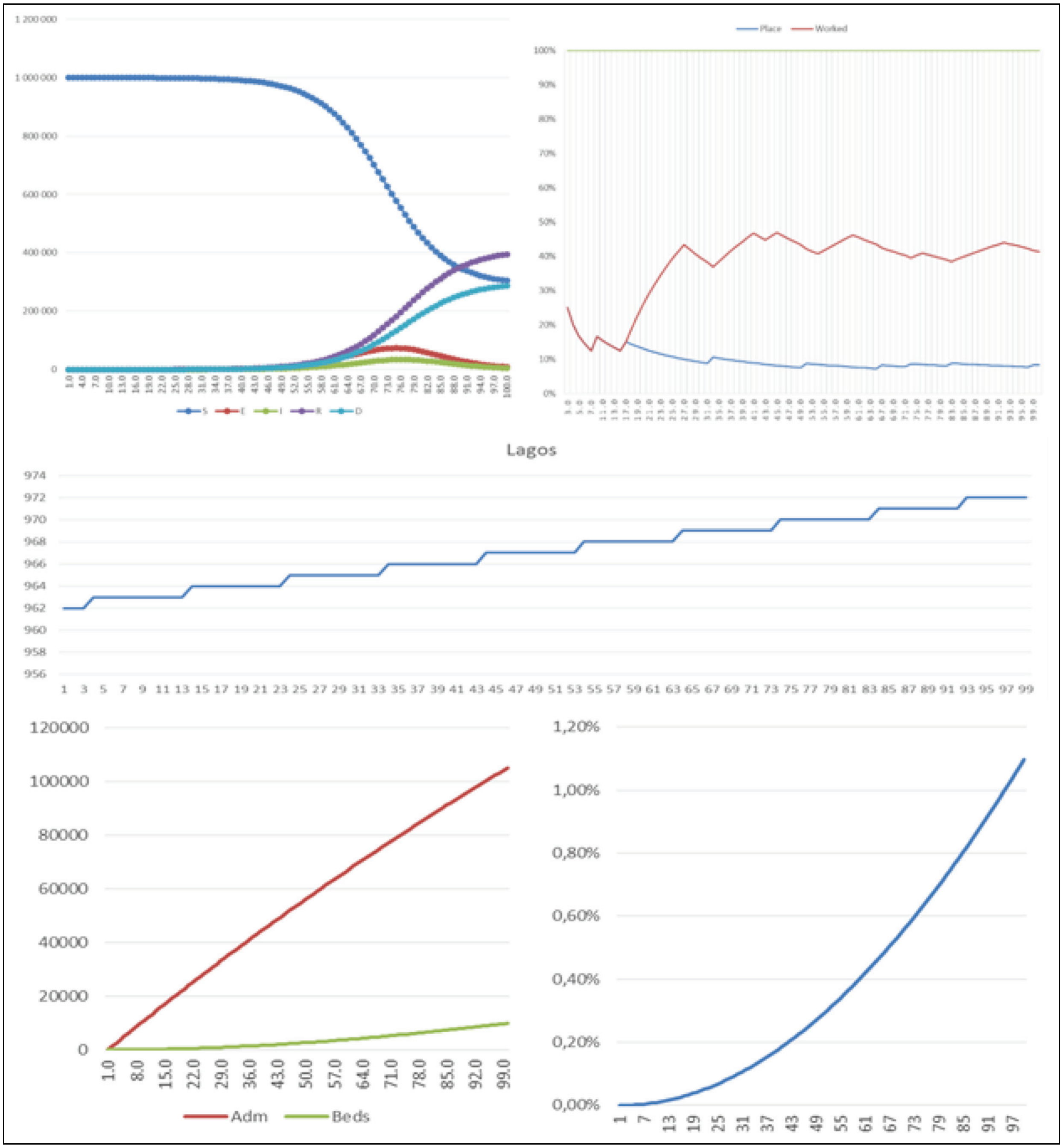

Figure 14. Holistic simulation results. (Color online only.)

respectively the disease-related variables (as the ones shown in Figure 5) and job performances of daily workers in relation to the frequency of relocations. In 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.

4.6. 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 are abstractions and

Table 2. A benchmark of integrated healthcare Modeling and Simulation (M&S) frameworks.

Integrated healthcare M&S frameworks	*Resource allocation*	*Health diffusion*	*Population dynamics*	*Individual behavior*
[44]	✓			✓
[45]	✓	✓		✓
[46]	✓			✓
[47]		✓	✓	
[48]		✓		✓
[49]	✓			✓
[50]		✓	✓	
[51]		✓		✓
[52]	✓			✓
[53]	✓			✓
[54]			✓	
[55]	✓			✓
[56]			✓	✓
[57]	✓			✓
[58]				
[59]	✓	✓	✓	

approximations by essence, so 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 is why the resulting global model allows deriving results that could not 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.

1. In the static integration approach, a model's parameters remain constant during a simulation. Each variation of a 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.
2. In the 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 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 many as the number of health centers of the state), and many individual behavior models (for categories of workers). Such a fine-grained holistic model, thought to be computationally more expensive than simple models, provides 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.

5. Related works

A literature review in healthcare M&S shows a huge amount of efforts and results. Surveys can be found in Thorwarth and Arisha,[32] Katsaliaki and Mustafee,[33] Almagooshi,[34] and Powell and Mustafee,[35] among others. We argue that our contribution is original in that none of these works offer a systematic way to identify, address concurrently, and simulate the four perspectives of our framework in a holistic way and in a multi-formalism context. A classification of perspectives is given by Roberts,[14] but is limited to two perspectives: (a) patient flow optimization and analysis; and (b) healthcare asset allocation. The idea of a framework allowing multi-level abstraction and multi-views modeling of the healthcare domain, which provides a multi-disciplinary coverage, has also been suggested by Barjis,[36] although it is not yet nurtured to maturity. Many research works concentrate on only one of our four perspectives.[13,37–43] Some works combine two or three of them. Table 2 shows a representative sample of such contributions.

The closest work to our contribution is Jeffers,[59] in which a similar integration approach is proposed, with all models developed in Forrester's System Dynamics. This work, although not proposing a generic framework, is a perfect illustration of a possible application of our framework, where models have been developed in three 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 2.

Another dimension of our work that is not conveyed in the related works mentioned is the use of a 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. Examples of environments, which are based on discrete event simulation formalisms, have been reported by Kofman et al.,[60] Mittal and Martín,[61] Bonaventura et al.,[62] Ighoroje et al.,[63] Zeigler,[64] Mittal and Douglass,[65] and Risco-Martín et al.[66] Comparative surveys of the relative strengths of some of these environments have been done independently by Aliyu et al.[23] and Franceschini et al.[67] Specific applications of MDE techniques to healthcare processes and systems are described by Jones et al.,[68] Song et al.,[69] and Antonacci et al.[70]

6. Conclusion

We have proposed a holistic modeling framework based on multi-perspective modeling of healthcare systems and their discrete event simulation. In this framework, different aspects of the same system can be modeled using same/different backgrounds (i.e., simulation paradigms and theoretical models), and the representations resulting from these views are combined to create a whole system. While all views can be specified with the same formalism, the framework also makes room for the use of multiple formalisms. A MDE approach is then used to assist the process of transforming the corresponding models into a homogeneous simulation code. We have shown through a running example how this framework can be applied. The general problem is broken down into the four perspectives suggested: (a) health diffusion; (b) resource allocation; (c) individual behavior; and (d) population dynamics. A library of theoretical models for healthcare simulation that are proposed in the literature and that all fall within one of these perspectives is used to derive specific models. Since a multi-formalism modeling approach will most likely be required to capture the concerns in the different perspectives, as described in Figure 1, the framework we propose applies MDE techniques to transform all the models expressed into a common denominator for simulation. This allows the stakeholders in the different perspectives to choose the most suitable formalisms to model their problems and yet have a common understanding of the holistic view of the simulations without going through the hurdles of manually translating the models.

The framework provides multiple levels of explanation in modeling and simulating healthcare systems. 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 could not 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 one to link models that have not been initially designed for this purpose. This is a significant difference compared 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.

DEVS is the common denominator for simulation in the framework proposed. However, any simulation formalism can be used instead, provided that it subsumes all other formalisms used during the multi-perspective modeling process. A corollary is that this also imposes the strategy of simulation adopted, whether discrete, continuous, or hybrid. In the case that the common denominator formalism chosen allows only discrete event simulation (respectively only continuous simulation), all continuous (respectively discrete event) models built during the modeling process in the various perspectives need to be approximated by their discrete event (respectively continuous) counterparts before or during their transformation into the final formalism. An alternative to choosing a common denominator formalism is to build in the framework a mechanism allowing co-simulation, that is, the concurrent execution and coordination of all models (whether discrete or continuous). We do not adopt this strategy.

Our future direction is to expand on each of the developed models, toward a complete global model for the Nigerian healthcare system.

Appendix

DEVS model

A DEVS model is defined by the tuple $X, Y, S, \delta_{int}, \delta_{ext}, \delta_{conf}, \lambda, ta$ where:

- X, Y, and S are respectively the input set, output set, and state set (at any time, the system modeled is in one of the possible states);
- $ta : S \to \mathbb{R}_0^{+\infty}$ is the time advance function (i.e., it gives the lifespan of each state), with $\mathbb{R}_0^{+\infty}$ designating the set of non-negative real numbers, including $+$;
- $\delta_{int} : S \to S$ is the internal transition function (i.e., it is triggered only when the elapsed time in the system's current state s_{curr} has reached $ta(s_{curr})$ without the system being disturbed by any receipt of input);
- $\lambda : S \to Y$ is the output function (i.e., it computes the output of the system, each time an internal transition is occurring);
- $\delta_{ext} : Q \times X \to S$ is the external transition function (i.e., it is triggered only when the system receives an input, while the elapsed time in the system's current state s_{curr} has not reached $ta(s_{curr})$, and $Q = \{(s, e) | s \in S, 0 \leqslant e < ta(s)\}$ is called the total state;
- $\delta_{conf} : S \times X \to S$ is the confluent transition function (i.e., it is triggered only when the system receives an input at exactly the time that the elapsed time in the system's current state s_{curr} has reached $ta(s_{curr})$).

HiLLS representation of a DEVS model

HiLLS allows one to define DEVS models visually. A template of how HiLLS represents an un-parameterized DEVS model is shown below (Figure A).

Formally, such a model is a DEVS model $X, Y, S, \delta_{int}, \delta_{ext}, \delta_{conf}, \lambda, ta$ where:

- X is the abstract set defining the input ports and their domains;
- Y is the abstract set defining the output ports and their domains;
- S is the cross-product of the domains of all state variables;
- δ_{int} is the set of all internal transition relationships visually defined between two states in the transition diagram;
- δ_{ext} is the set of all external transition relationships visually defined between two states in the transition diagram;
- δ_{conf} is the set of all confluent transition relationships visually defined between two states in the transition diagram;
- λ is the set of all output relationships associated to internal transitions in the transition diagram;
- ta is the set of all lifespan relationships defined for states in the transition diagram.

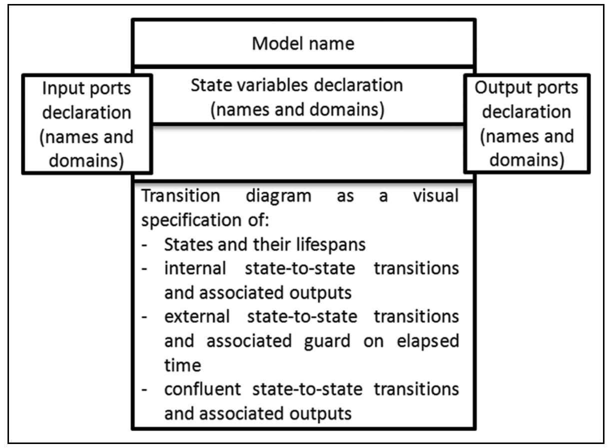

Figure A. Template for HiLLS representation of an un-parameterized Discrete Event System Specification model.

HiLLS representation of a parameterized DEVS model

A template of how HiLLS represents a parameterized DEVS model is shown below (Figure B).

Formally, such a model is a DEVS model $X^P, Y^P, S^P, \delta_{int}{}^P, \delta_{ext}{}^P, \delta_{conf}{}^P, \lambda^P, ta^P$, where:

- P is the vector of parameters;
- $X, Y, S, \delta_{intP}, \delta_{extP}, \delta_{conf\,P}, \lambda_P, ta_P$ is the strain model, that is, the DEVS model obtained with the first template, but whose governing functions depend on P (i.e., they compute their values, using the values of P);
- $X^P = X \times dom(P)$;
- $Y^P = Y$;
- $S^P = S \times P \times \mathbb{R}_0^{+\infty}$;
- $ta^P : S^P \to \mathbb{R}_0^{+\infty}$
- $ta^P(s, p, \sigma) = \sigma$;
- $\delta_{int}{}^P : S^P \to S^P$
- $\delta_{int}{}^P(s, p, \sigma) = (\delta_{intp}(s), p, ta_p(s))$;
- $\lambda^P : S^P \to Y^P$
- $\lambda^P(s, p, \sigma) = \lambda_p(s)$;
- $\delta_{ext}{}^P : Q^P \times X^P \to S^Y$ with $Q^P = \{(s, p, \sigma, e) | (s, p, \sigma) \in S^P, 0 \leqslant e < \sigma\}$
- $\delta_{ext}{}^P(s, p, \sigma, e, \emptyset, q) = (s, q, \sigma - e))$
- $\delta_{ext}{}^P(s, p, \sigma, e, x, \emptyset) = (\delta_{extP}(s, e, x), p, ta_P(\delta_{extP}(s, e, x)))$
- $\delta_{ext}{}^P(s, p, \sigma, e, x, q) = (\delta_{extP}(s, e, x), q, ta_q(\delta_{extP}(s, e, x)))$;
- $\delta_{conf}{}^P : S^P \times X^P \to S^P$
- $\delta_{conf}{}^P(s, p, \sigma, x, \emptyset) = (\delta_{conf\,P}(s, x), p, ta_P(\delta_{conf\,P}(s, x)))$
- $\delta_{conf}{}^P(s, p, \sigma, x, q) = (\delta_{conf\,P}(s, x), q, ta_q(\delta_{conf\,P}(s, x)))$.

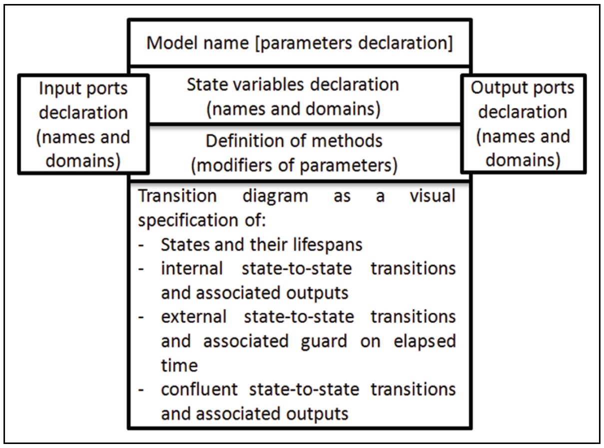

Figure B. Template for HiLLS representation of a parameterized Discrete Event System Specification model.

The parameterized model has the following characteristics.

- It distinguishes inputs that impact on the strain model's state from inputs that only modify the values of parameters.
- The σ variable memorizes the remaining time in any current state of the strain model (i.e., time before the lifespan expires). It defines the time advance function in the parameterized model (while *ta* defines the time advance function in the strain model).
- A call to a method of the HiLLS representation corresponds to an input to the parameterized model. It changes the state of the strain model according to its internal transition function (and σ is updated), but does not affect the parameters. The output of the parameterized model is then the one of the strain model.
- A receipt of message on an input port of the HiLLS representation corresponds to an input to the strain model. It changes the state of the strain model according to its external transition function and time advance function.
- When both a call is made to a method and a message is received on an input port of the HiLLS representation (which correspond respectively to input for modification of parameters, and input impacting the strain model's state), 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 old 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.

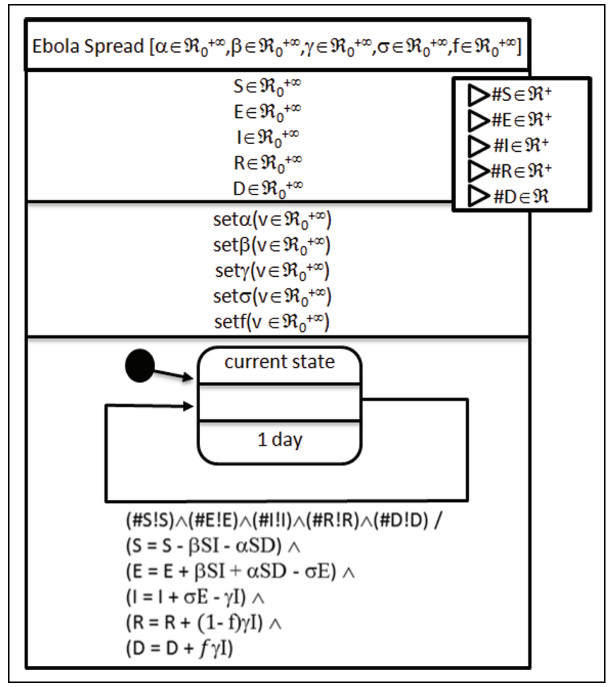

Figure C. HiLLS model of Ebola spread.

HiLLS model for Ebola spread

The HiLLS description of the Ebola spread model is given below (Figure C), and its DEVS counterpart is specified as follows:

$M_{EbolaSpread} = X^P, Y^P, S^P, \delta_{int}{}^P, \delta_{ext}{}^P, \delta_{conf}{}^P, \lambda^P, ta^P,$

where:

- $P = (\alpha \in \mathbb{R}_0^{+\infty}, \beta \in \mathbb{R}_0^{+\infty}, \gamma \in \mathbb{R}_0^{+\infty}, \sigma \in \mathbb{R}_0^{+\infty}, f \in \mathbb{R}_0^{+\infty});$
- $X^P = \{(p, v), p \in \{set\alpha, set\beta, set\gamma, set\sigma, setf\}, v \in \mathbb{R}_0^{+\infty}\};$
- $Y^P = \{(p, v), p \in \{\#S, \#E, \#I, \#R, \#D\}, v \in \mathbb{R}_0^{+\infty}\};$
- $S^P = \{current\} \times (\mathbb{R}_0^{+\infty} \times \mathbb{R}_0^{+\infty} \times \mathbb{R}_0^{+\infty} \times \mathbb{R}_0^{+\infty} \times \mathbb{R}_0^{+\infty}) \times \mathbb{R}_0^{+\infty};$
- $ta^P : S^P \rightarrow \mathbb{R}_0^{+\infty}$
- $ta^P(current, p, phase) = phase;$
- $\delta_{int}{}^P : S^P \rightarrow S^P$
- $\delta_{int}{}^P(current, \alpha, \beta, \gamma, \sigma, f, phase) = (\text{current}, , , , , f, 1\text{day});$
- $\lambda^P : S^P \rightarrow Y^P$
- $\lambda^P(current, \alpha, \beta, \gamma, \sigma, f, phase) = \{(\#S, S), (\#E, E), (\#I, I), (\#R, R), (\#D, D)\};$
- $\delta_{ext}{}^P : Q^P \times X^P \rightarrow S^Y$ with $Q^P = \{(s, p, sigma, e) | (s, p, sigma) \in S^P, 0 \leqslant e < sigma\}$
- $\delta_{ext}{}^P(current, \alpha, \beta, \gamma, \sigma, f, sigma, e, (set\alpha, v)) = (current, v, \beta, \gamma, \sigma, f, sigma - e)$

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

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