Comparative Analysis of Simulation models

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Abstract

Using computer simulations in examining, explaining and predicting social processes and relationships as well as measuring possible impact of policies has become an important part of policymaking process. In this paper, we presented a comparative analysis of simulation models in the field of policy decision making. We examined different modelling theories and learned that there are several techniques used for modelling, each suitable for representing different aspects of socio-economic phenomena, such as economic processes (e.g. production, dissemination and exploitation of products and services), demographic processes (education, migration, social contacts, spread of diseases, etc.) and nature processes (such as earthquakes and other natural or human-produced disasters). Unifying all of these phenomena under one umbrella could be done by using a “clever” junction of a collection of smaller self-contained models dedicated to each of the phenomena to be modelled. We argue that unification of modelling theories is not only beneficial for the policymaking process but also necessary next step in the development of simulation modelling.

1. Introduction

Using computer simulation as an important tool in examining, explaining and predicting social processes and relationships started intensively during 1990s (Gilbert, et al., 2005). The following two decades showed a growing recognition of the role that simulation models can play in the public decision modelling process (van Egmond, et al., 2010) because through simulation models is possible to closely examine complex social processes and relationships between entities. For example, simulation models can be used to examine the impact of school closure and vaccination in stopping the spread of influenza (cf. simulation models VirSim in Table 3 and MicroSim Table 4) or examine the influence of different policies in the early years of life (cf. simulation model MEL-C in Table 5).

This paper presents a comparative analysis of various simulation models with respect to their role in public decision-making process. The focus of our research is on the differences between particular simulation models and how to effectively use simulation models in the policymaking process. The collection of examined models, rather than to be exhaustive, presents an informative choice of different domain-specific simulation models corresponding to different modelling theories. First, we examine the most popular and widely used simulation modelling theories in order to establish common grounds for simulation modelling in policymaking. Subsequently, we analyse the simulation models using a comparative analysis framework in order to support extracting the major aspects and the core information about the examined simulation models. The goal is to provide a brief overview of simulation models, present them in a way they are comparable to each other and draw conclusions from the comparative analysis.

The paper is organised as follows. Section 1 briefly presents the design of the performed comparative analysis including the comparative analysis framework as well as the research questions. Section 2 describes the usage of simulation modelling techniques in the policy modelling process and gives an overview of the theoretical grounds and definitions about theories that lie in the core of simulation modelling. Section 3 describes a comparative analysis of simulation models performed using the above mentioned framework, while Section 4 broadens the discussion about the comparison of the presented simulation models and modelling theories. Section 5 presents the research and practice implications drawn from the comparative analysis, while Section 6 concludes our work with a summary of the performed comparative analysis.

1. Research Design

1.1. Approach to comparative analysis

We carried out the research using comparative analysis framework that was developed as part of the eGovPoliNet[1] comparative analysis research in order to support extracting major aspects and core information from examined simulation models. The goal of the framework is to provide a brief overview of domain-specific simulation models and present them in a way they are comparable to each other. The framework for simulation models (cf. Table 1) consists of a set of entries containing general metadata with basic information about a simulation model in question and as well as more specific conceptual data.

Table 1: Domain-specific simulation models: Aspects for comparison

Metadata
Name of the model
Developer
Publication Date
Background documents used in developing the model
Abstract
Reference(s)
Tools needed to run the model
Source of the model
Conceptual aspects
Discipline(s) covered by the model
Based on theory
Developed through method
Emerging from framework
Tool(s) used to develop the model
Application domain(s) of the model
Constraints of using the model in a particular way
Examples of (re)use of the formal model (reference to projects / cases)
Transferability of formal model in other domains or disciplinary contexts
Concluding recommendations on formal model development and/or use

Based on the information identified applying the comparative analysis framework to the particular simulation models (cf. Section 3), we discussed the usage and benefits of simulation models for policy

[1] http://policy-community.eu/

decision-making process and compared simulation models and modelling theories with respect to their role in policy modelling (cf. Section 4). Moreover, we examined the possibility of the transfer between the domains. We also investigated the potential of combining several modelling approaches in order to make the best use of simulation modelling in policy decision-making process.

1.2. Research Questions

We formulated a set of research questions to support and guide our investigation and the comparative analyses of the usage of simulation models in the policy modelling processes:

1. What types of simulation models are used in policy-making, and for what purpose?
2. On the ground of what particular theories, frameworks and/or methods are models developed?
3. What are the differences between particular simulation models and underlying theories, methods and approaches?
4. What is the benefit of simulation models in policy modelling?
5. What lessons can be drawn from the comparative analysis and what conclusions can be made on the practical use of models?

2. Theoretical Grounds

2.1. Introduction to simulation modelling and analysis

There exist different types of models, such as simulation models, conceptual models, meta-models, etc. In the OCOPOMO[2] project, for example, conceptual models are defined for each policy case (domain models represented as ontologies in XML format), simulation models are programmed in java code (declarative and rule-based agent models for each domain), meta-models are developed for the conceptual models and for the simulation models, and statistical models are represented graphically through charts for each domain (Scherer, et al., 2013), (Scherer, et al., 2011). In this paper, we concentrate on investigating the simulation models.

A simulation model can be defined as "a simplification – smaller, less detailed, less complex, or all of these together – of some other structure or system" (Gilbert, et al., 2005). Simulation model is a computer program that captures the behaviour of a real-world system and its input processes. The simulation output is a set of measurements concerning the observable reactions and the performance of the real-world system. Simulation models may output forecasts or projections into the future, hence supporting policy-making and stakeholders, using simulation models, as a support tool in examining possible impacts of different policies. Simulation models can be also used for a better understanding of the real-world processes, relationships and issues (Gilbert, et al., 2005). Another common application area is describing behaviours of different interest groups and sometimes even instead of a human expert (e.g. medical expert systems). Simulation models can be also used for education and trainings (e.g. simulation model GAIM[3]) and for entertainment (e.g. simulation game MoPoS[4] where a player is a central bank governor). On the higher level, simulation models can be used for the formalisation of social theories producing social science specifications (Gilbert, et al., 2005).

Prior to building a simulation model, the following necessary steps have to be performed (cf. **Fehler! Verweisquelle konnte nicht gefunden werden.**).

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[2] http://www.ocopomo.eu/

[3] GAIM – Gestione Accoglienza IMmigrati (Sedehi, 2006) is used for the trainings of foreign intercultural mediators in the immigration housing management courses.

[4] MoPoS - A monetary Policy Simulation Game (Lengwiler, 2004)

The first step is to collect and analyse the source data. The analysis depends on a type of a simulation model whereas, the data analyses' complexity varies between modelling approaches (cf. Figure 2). The inputs for the data analyses are the features, descriptions, relationships and specifications of the observed real-world system (Gilbert, et al., 2005).

The next step is conceptual modelling because the simulation models are the simplifications of the reality (Zeigler, 1976). Practically, this means to decide which characteristics of the real-world system are to be included in the simulation model and which are not (Gilbert, et al., 2005).

The next step is the design of the simulation model.

Data analyses, conceptual modelling and the design of the simulation model, performed in that order, are necessary steps prior to building the simulation model. Actually, building the model usually means developing a computer program or using already existing tools for developing a simulation, such as AnyLogic or NetLogo (cf. simulation models in Section 3 for more modelling tools). The last step in modelling a simulation are the verification and validation - check if the simulation model behaves as desired (the step referred to as verification) as well as whether the model describes the intended real-world system in a satisfactory way and gives reliable outputs (i.e. validation of the simulation model). Validation can be conducted by comparing known behaviour of a real-world system with the outputs of the simulation model obtained by using the input parameters for the known behaviour of the real-world system (Maria, 1997).

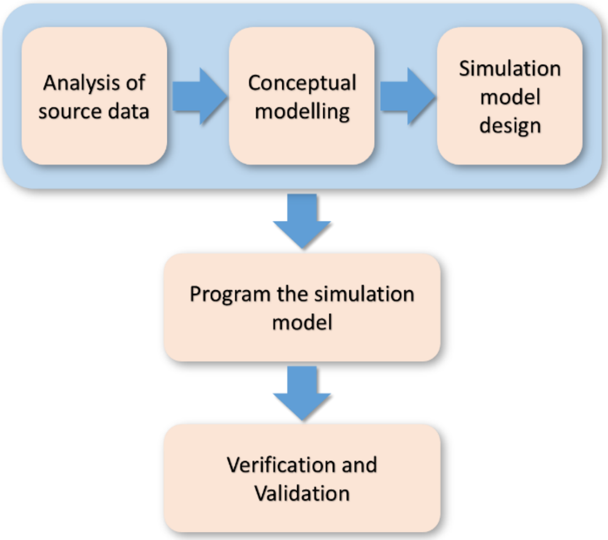

Figure 1: Method for designing a simulation model

Simulation models are useful for many reasons, such as:

- It is easier, less expensive and in many cases the only appropriate and possible solution (e.g. spreading of a disease), to simulate the reality rather than to experiment with the real world.
- The consequences of some policy decisions can be seen only many years ahead (e.g. policies regarding urbanism).

2.2. Simulation modelling theories

The approaches to simulation modelling considered in this paper are macro-simulation methods (System Dynamics and Dynamic Stochastic General Equilibrium models), Agent-based modelling theory and Micro-simulation modelling method. They focus on different aspects of the reality and use different methods to produce a simulation model. In the remaining part of this Section, we described briefly each of the modelling theories.

2.2.1. System Dynamics

Simulation models based on the System Dynamics modelling approach describe the real-world systems using the analytical means via systems of differential equations (Gilbert, et al., 2005). The real-world system is described and analysed as a whole on the macro level (Forrester, 1961) and represented using flow diagrams and internal feedback loops (Harrison, et al., 2007). The output of the model consists of plots describing the behaviour and changes of the values of the variables and parameters of the model over the time. To describe a behaviour of the real-world process accurately, a model needs to be run many times with different parameter values so that the outputs of the model can be compared and analysed (Maria, 1997). A typical use of the system dynamics models can be observed in the policy domain for the macro-economic modelling. However, as shown in Section 4, the system dynamics models are the best to use for predicting short-term policy impacts. As an example of the system dynamics modelling approach, Table 3 describes the simulation model VirSim.

2.2.2. DSGE (Dynamic Stochastic General Equilibrium) Modelling

2.2.3. Agent Based Modelling

In artificial intelligence, agents are referred to as “self-contained programs that can control their own actions based on their perceptions of the operating environment” (Gilbert, et al., 2005). Applied to the social processes, this means that agents are individuals or groups of individuals that are aware of their environment and at the same time proactive and interacting with each other and the surroundings. Agent-based simulation modelling captures and explains the behaviour and the dynamics of social interactions between agents and usually it does not assume predictions for the future (Srbljanovic, et al., 2003), (Gilbert, et al., 2005). It can be considered as a powerful tool for developing, testing and formalising social theories and examining complex social interactions (Gilbert, et al., 2005). An interesting characteristic of agent-based simulations is the ability to describe complex social phenomena at the global macro level emerging from simple micro level interactions between the agents (Srbljanovic, et al., 2003). Table 6 and Table 7 present examples of agent-based simulation models.

2.2.4. Micro-simulation

Complex policy issues require approaches that enable research synthesis and use systems thinking (Milne, et al., 2014). Micro-simulation modelling has the potential to represent systems and processes in various social domains and to test their functioning for policy purposes (Anderson, et al., 2011), (Zaidi, et al., 2009). The micro-simulation model, based on empirical individual-level data, can account for social complexity, heterogeneity, and change (Orcutt, 1957), (Spielauer, 2011). It relies on data from the real world to create an artificial one that mimics the original but upon which virtual experiments can be performed (Gilbert, et al., 2005). It operates at the level of individual units each with a set of associated attributes as a starting point. A set of rules, for example equations derived from statistical analysis of (often multiple) survey data sets, is then applied in a stochastic manner to the starting sample to simulate changes in state or behaviour. Modifications of influential factors can then be carried out to test hypothetical ‘what if’ scenarios on a key outcome of policy interest (Davis, et al., 2010). Micro-simulation can integrate, and accommodate the manipulation of, the effects of variables across multiple model equations (often derived from multiple data sources) in a single simulation run. Thus, each otherwise separate equation is given its social context and influence among the other equations, representing a system of inter-dependent social processes.

Table 4 and Table 5 describe simulation models MicroSim and MEL-C based on micro-simulation modelling theory.

2.2.5. Complex Systems Theory

A complex system, roughly speaking, is one with many parts, whose behaviours are both highly variable and strongly dependent on the behaviour of the other parts. Clearly, this includes a large fraction of the universe! Nonetheless, it is not vacuously all embracing: it excludes both systems whose parts just cannot do very much, and those whose parts are independent of each other. "Complex systems science" is the field whose ambition is to understand complex systems. Complex system is broadly interdisciplinary field that deals with systems composed of many interacting units, often called "agents." Of course, this is a broad endeavour, overlapping with many even larger, better-established scientific fields. The foundational elements of the field predate the current surge of interest in it, which started in the 1980s, but substantial recent advances in the area coupled with increasing interest both in academia and industry have created new momentum for the study and teaching of the science of complex systems (Chan, 2001).

There is no precise technical definition of a "complex system," but most researchers in the field would probably agree that it is a system composed of many interacting parts, such that the collective behaviour of those parts together is more than the sum of their individual behaviours. The collective behaviours are sometimes also called "emergent" behaviours, and a complex system can thus be said to be a system of interacting parts that displays emergent behaviour.

Classic examples of complex systems include condensed matter systems, ecosystems, the economy and financial markets, the brain, the immune system, granular materials, road traffic, insect colonies, flocking or schooling behaviour in birds or fish, the Internet, and even entire human societies.

Complex systems theory is divided between two basic approaches. The first involves the creation and study of simplified mathematical models that, while they may not mimic the behaviour of real systems exactly, try to abstract the most important qualitative elements into a solvable framework from which we can gain scientific insight. The tools used in such studies include dynamical systems theory, information theory, cellular automata, networks, computational complexity theory, and numerical methods (Shalizi, 2006). The second approach is to create more comprehensive and realistic models, usually in the form of computer simulations, which represent the interacting parts of a complex system, often down to minute details, and then to watch and measure the emergent behaviours that appear. The tools of this approach include techniques such as Monte Carlo simulation and, particularly, agent-based simulation, around which a community of computer scientists and software developers has grown up to create software tools for sophisticated computational research in complex systems.

3. Domain-specific Simulation Models

In this Section, we presented a comparative analysis of our choice of simulation models with respect to their contribution to policy modelling in different public domains. The models are based on modelling theories presented in Section 2.2. We do not aim at presenting an exhaustive list of models and choose the collection of simulation models (cf. Table 2) to be rather an informative collection of domain-specific simulation models corresponding to different modelling theories.

Table 2: Simulation models examined in the comparative analysis

Based on theory	Simulation model

System Dynamics	VirSim – A Model to Support Pandemic Policy Making (cf. Table 3)
Micro-simulation	MicroSim (cf. Table 4)
	MEL-C - Modelling the Early Life-Course (cf. Table 5)
Agent-based modelling	Kosice model (OCOPOMO) (cf. Table 6)
	SKIN - **S**imulating **K**nowledge Dynamics in **I**nnovation **N**etworks (cf. Table 7)

In the remaining part of this Section, we presented each simulation model from Table 2 examined within the framework described in Section 1.1.

Table 3: Simulation model VirSim

Simulation models (domain-specific) **Aspects for comparison**	**VirSim**
Metadata	
Name	VirSim
Developer	Tobias Fasth, Marcus Ihlar, Lisa Brouwers
Publication Date	2010
Background documents	• Used to segregate the population into three age groups: (Statistics Sweden (Statistiska centralbyrån, SCB), 2009) • Used to estimate contacts between and within age groups: (Wallinga J., Teunis P., Kretzschmar M., 2006) • Used to decide on the duration of a latent period: (Carrat, et al., 2008), (Fraser, et al., 2009)
Abstract	VirSim (Fasth, et al., 2010) is a simulation model that simulates spread of pandemic influenza and enables evaluating the effect of different policy measures connected to school closure and vaccination. The main goal is to find the most optimal policies connected to the starting time and the duration of school closure as well as the pace and the vaccination coverage. It is also possible to estimate public costs due to absence from work during a sick leave. The model considers real population data in Sweden on both national and regional level (Fasth, et al., 2010). The idea behind VirSim is that the whole population is divided into three age groups: below 20, from 20 to 59, and 60 and more, and the influenza is spreading within and between groups with different probabilities. For each age group constructed is a SEIR model (**S**usceptible, **E**xposed, **I**nfected, and **R**ecovered) representing the dynamics of disease spreading. VirSim supports scenario analysis (i.e. “what-if” analysis), which means that a user can combine a number of different parameters producing “real” scenarios and examine the impact of policies.
Reference(s)	(Fasth, et al., 2010)
Tools needed to run the model	Web browser, Internet

Source of the model	http://www.anylogic.com/articles/virsim-a-model-to-support-pandemic-policy-making http://people.dsv.su.se/~maih4743/VirSim/VirSim.html
Conceptual aspects	
Discipline(s)	Health science, Information technology / E-Government
Based on theory	System Dynamics VirSim uses SEIR model (**S**usceptible, **E**xposed, **I**nfected, **R**ecovered) for each of the age groups for modelling the population. This means that each individual is assigned to one of the four infection groups over time. For example, a healthy person starts as a susceptible (S), becomes exposed (E), then infected (I) and, after some time recovered (R) (or dead). During time, a person changes between the categories. The flow of people between different groups over time can be described by systems of differential equations. In addition, System Dynamics models are fast to run and not memory demanding, while at the same time provide an efficient way to examine the effect of policies undertaken in the specific conditions of the spread of influenza.
Developed through method	SEIR model (**S**usceptible, **E**xposed, **I**nfected, **R**ecovered) for modelling the population
Emerging from framework	
Tool(s) used to develop the model	AnyLogic[5]
Application domain(s)	Policy making under pandemic influenza
Constraints of using the model in a particular way	VirSim model does not take into account some parameters that are important for the transmission and spreading the influenza virus, such as effect of weather and temperature conditions and geographical differences between regions as well as diverse social structures including travelling frequency, gender and hygiene habits. It is not possible to analyse many of the missing parameters since the underlying SEIR model and System Dynamics method do not take into consideration social differences therefore to all people within the age group was assigned the same infection probability.
Examples of (re)use of the formal model (ref to projects / cases)	Policy making under pandemic influenza in Sweden in 2009. Tested policies are vaccination and school closure (Fasth, et al., 2010) (p. 6).
Transferability of formal model in other domains or disciplinary contexts	The authors assumed initial values for all parameters (for example the starting time of vaccination or the infection risk for different age groups) based on documents and data available in the time of developing the model. However, VirSim allows for a change of all parameter values, including those initially assumed. This assures that the model is re-usable with other data. To our knowledge, the model is not transferable to other domains and contexts since it does not allow for a change of the number of parameters and the underlying differential equations.

[5] http://www.anylogic.com/

Concluding recommendations on formal model development and/or use	The model is based on the scenario analysis – a user can post a question and get an answer in the form of suitable plots what would happen if apply certain policy under certain conditions. This allows policy-making officials to discuss policies further toward finding the most suitable ones for different conditions. To provide accurate and significant results, VirSim uses real population data in Sweden, at national and regional level (Fasth, et al., 2010) (p. 1). While running the simulation model VirSim, we noticed that it runs fast and a user can easily manipulate different parameters. However, user interface did not include descriptions of the parameters; a user had to guess their meaning and a range of values, based on their names. In some cases, this was difficult. For example, for the parameter "vaccination … starts after" with the initial value of 147 was not clear for what the given initial value stands. Apart from this issue, the model is intuitive and easy to work with. The recommendation on formal model development could be to extend the model to support defining custom variables and at least some class of differential equations that is suitable for modelling similar phenomena. Also, based on supported types of processes, the description of possible domains of application to which the model is transferrable would be recommended. Discussion about VirSim and comparison to other simulation models is continued in Section 4.

Table 4: Micro-simulation model MicroSim

Simulation models (domain-specific) **Aspects for comparison**	**MicroSim**
Metadata	
Name	MicroSim - Micro-simulation model: Modelling the Swedish Population
Developer	Lisa Brouwers, Martin Camitz, Baki Cakici, Kalle Mäkilä, Paul Saretok
Publication Date	2009
Background documents	The MicroSim model uses registry data obtained from Statistics Sweden (Statistiska centralbyrån, SCB)[6] to generate the simulated population: • National Population Register (2002) to describe age, marital status, children, employment, IDs father and mother; • Employment Register (2002) to describe company, workplace, branch, municipality of the workplace for each individual; • Geographic database (2003) to obtain family household coordinates, workplace coordinates, and school coordinates.
Abstract	MicroSim is event driven with discrete time steps of an hour, micro-simulation model developed for exploring impact of different intervention policy strategies to the spread of influenza in Sweden, such as vaccination, isolation and social distancing. Each individual living in Sweden is modelled in many details, including age, family status, employment details, and

[6] http://www.scb.se

	important geographical data, such as home and workplace coordinates. Such modelling strategy provided fine-grained differentiation between age groups, people's daily routines and their education level. This enabled examining the spread of influenza through different social contacts as well as the spatial spread of the disease.
Reference(s)	(Brouwers, et al., 2009), (Brouwers, et al., 2009)
Tools needed to run the model	
Source of the model	https://smisvn.smi.se/sim/
Conceptual aspects	
Discipline(s)	Health science, Information technology / E-Government
Based on theory	Micro-simulation
Developed through method	Population analysis
Emerging from framework	C++
Tool(s) used to develop the model	
Application domain(s)	Policy making under pandemic influenza
Constraints of using the model in a particular way	
Examples of (re)use of the formal model (ref to projects / cases)	Policy making under pandemic influenza in Sweden in Autumn of 2009.
Transferability of formal model in other domains or disciplinary contexts	The model can be used as a basis for examining effects of different policies and real-world systems and processes based on social and geographical distribution.
Concluding recommendations on formal model development and/or use	Although usually micro-simulation models use only sample data of the population, MicroSim uses personal, employment and geographic data of the complete Swedish population (around nine million people), which provides an explicit enhancement of the model's accuracy and reliability. Such detailed representation provides conditions suitable for realistic simulations of influenza outbreaks in Sweden. However, micro-simulation model based on the ontology of the population is not robust toward demographic changes in the social structure of the population. Discussion about MicroSim and comparison to other simulation models is continued in Section 4.

Table 5: Micro-simulation model MEL-C

Simulation models (domain-specific) **Aspects for comparison**	**MEL-C Model**
Metadata	
Name	Modelling the Early Life-Course (MEL-C)

Developer	COMPASS[7]
Publication Date	2014
Background documents	(Fergusson DM, Horwood LJ, Shannon FT, Lawton JM., 1989), (Solar O, Irwin AA.)
Abstract	MEL-C is a **K**nowledge-based **I**nquiry tool **W**ith **I**ntervention modelling (KIWI) developed on the early life-course as a decision support to policy analysts and advisors. It is a dynamic discrete-time micro-simulation model using a social determinants framework for which the key parameters have been estimated from the analysis of existing longitudinal studies in New Zealand, initially the Christchurch Health and Development Study. It can be interrogated with realistic policy scenarios by changing baseline features or parameters in the model. The model interface and inquiry system have been developed in cooperation with central government policy advisors drawn from the agencies with a special interest in the early life-course.
Reference(s)	(Mannion, et al., 2012), (Milne, et al., 2014), (McLay, et al., 2014), (Lay-Yee, et al., 2014)
Tools needed to run the model	The MEL-C executable, which includes JAMSIM (consisting of ASCAPE, JAVA and R) and simulation code run with R and tailored functions from the R Simario package developed by COMPASS.
Source of the model	See http://code.google.com/p/jamsim/ See http://code.google.com/p/simario/ On request from the COMPASS research centre.
Conceptual aspects	
Discipline(s)	Social and health sciences (sociology, psychology, epidemiology), statistics, computer science, policy sciences.
Based on theory	Child development, Social determinants of health, Micro-simulation.
Developed through method	• Regression analysis • R and JAVA programming • Micro-simulation modelling • End-user engagement • Cluster matching and data imputation
Emerging from framework	A single executable software application in which users can interrogate the model from the "front end" and not need to deal with the "behind-the-scenes" computer programs and statistical models. Eclipse, StatEt, Git control, Ivy.
Tool(s) used to develop the model	• ASCAPE[8] – for front end • Jamsim[9] (JAVA) – for front end • Simario (R)[10] – for execution of models
Application domain(s)	• Early life-course • Health, Justice, Education, Social Policy

[7] http://www.arts.auckland.ac.nz/en/about/ourresearch-1/research-centres-and-archives/centre-of-methods-and-policy-application-in-the-social-sciences-compass/about-compass.html
[8] http://ascape.sourceforge.net/
[9] http://code.google.com/p/jamsim/
[10] http://code.google.com/p/simario/

	• Policy scenarios • User interface
Constraints of using the model in a particular way	• Limited by variables available in the source data sets. • Relationships between variables are uni-directional with no feedback. • Scenarios tested involve changing the distribution of variables not the effects (e.g. the effect of X on Y). • Potential geographical and period limits of data sources. • Discrete time only.
Examples of (re)use of the formal model (ref to projects / cases)	• Illustrative application to social determinants of health. • Illustrative application to end-user engagement.
Transferability of formal model in other domains or disciplinary contexts	• The model is of generic applicability in early life-course analysis. • Subject to data availability and funding, It may be possible to extend the model to later periods in the life-course and other domains. • There may be other dynamic socio-demographic processes where this approach can be applied.
Concluding recommendations on formal model development and/or use	• The model is restricted to a notional "evidence-based"/science-informed approach to policy development. • The model is conceptually predicated on the primacy of social determinants. • The role of stakeholders is limited to the rather formal role of a policy advisor or analyst seeking to weigh different options within a prescribed range. • The model is able to reproduce actualities and to produce plausible substantive results in scenario testing. • The model has the great potential of combining a realistic data framework with estimates derived from trials, systematic reviews and other research sources. • The model is a simplification of reality but is nevertheless a powerful source of information that can be interrogated by end-users and can be considered alongside other evidence for policy.

Table 6: Kosice simulation model

Simulation models (domain-specific) **Aspects for comparison**	**Kosice model**
Metadata	
Name	Kosice model
Developer	OCOPOMO
Publication Date	8/5/2013
Background documents	• Description of the Kosice pilot case, pp. 22-45 of Deliverable 1.1 • Description of the pilot model from Warsaw team • Analysis of structural funds (2007-2013) and Projects Approved in 2009 in the KSR • Energy policy of the KSR (2007)

	• Strategy of the Renewable Energy Sources Utilization in the KSR (2006) • Demographic composition of the households (1996) • Annual report 2009, Regulatory Office for Network Industries • Regional Statistics Database (2010) • Interviews
Abstract	The idea behind the simulation model developed in Kosice case is to capture the behaviour of key stakeholders and the decision making process in the energy domain. It combines different scenarios based on: • interrelations between stakeholders, • economic conditions of the region, • realistic social dynamics. This simulation model is valuable for policy modelling officials since it provides a basis for testing the effectiveness of various public policies under different conditions such as abnormal climatic phenomena or changes in the availability of raw materials, such as gas, coal, and biomass.
Reference(s)	(Scherer, et al., 2013), (Scherer, et al., 2011), (Wimmer, 2011), (Lotzmann, et al., 2011), (Lotzmann, et al., 2011), (Butka, et al., 2011), (Bicking, et al., 2010), (Moss, et al., 2011), (Bicking, et al., 2013), (Bicking, et al., 2013)
Tools needed to run the model	• Collaborative participation platform for scenario generation and stakeholder interaction ALFRESCO[11] (wiki, discussion, voting) • DRAMS[12] – the Declarative Rule-based Agent Modelling system • Consistent Conceptual Modelling (CCD)[13]
Source of the model	http://www.ocopomo.eu/results/software-and-models/software-and-model-artefacts/eclipse-based-tools-and-simulation-models
Conceptual aspects	
Discipline(s)	Social Science, Information Systems / E-Government
Based on theory	Model-driven Architecture, Macroeconomic model, Complex Systems Theory
Developed through method	• Stakeholder engagement • Consistent Conceptual Modelling (CCD) • Agent-based modelling • Traceability
Emerging from framework	• Eclipse Modelling Framework (EMF)[14] • Eclipse Graphical Modelling Framework (GMF)[15] • Graphical Editing Framework (GEF)[16]
Tool(s) used to develop the model	• Collaborative participation platform for scenario generation and stakeholder interaction ALFRESCO (wiki, discussion, voting) • DRAMS – the Declarative Rule-based Agent Modelling system • Consistent Conceptual Modelling (CCD)
Application domain(s)	The simulation model is used for policy development in the field of energy with the focus on:

[11] http://www.alfresco.com/?pi_ad_id=39517088287
[12] (Lotzmann, et al., 2011)
[13] http://www.ocopomo.eu/results/glossary/consistent-conceptual-description
[14] https://www.eclipse.org/modeling/emf/
[15] http://www.eclipse.org/modeling/gmp/
[16] http://www.eclipse.org/gef/

	• Energy efficiency • Decrease of energy consumption (heating) • Utilization of renewable energy sources
Constraints of using the model in a particular way	Agent-based Modelling is particularly applicable for examining social behaviour but cannot be the only source for policymaking.
Examples of (re)use of the formal model (ref to projects / cases)	Heating in Kosice Self-Governing Region (KSG), Slovakia
Transferability of formal model in other domains or disciplinary contexts	In analysing simulation results, the natural conditions of the Kosice region (terrain, location of and distance from the renewable energy sources, concentration of housing, available infrastructure etc.) have to be taken into account. These important issues highly influence the output of the model.
Concluding recommendations on formal model development and/or use	• The simulation model is evidence-based and built around the descriptions, expectations, interactions and beliefs of stakeholders in the policymaking process. • The modelling process involves stakeholders who express their views and concerns on a policy via collaborative scenarios and e-participation tools. They act as partners and researchers in the modelling process.

Table 7: Simulation model SKIN

Simulation models (domain-specific) **Aspects for comparison**	**SKIN**
Metadata	
Name	**S**imulating **K**nowledge Dynamics in **I**nnovation **N**etworks (SKIN)
Developer	Gilbert, Nigel; Ahrweiler, Petra; Pyka, Andreas
Publication Date	Since 2001 continuous updates
Background documents	Literature from Evolutionary Economics, Economic Sociology, and Science and Technology Studies (no specific reference to be singled out)
Abstract	Simulating Knowledge Dynamics in Innovation Networks (SKIN) is an agent-based model used to understand innovation policy initiatives which contain heterogeneous agents, who act and interact in a large-scale complex and changing social environment. The agents represent innovative actors who try to sell their innovations to other agents and end users but who also have to buy raw materials or more sophisticated inputs from other agents (or material suppliers) to produce their outputs. This basic model of a market is extended with a representation of the knowledge dynamics in and between the agents. Each agent tries to improve its innovation performance and its sales by improving its knowledge base through adaptation to user needs, incremental or radical learning, and co-operation and networking with other agents.
Reference(s)	(Gilbert, et al., 2001), (Ahrweiler, et al., 2004), (Gilbert, et al., 2007), (Pyka, et al., 2007), (Scholz, et al., 2010), (Ahrweiler, et al., 2011), (Ahrweiler, et al., 2011), (Gilbert, et al., 2014)

Tools needed to run the model	Netlogo[17] (versions available in other languages such as Java)
Source of the model	http://cress.soc.surrey.ac.uk/SKIN/
Conceptual aspects	
Discipline(s)	Economics, Sociology, Science and Technology Studies, Policy Research, Business Studies
Based on theory	Evolutionary Economics, Organizational Theory, Organizational Learning, Field Theory, Complex Systems Theory,
Developed through method	Theory formation, empirical research, implementing theoretical concepts and empirical insights, consistent conceptual modelling, Agent-based modelling
Emerging from framework	Innovation Networks
Tool(s) used to develop the model	Netlogo
Application domain(s)	Knowledge-intensive industries, EU Framework Programmes, National Innovation Policies, role of specific actors in innovation networks
Constraints of using the model in a particular way	SKIN is about knowledge and agent networks embedded in a dynamic environment. Not applicable if domain has nothing to do with it.
Examples of (re)use of the formal model (ref to projects / cases)	EU projects • Simulating Self-Organizing Innovation Networks (SEIN) [18], 1998-2001 • Network models, governance, and R&D collaboration networks (NEMO)[19], 2006-2009 • Managing Emerging Technologies for Economic Impact (ManETEI) [20], 2010-2014 • Using Network Analysis to monitor and track Effects resulting from Changes in Policy Intervention and Instruments, (SMART 2010/0025) 2010-2011 • Governance of Responsible Research and Innovation (GREAT)[21], 2013-2016
Transferability of formal model in other domains or disciplinary contexts	SKIN is a multi-disciplinary initiative (see above Discipline(s)) and is therefore used in various disciplinary contexts.
Concluding recommendations on formal model development and/or use	• The advantages of using SKIN for policy modelling include: The experiments can be run many times to find statistically average behaviour. Experiments can be used to give an indication of the likely effect of a wide variety of policy measures Empirical 'Un-observables' such as the amount of knowledge generated, and the number of proposals started but abandoned before submission, can be measured by instrumenting the simulation

[17] http://ccl.northwestern.edu/netlogo/
[18] http://ec.europa.eu/research/social-sciences/projects/097_en.html
[19] http://cress.soc.surrey.ac.uk/SKIN/research/projects/nemo
[20] http://lubswww.leeds.ac.uk/manetei/home/
[21] http://www.great-project.eu/

	The problems included determining: • What are the ultimate policy objectives for the support of Research and Development? • When were the policies being formulated and by whom? • How can the research be presented so that it is interesting and comprehensible to a policymaking audience?

4. Comparative Analysis of Simulation Models

Each of the examined approaches has strengths and weaknesses that limit its usability in analysing impacts of policies. Figure 2 presents a comparison between the micro-, the agent-based and the macro-simulation models. Micro-simulation models represent ontology of the population based on individuals and are the most demanding regarding data needed for establishing the model. Agent-based models are less data demanding, less complex and well suited for representing groups of actors and their social behaviour (Gilbert, et al., 2005). Macro models, represented in this paper with System Dynamics and DSGE models, are the least demanding – they model a situation on the global level and require least data. However, their results are better rather for the analysis of the short-term policy impacts than for the long-term ones (Astolfi, et al., 2012). An example is that the major macro-economic models, which were macro-simulation-based, were not able to predict the financial crises that hit the Europe in 2008 (Freedman, 2011), (Colander, et al., 2009).

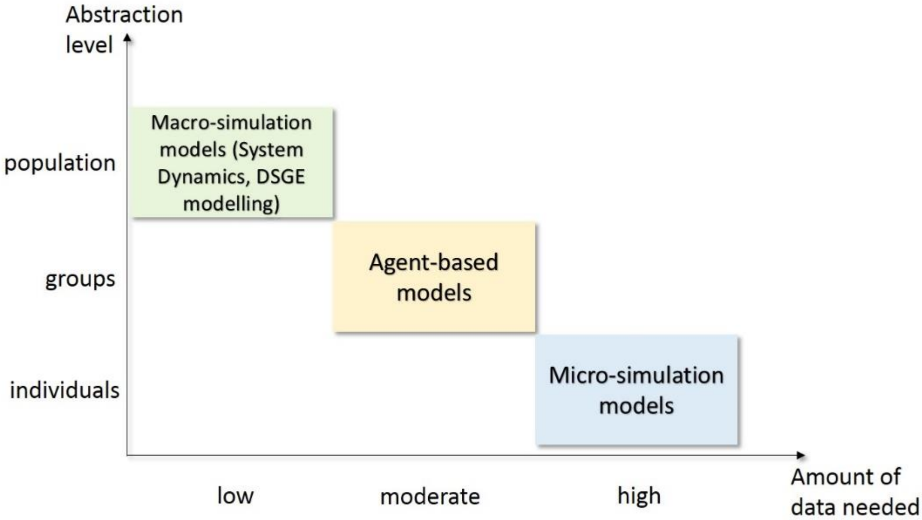

Figure 2: Comparison of simulation modelling theories

The main advantage of system dynamics based simulation models is they are fast to run and technologically not demanding while providing useful information about the real-world processes and possible impacts of different policies. However, models based on System Dynamics face number of restrictions. For example, system dynamics based simulation model VirSim (cf. Table 3) assumes infection probabilities at which elderly people (age group 60 and more) have considerably fewer chances to be infected with influenza compared to the other two age groups (Fasth, et al., 2010). However, the applied SEIR modelling approach cannot predict this and explain why this occurs. The authors used this result from the micro-simulation model MicroSim (cf. Table 4) describing the same real-world process of spreading influenza and assumed this phenomenon happens because of less social contacts of elderly people or some prior immunity. VirSim model cannot explain this phenomenon because System Dynamics does not include modelling of various social interactions and other similar dependencies between actors since all variables are averaged over particular groups and the population in general - in the case of VirSim within members of a particular age group. Apart from the categories of people based on their age, VirSim model cannot define fine-grained categories of people that have higher probability to be infected. For example, a student has more chances to be exposed and therefore infected than a researcher working in the same University due to more frequent social interactions. It is also important to identify other closed environments that have high risk of spreading influenza, for example boarding and nursing homes. From the policy-modelling point of view, it is important to identify high-risk groups to start the vaccination from there. We assume this would have a positive effect against spreading influenza. One could define refined categories of actors by defining more variables, but in general, it would not be possible to represent relations between subcategories, such as taxonomies or ontologies needed to represent social contacts or mutual interactions of actors, due to the lack of representation apparatus in system dynamics models. It is clear from the discussion that non-linear processes and systems are actually difficult to be described analytically (Gilbert, et al., 2005). To be able to examine interactions between simulation units, their motives and intentions, we need to consider other modelling techniques such as Agent-based modelling, or for the social heterogeneity and structures we need Micro-simulation models.

Micro-simulation models, usually based on a weighted sum of a representative sample of a population, consider characteristics of individuals and are able to reproduce social reality (Martini, et al., 1997). They are beneficial in predicting both, short-term as well as long-term impact of policies (Gilbert, et al., 2005). However, micro-simulation models are costly to build and complex, especially at the level of data analysis requirements – in the case of MicroSim, the complete Swedish population of approximately nine million people was modeled in many details (Brouwers, et al., 2009). Moreover, in “simple” cases, especially in demographics, a micro-simulation model will produce similar results as a System Dynamics-based model (Gilbert, et al., 2005). This proved true in the case of MicroSim and VirSim models: The latter confirmed the results of the former, although with a bit greater difference between vaccination and non-vaccination results (The National Board of Health and Welfare, 2011). Micro-simulation is best to use when population heterogeneity matters; when there are too many possible combinations to split the population into a manageable number of groups; in situations when the micro level explains complex macro-behaviours; or when individual history is important for model’s outcomes (Spielauer, 2011).

Although agent-based models lack of predicting possibilities, they are a valuable tool for describing and explaining complex social interactions and behaviours, contributing to the understanding of the real-world social systems and a better management of different social processes. Agent-based simulations are able of representing real-world systems where small changes in parameter values induce big changes in the model’s outputs. This property shifts attention from the importance of predictions of the system’s future behaviour to the management of critical processes responsible for the changes. However, agent-based simulations alone are not sufficient to model the reality. Another possible problem is a high degree of freedom in modelling agents, which amplifies importance of proper validation in the process of building a simulation model (Schindler, 2013).

On the other hand, although Agent-based modelling and Micro-simulation would be able to show that an elderly person has less infection probability, it is questionable whether they would be able to answer why an elderly person is less infected by influenza. It might happen that hidden variables and parameters influence this age group. For this reason, in order to model correct probabilities for different age groups, we have to use uncertain models, such as (dynamic) Bayesian models or Markov chains. In addition to the previous, if the past should be also considered (for example, a person has less chances to be infected now because he/she was infected in the recent past), then we have to use more complex probability models, such as Dempster-Shafer model (Ronald, et al., 1991), (Jameson, 1996).

Statistical models can be used to predict values of some dependant variables (Gilbert, et al., 2005). However, statistical models assume linear relationships between parameters, which becomes a restrictive assumption in the case of complex social systems.

5. Research and Practice Implications

From the performed comparative analysis, we noted that different theories can be used to model different policy domains (research question 2). For example, Dempster-Shafer theory can be used to model the past uncertainties, Markov chains can be used for one-step iterations in time followed by the use of analytical models based on differential equations (e.g. System Dynamics modelling) or social modelling theories such as Micro-simulation for representing social structures and Agent-based modelling for examining interactions between agents. However, none of the theories alone is able to address complex policy interactions (Astolfi, et al., 2012). The question is would it be possible to build and maintain a complex simulation model consisting of a few sub-models built on different modelling theories which communicate with each other by setting up and propagating particular parameters after each reasoning iteration? Based on our analysis (research question 5) we believe this is the next step in simulation modelling development. Modern research confirms our conclusion (Astolfi, et al., 2012). These hybrid models can be considered as modelling platforms or complex systems consisting of sub-models. However, it is necessary to research methodologies and ways of combining different modelling methods in order to provide reliable simulation models. Current research shows this tendency, the example of which is the micro-macro Chronic Disease Prevention Model developed in Australia (Brown, et al., 2009).

Our recommendations for the future use of simulation models in policy modelling include the following steps:

- choosing the collection of smaller (sub) models each describing certain aspects of a given domain of modelling;
- finding the junction points of those models with each other by defining the input and output parameters for each of the sub-models,
- determine the workflow of a simulation process by means of e.g. a sequence and timing of exchanging the values of input and output parameters between smaller models in the combined hybrid meta-model.

6. Conclusions

In this paper, we presented a comparative analysis of simulation models in the field of policy decision making. We learned that there are several techniques used for modelling, each suitable for representing different aspects of socio-economic phenomena (research question 1), such as economic processes (e.g. production, dissemination and exploitation of products and services), demographic processes (education, migration, social contacts, spread of diseases, etc.) and nature processes (such as earthquakes and other natural or human-produced disasters). Unifying all of these phenomena under one umbrella could be done by using a "clever" junction of a collection of smaller self-contained models dedicated to each of the phenomena to be modelled. We examined the differences between particular simulation models and underlying theories and simulation methods (research question 3).

Finally, to summarise, based on the comparative analysis, what are the strengths and weaknesses of the usage of Simulation models in policy modelling (research question 4)? The main strengths are the possibility of understanding real-world systems and relationships, experimenting with new situations, forecasting outputs of different situations based on the given values of parameters, as well as being in control of a social process by means of having an opportunity to make an impact on the result of the real-world situation by modifying the input parameters (i.e. measuring impact of policies). Simulations are also beneficial for developing and exploring modelling theories. The weakness of such models is connected to missing parameters where a model often lack some precision because of the missing factors not accounted for or not easy to find, especially before there is any effect caused by them (e.g. late symptoms of a disease). This problem occurs especially in modelling situations that have not yet occurred in the reality. Appropriate level of details included in the model description, being not too complex, not too simple is one of the key features that determine success of a model.

References

Ahrweiler, P., Gilbert, N. and Pyka, A. 2011. Agency and Structure. A social Simulation of knowledge-intensive Industries. *in: Computational & Mathematical Organization Theory, Vol. 17 (1), 59-76.* 2011.

Ahrweiler, P., Pyka, A. and Gilbert, N. 2011. A new model for university-industry links in knowledge-based economies. *in: Journal of Product Innovation Management, Vol.28 (2), 218-235.* 2011.

—. 2004. Simulating Knowledge Dynamics in Innovation Networks (SKIN). *in: R. Leombruni, und M. Richiardi (eds.), The Agent-Based Computational Approach, World Scientific Press, Singapore, 284-296.* Singapore : World Scientific Press, 2004.

Anderson, R. E. and Hicks, C. 2011. Highlights of contemporary microsimulation. *Social Science Computer Review, 29(1), 3-8.* 2011.

Astolfi, R., Lorenzoni, L. and Oderkirk, J. 2012. A Comparative Analysis of Health Forecasting Methods. *OECD Health Working Papers, No. 59, .* s.l. : OECD Publishing doi=http://dx.doi.org/10.1787/5k912j389bf0-en, 2012.

Bicking, et al. 2010. D1.1 Stakeholder Identification and Requirements for Toolbox, Scenario Process and Policy Modelling, Deliverable 1.1. s.l. : OCOPOMO, 2010.

Bicking, et al. 2013. D7.1 Evaluation Strategy, Trial Design and Evaluation Results. *Deliverable 7.1.* s.l. : OCOPOMO, 2013.

Bicking, et al. 2013. WP6: Policy Modelling and Scenario Process Implementation. *Deliverable 6.1.* s.l. : OCOPOMO, 2013.

Brouwers, L., et al. 2009. Economic consequences to society of pandemic H1N1 influenza 2009 – preliminary results for Sweden, Euro Surveill. 009;14(37):pii=19333. s.l. : Available online: http://www.eurosurveillance.org/ViewArticle.aspx?ArticleId=19333, 2009.

Brouwers, L., et al. 2009. MicroSim: Modeling the Swedish Population. s.l. : arXiv:0902.0901, Available from: http://arxiv.org/abs/0902.0901, 2009.

Brown, L., et al. 2009. Linking micro-simulation and macro-economic models to estimate the economic impact of chronic disease prevention. *In: Zaidi A, Harding A, Williamson P, editors. New Frontiers in Microsimulation Modelling. Ashgate: European Centre Vienna: 527-556.* European Centre Vienna : s.n., 2009.

Butka, Peter, et al. 2011. Design of a System Architecture for Support of Collaborative Policy Modelling Processes. *In: Proceedings of SACI 2011, 6th IEEE International Symposium on Applied Computational Intelligence and Informatics, pp. 193-198, Red Hook, NY, USA, Óbuda University, Hungary, IEEE, Curran Associates, Inc.* Óbuda University, Hungary, : IEEE, 2011.

Carrat, F., et al. 2008. Time lines of infection and disease in human influenza: a review of volunteer challenge studies. s.l. : Am J Epidemiol. 2008 Apr 1;167(7):775-85. Epub 2008 Jan 29. PubMed PMID: 18230677, 2008.

Chan, S. 2001. *Complex adaptive systems.* s.l. : Cambridge: MIT, 2001.

Colander, David, et al. 2009. The Financial Crisis and the Systemic Failure of Academic Economics. *SSRN 1355882 (March 9, 2009), Univ. of Copenhagen Dept. of Economics Discussion Paper No. 09-03.* s.l. : Univ. of Copenhagen Dept. of Economics, 2009.

Davis, P., Lay-Yee, R. and Pearson, J. 2010. Using micro-simulation to create a synthesized data set and test policy options: The case of health service effects under demographic ageing. *Health Policy, 97, 267-274.* 2010.

Fasth, Tobias, Ihlar, Marcus and Brouwers, Lisa. 2010. VirSim – A Model to Support Pandemic Policy Making. *PLOS Currents Influenza. 2010 Sep 22 [last modified: 2012 Mar 29]. Edition 1. doi: 10.1371/currents.RRN1181.* 2010.

Fergusson DM, Horwood LJ, Shannon FT, Lawton JM. 1989. *The Christchurch Child Development Study: A review of epidemiological findings.* s.l. : Paediatric & Perinatal Epidemiology 1989, 3, 278-301, 1989.

Forrester, J. W. 1961. Industrial dynamics. Cambridge : MA: MIT Press, 1961.

Fraser, C., et al. 2009. WHO Rapid Pandemic Assessment Collaboration. Pandemic potential of a strain of influenza A (H1N1): early findings. s.l. : Science. 2009 Jun 19;324(5934):1557-61. Epub 2009 May 11. PubMed PMID: 19433588., 2009.

Freedman, David H. 2011. *A Formula for Economic Calamity.* s.l. : In: Scientific American 305, 76 – 79, 2011.

Gilbert, N. and Troitzsch, K. 2005. Simulation for the Social Scientist. s.l. : Maidenhead: Open University Press., 2005.

Gilbert, N., Ahrweiler, P. and Pyka, A. 2007. Learning in Innovation Networks – Some Simulation Experiments. *Physica A: Statistical Mechanics and its Applications, Vol. 374(1), 100-109.* 2007.

—. 2014. Simulating Knowledge Dynamics. *in Innovation Networks.* Heidelberg / New York : Springer, 2014.

Gilbert, N., Pyka, A. and Ahrweiler, P. 2001. Innovation Networks - A Simulation Approach. *Journal of Artificial Societies and Social Simulation, Vol. 4, Issue 3.* 2001.

Harrison, Richard J., et al. 2007. Simulation Modeling in Organizational and Management Research. s.l. : In: Academy of Management Review 2007, Vol. 32, No. 4, 1229-1245, 2007.

Jameson, Anthony. 1996. *Numerical Uncertainty Management in User and Student Modeling: An Overview of Systems and Issues.* s.l. : In User Modeling and User Adapted Interaction, 5, 1996, in a special issue on Numerical Uncertainty Management in User and Student Modeling, p. 193-251, 1996.

Lay-Yee, R., et al. 2014. Determinants and disparities: A simulation approach to the case of child health care. s.l. : Under Review., 2014.

Lengwiler, Yvan. 2004. A monetary Policy Simulation Game. *The Journal of Economic Education, Vol. 35, No. 2 (Spring, 2004), pp. 175-183.* s.l. : Published by: Taylor & Francis, Ltd., Article stable URL: http://www.jstor.org/stable/30042588, 2004.

Lotzmann, Ulf and Meyer, Ruth. 2011. A Declarative Rule-Based Environment for Agent Modelling Systems. *In: The Seventh Conference of the European Social Simulation Association, ESSA 2011.* s.l. : ESSA , 2011.

—. 2011. DRAMS - A Declarative Rule-based Agent Modelling System. *In: 25th European Conference on Modelling and Simulation, pp. 77-83.* 2011.

Mannion, O., et al. 2012. JAMSIM: A microsimulation modelling policy tool. *Journal of Artificial Societies and Social Simulation 2012, 15(1)8. .* s.l. : http://jasss.soc.surrey.ac.uk/15/1/8.html, 2012.

Maria, Anu. 1997. Introduction to Modelling and Simulation. s.l. : In: Proceedings of the Winter Simulation Conference, 1997:7-13, 1997.

Martini, Alberto Paolo and Trivellato, Ugo. 1997. *The role of survey data in microsimulation models for social policy analysis.* s.l. : Labour, 11(1), pp. 83-112, 1997.

McLay, J., et al. 2014. Statistical modelling techniques for dynamic microsimulation: An empirical performance assessment. s.l. : Under Review, 2014.

Milne, B. J., et al. 2014. A collaborative approach to bridging the research-policy gap through the development of policy advice software. *Evidence and Policy, 10(1), 127-136.* 2014.

Moss, et al. 2011. Scenario, Policy Model and Rule-based Agent Design. *Deliverable 5.1.* s.l. : OCOPOMO, 2011.

Orcutt, G. 1957. *A new type of socio-economic system.* s.l. : Review of Economics & Statistics, 39(2), 116-23, 1957.

Pyka, A., Gilbert, N. and Ahrweiler, P. 2007. Simulating Knowledge-Generation and – Distribution Processes. *in Innovation Collaborations and Networks, Cybernetics and Systems, Vol. 38, 667-693.* s.l. : in Innovation Collaborations and Networks, Cybernetics and Systems, Vol. 38, 667-693., 2007.

Ronald, Fagin and Halpern, Joseph Y. 1991. Uncertainty, belief and probability. *In Computational Intelligence 7, 1991, pp. 160-173.* 1991.

Scherer, S., Wimmer, M. A. and Markisic, S. 2013. Bridging narrative scenario texts and formal policy modeling through conceptual policy modeling. *In: Artificial Intelligence and Law, Volume 21/4, pp. 455-484, doi = 10.1007/s10506-013-9142-2.* 2013.

Scherer, Sabrina and Wimmer, Maria A. 2011. Consistent Conceptual Descriptions to Support Formal Policy Model Development: Metamodel and Approach. *In: Proceedings of the Workshop on Modelling Policy-making (MPM 2011) in conjunction with The 24th International Conference on Legal Knowledge and Information Systems (JURIX 2011), Ed. Adam Wyner and Neil Benn, p. 23-28.* 2011.

Scherer, Sabrina, Wimmer, Maria A and Markisic, Suvad. 2013. Bridging narrative scenario texts and formal policy modeling through conceptual policy modeling. *In: Artificial Intelligence and Law, Volume 21/4, pp. 455-484, doi = 10.1007/s10506-013-9142-2.* 2013.

Schindler, Julia. 2013. About the Uncertainties in model Design and Their Effects: An Illustration with a Land-Use Model. s.l. : in: Journal of Artificial Societies and Social Simulation 16 (4) 6, 2013.

Scholz, R., et al. 2010. The agent-based NEMO model (SKEIN): simulating European Framework Programmes. *in: Ahrweiler, P. (ed.), Innovation in Complex Social Systems, Routledge Studies in Global Competition, 300-314.* 2010.

Sedehi, H. 2006 . GAIM (Gestione Accoglienza IMmigrati): A System Dynamics Model for Immigration "housing" Management. Nijmegen, The Netherlands : In Proceedings of International Conference of the System Dynamics Society, July 23-27, 2006 Nijmegen, The Netherlands, pp. 3359-3367, 2006 .

Shalizi, C. R. 2006. *Methods and Techniques of Complex Systems Science: An Overview Complex Systems Science in Biomedicine, T. S. Deisboeck and J. Y. Kresh (eds.),.* s.l. : Springer US, pp. 33-114, 2006.

Solar O, Irwin AA. *A conceptual framework for action on the social determinants of health.* Geneva : World Health Organization, 2010. Discussion paper 2.

Spielauer, M. 2011. *What is social science microsimulation.* s.l. : Social science Computer Review, 29(1), pp. 9-20, 2011.

Srbljanovic, Armando and Skunca, Ognjen. 2003. An Introduction to Agent-based Modelling and Simulation of Social Processes. s.l. : In: Interdisciplinary Description of Complex Systems 1 (1-2), 1-8, 2003, 2003.

Statistics Sweden (Statistiska centralbyrån, SCB). 2009. *Sweden's Population by sex and age on 31/12/2008.* s.l. : Homepage on the Internet:
http://www.scb.se/Pages/TableAndChart____262460.aspx (accessed January 20, 2010), 2009.

The National Board of Health and Welfare. 2011. *A(H1N1) 2009 - An evaluation of Sweden's preparations for and management of the pandemic.* s.l. : 2011-8-4, ISBN: 978-91-86885-37-3, 2011.

van Egmond, Stans and Zeiss, Ragna. 2010. Modeling for Policy. s.l. : Science Studies, 23, 58-78, 2010, Vol. 23, pp. 58-78.

Wallinga J., Teunis P., Kretzschmar M. 2006. *Using data on social contacts to estimate age-specific transmission parameters for respiratory-spread infectious agents.* s.l. : Am J Epidemiol. 2006 Nov 15;164(10):936-44. Epub 2006 Sep 12. PubMed PMID: 16968863., 2006.

Wimmer, M. A. 2011. Open Government in Policy Development: From Collaborative Scenario Texts to Formal Policy Models. *In: 7th International Conference on Distributed Computing and Internet Technologies (ICDCIT – 2011) , vol. Berlin Heidelberg, Springer Verlag , pp. 76–91.* Berlin Heidelberg : Springer Verlag, 2011.

Zaidi, A., Harding, A. and Williamson, P. 2009. New frontiers in microsimulation modeling. *Public policy and social welfare, vol. 36. .* England : Ashgate Publishing, 2009.

Zeigler, B.P. 1976. *Theory of Modeling and Simulation.* New York : Wiley, 1976.