Modeling Healthcare Systems

Approaches from Social Science

Doctoral Thesis

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November 2009

Acknowledgment

I would like to thank all those who contributed to this dissertation by their positive support, constructive criticism and their helpful suggestions. First I would like to thank my advisor, Prof. Siegfried Vössner, for his guidance, support, inspirations, the needed and his belief in my capabilities to finish this project.

I would like to thank my co advisor Prim. Gerhard Stark first of all for making this research project possible and secondly for always supporting it. I would also like to thank him for his suggestions and valuable comments during our discussions.

Special thanks the project partner KAGes and all the involved persons especially the old and the new managing director DI Christian Kehrer and DI Dr. Werner Leodolter for sponsoring the project.

I would also like to thank Wolfgang Alexander Schmid and Christoph Schinko for their reviews and comments and all members of the MBI for their support and friendship during this project.

Finally, I thank my mother, Margit Martischnig, her friend Heinz Bintner and my father Herbert Martischnig for their support during my whole life.

Graz, November 2009 Andreas Martischnig

Affirmation

I hereby declare that this doctoral thesis is my own work. It is based on my original research and expressed in my own words. Any use made within it of works of others in any form (e.g. ideas, figures, text, and tables) is properly acknowledged at the point of use.

I have not submitted this thesis for any other course or degree.

Graz, 20.11.2009

Contents

List of Abbreviations

ABM	Agent Based Modeling
ABSS	Agent-Based Social Simulation
AGES	Agency for Health and Food Safety
BDI	Belief-Desire-Intention
BMBWK	Federal Ministry of Education, Science and Cultures
BMGF	Federal Ministry of Health and Women
CA	Cellular Automata
CAS	Complex Adaptive Systems
CLD	Causal Loop Diagram
CM	Compare Module
DAI	Distributed Artificial Intelligence
DMS	Dynamic Micro Simulation
DRE	Digital Rectal Exam
DRG	Diagnosis-related groups
FOBT	Fecal Occult Blood Test
GE	General Electric
GOL	Game of Life
HDG	Main diagnoses groups
IB	Individual Based
IBM	Individual Based Modeling
ICD	International Classification of Diseases
LDF	Procedure- and diagnosis-oriented case groups
LKF	Performance oriented hospital financing schema
LMS	Longitudinal Micro Simulation
MABS	Multi-Agent-Based Simulations
MAM	Multi Agent Models
MDM	Medical Demand Module
MEL	Single medical procedures
MIT	Massachusetts Institute of Technology
MS	Micro Simulation

OECD	Organization for Economic Co-operation and Development
OOP	Object Oriented Programming
PCCP	Preventive Cancer Checkup Process
SD	System Dynamics
SDM	Specialists-service Demand Module
SFD	Stock and Flow Diagram
SMS	Static Micro Simulation
SSM	Specialists-service Supply Module
UML	Unified modeling language
WD	Weighted Differences
WHO	World Health Organization

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1 Introduction

Due to the currently pervasive financial and economic crisis world-wide many industries experience a harsh loss of financial resources. Health care systems, although mostly financed by states, are not unaffected of this threat and will also experience deep cuts regarding these resources in the near future. However in order to keep such systems performance and cost efficient, it is necessary to perform a demand driven supply and resource planning.

Health systems are complex and large and coined by multilayered dynamic influences making it hard to understand all the dependencies and influences, as drafted in Figure 1. The changing population age pyramid and with it a shift of disease patterns and incidences (for example more joint spare therapies, fewer births), the rapid medical progress, a higher requirement behavior of the patients and limited financial resources are only some of the influencing factors, affecting future health care systems. However this large number of dynamic influences and the constantly changing economic boundary conditions make it impossibly to give qualitative or quantitative statements and recommendations for actions concerning future resource planning, without adequate scientific modeling and simulation.

Therefore it is necessary to model future health care scenarios to get valid answers to problems arising from these systems because media seems to continuously bombard us with one horror scenario of health care issues after the other. For example the amount of people in Austria above the age of 60 will grow till 2030 by 54% although the whole population will just grow by 8% according to Statistik Austria (2007). Is this significant increase in older people an indication requiring 50% more medical specialists to cope the demand in this age group? Or is the USA really facing a tremendous lack of specialist as you could read in February 2008 in the NZZ[1] where experts stated an increasing lack of medical staff in the next years, where according to their estimates in 2020 up to 200.000 physicians and 800.000 nurses could be needed, and will this scenario occur in Austria too?

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[1] NZZ: Neue Zürcher Zeitung, www.nzz.ch.

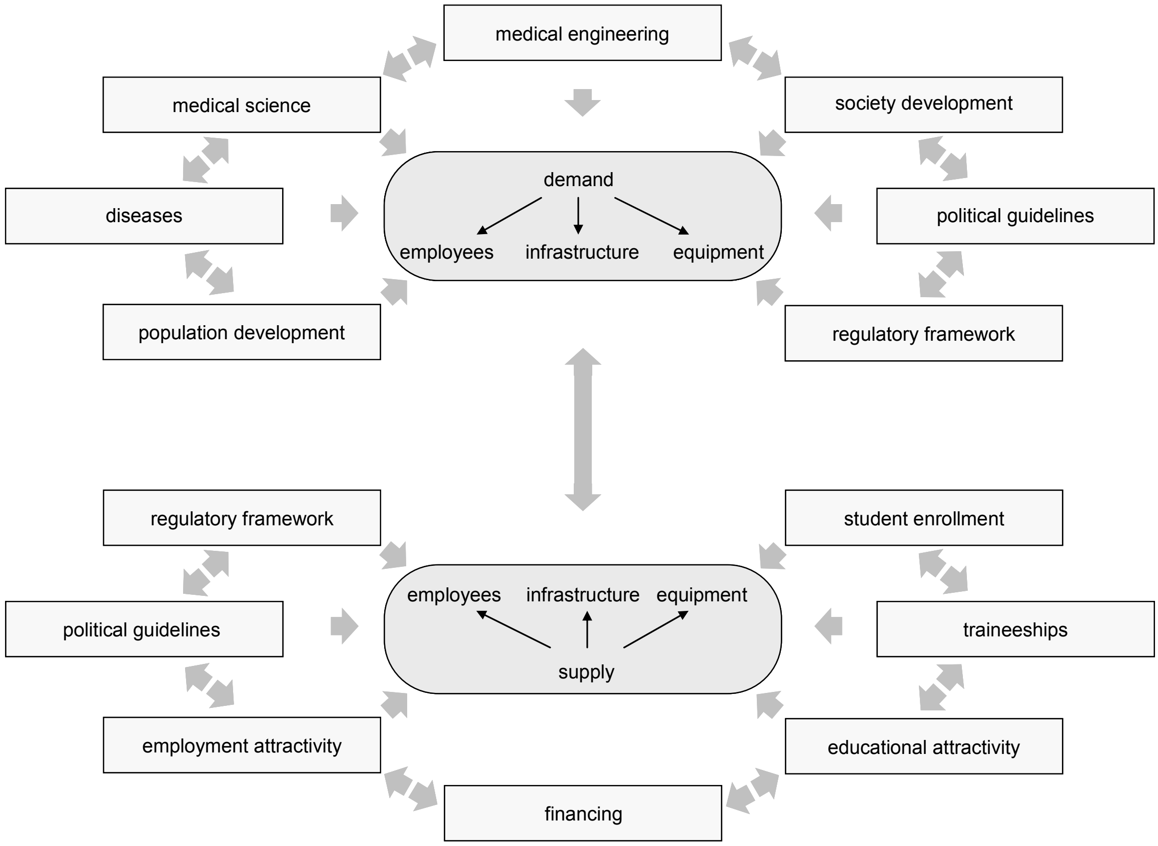


Figure 1: Various influences to healthcare systems

In order to give accurate answers to question concerning the future demand of performance determining know-how bearers in healthcare systems, the goal of this thesis is to develop a generic framework which is capable to give adequate quantitative and qualitative statements both on the macro and on the micro level.

In medical science, especially health care, computer simulation is still a relatively young field. In contrast to that social sciences use computer simulation as a well-established domain of research, to gain insight to a system and make predictions for the future. Troitzsch (1997) divided prediction into two parts: (1) qualitative prediction, which is prediction of behavior modes, and (2) quantitative prediction, which is to predict a certain system state in timeline. Currently there are two major schools, System Dynamics and Agent Based Modeling (as part of the Individual Based Approaches), which use computer simulation to gain insight into non-linear social and socio-economic systems (Milling and Schieritz 2003). Both approaches have a broad overlap in research topics, but have been quite unnoticed by each other. (Phelan, 1999)

This thesis will give an overview and a comparison of the most common social-science approaches to model complex systems and demonstrate a generic healthcare model, modeled with these approaches. The relevant reference data was provided by a local Styrian healthcare organization (KAGes) that also funded this research project.

Furthermore the author is proud to announce, that the developed model of this thesis has been awarded with the Styrian research price for simulation and modeling 2009 as shown in the publication section.

1.1 Research questions

1. What approaches are suited to model complex social systems?
2. Which approaches are suitable to develop a generic model of a Healthcare system to give adequate qualitative and quantitative answers for the prediction of future needs?
3. Is this general model suitable to give adequate verified answers on the micro level?

1.2 Structure

The structure of this thesis is illustrated in Figure 2. It is divided into five separate chapters which are described below.

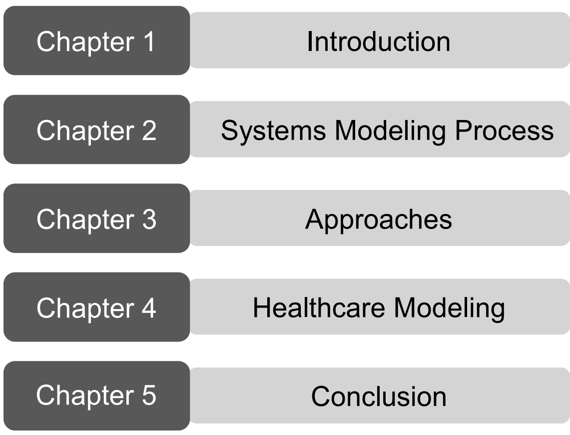


Figure 2: Structure of this thesis

The first chapter describes the main aim of this thesis and introduces the research questions.

The second chapter describes the necessary theory for this thesis. It starts with the definition of a system and the intended focus of this thesis - health care systems. After the first section the next one is about modeling, the process of modeling and the classification of models for the social science. After that the next section describes simulation as part of the modeling process and the history of social simulation, the types of simulation and the purpose of social science simulation. The last part of this chapter is about verification and validation throughout all steps in the modeling process. This step is one of the most important ones and it decides whether a model is correct for the intended purpose or it has to be adjusted.

The third chapter describes the modeling approaches that can be used in social science. The first approach described is System Dynamics, one of the oldest and best known ones when talking about feedback structures. The next approach is Agent Based Modeling as a quite opposing one to System Dynamics. After Agent Based Modeling the Cellular Automata approach is described, which can be seen as the predecessor of Agent Based Modeling. The next approach, Micro Simulation, was developed from a more statistical point a view. All three approaches can be summed up into the individual based approaches because they focus on the individual element of a system. A comparison of the approaches and their intended field of application forms the end of this chapter.

The fourth chapter describes the developed generic healthcare model to predict the future needs of physicians and treatment. First the whole concept of the model and then a short example for each question concerning the future need of physicians will be described. This starts with a more statistical model where all performed services are included and goes down to a micro model for individual disease. To give answers from demand to supply this chapter includes a description of a micro/agent based labor model.

The fifth and the last chapter gives a summary of the chapters before, a conclusion for this thesis and further work.

2 Systems Modeling Process

2.1 System

There are many definitions of systems and what characterizes a system in literature. This thesis will give a short overview of some selected definitions, a classification of the existing concepts and a categorization of system types.

According to Senge (1994) systems are: "*… a perceived whole whose elements, hand together because they continually affect each other over time and operate toward a common purpose.*"

According to Ropohl (1978) a system is the whole, which exhibits

(a) connections between certain attributes,

(b) consists of interconnected parts and/or subsystems and

(c) is delimited from its environment or excluded from a superior system.

This comprehensive system term contains the functional, structural and hierarchical concept. This definition means that a genuine system is existent only if functions, a structure and an environment are definable. However in order to not collide with common system-theoretical literature, we permit weaker formulations of systems, if at least attributes and functions or subsystems (elements) and relations are defined. Thus also purely functional and purely structural system theories are possible; the hierarchical system concept however presupposes the structural concept.

Buteweg (1988) structured the various conceptual system concepts into three main categories, as shown in Figure 3.

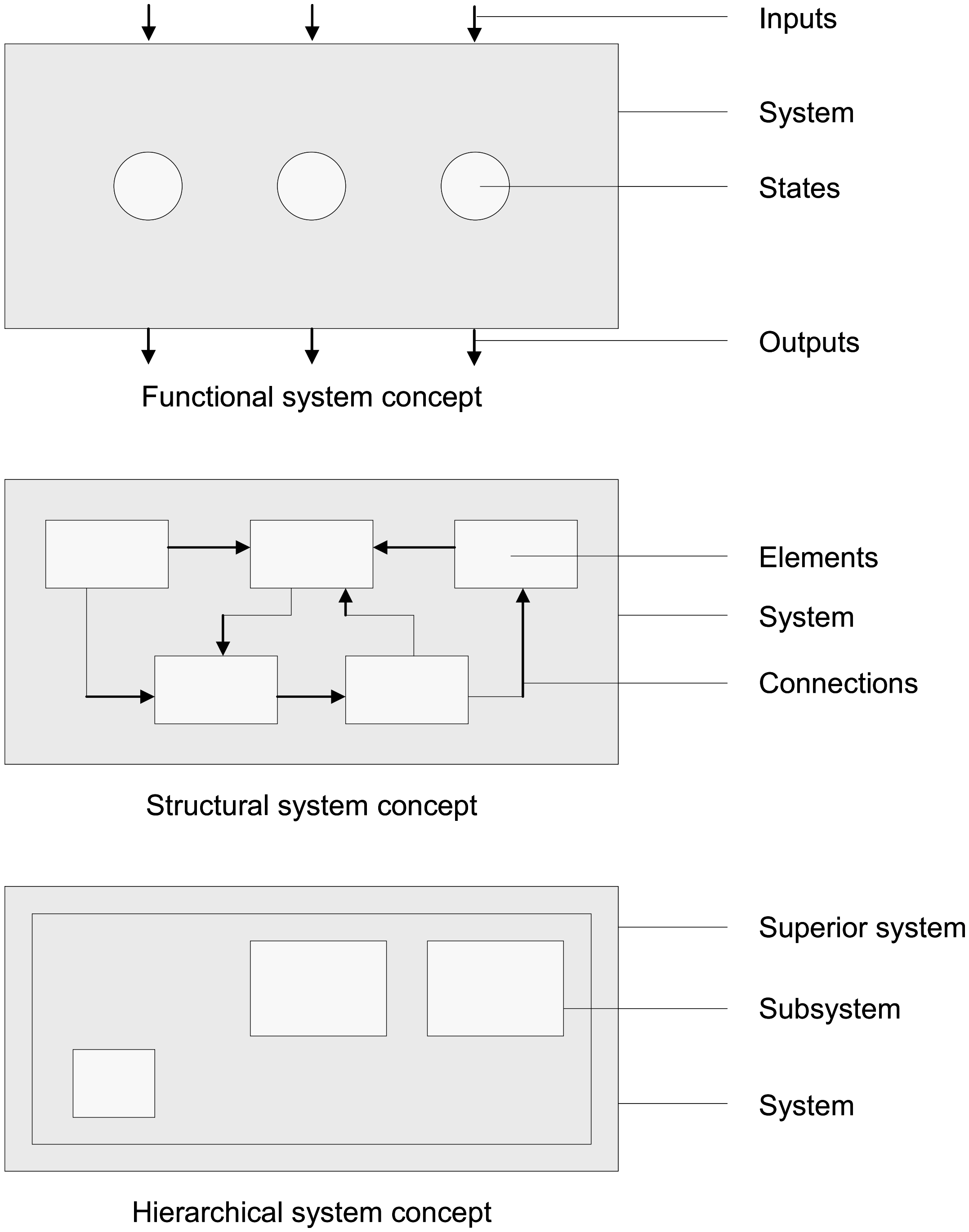


Figure 3: System concepts, according to Buteweg (1988)

(1) Functional system concept:

The basic core of the functional system concept is the black box theory, whose bases are the interactions of the system according to inputs and outputs. There is nothing known about the inner structure of the black box and only implications can be monitored. To get information about the systems structure and functionality the output is monitored to all possible types of input variations, without accounting possible interdependencies with the systems environment. This concept gives a good overview to the system behavior.

(2) Structural system concept:

The structural system concept divides the system into an amount of interconnected parts and states that the characteristic of the system can not only be explained by the characteristic of each part but only out of the special interaction of the parts. This concept gives a good overview of all existing parts of a system and their interconnection from which the whole system behavior can be explained.

(3) Hierarchical system concept:

The hierarchical system concept divides the system in levels and defines subsystems in each level. Each subsystem is a system on a higher level and analyzed from this higher level. This concept adds a level to the structural system concept where the system is just divided into interconnected parts and not subsystems as well.

According to Ulrich & Probst (1995) systems can be categorized into four different types, as shown in Figure 4.

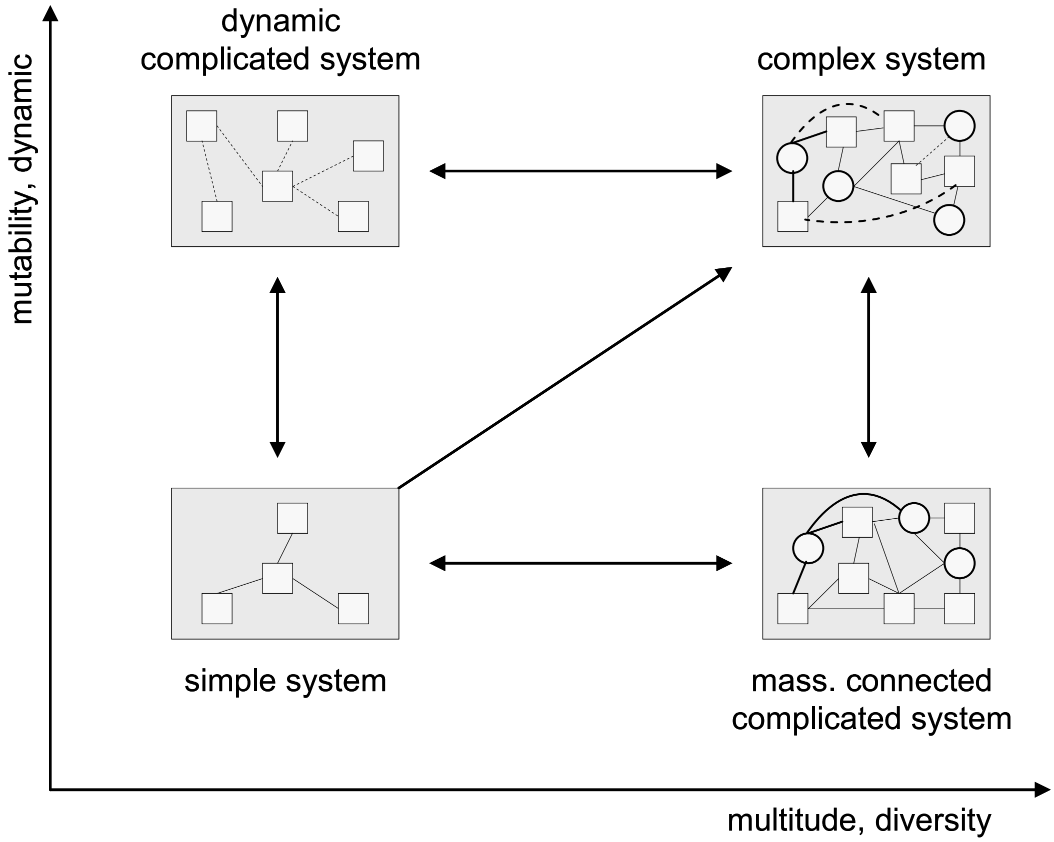


Figure 4: Types of systems, according to Ulrich & Probst (1995) and Bandte (2007)

(1) Simple System:

A simple system consists of only a few elements with fixed connections and few interactions between them. From a methodical point of few they can be completely described or solved by analytical approaches.

(2) Mass. connected complicated system:

Mass connected complicated systems are characterized by many elements and high variety. This is illustrated by squares and circles. The elements are statically connected, illustrated by continuous lines. Because of the widely random connections the behavior of those systems can be described with statistical approaches.

(3) Dynamic complicated system:

Dynamic complicated systems are characterized by the dynamic and changeability of the elements adjustment, their interactions and their connections. This is illustrated by dashed lines. In those systems elements and connections between them are homogenous and in contrast to mass. connected complicated systems the intensity of the connections is changeable and quite low.

(4) Complex system:

Complex systems are characterized by many heterogeneous elements, illustrated by squares and circles, dynamic, illustrated by dashed lines and feedback even between non neighbors. The big difference to complicated systems is that the behavior of the system may not be obvious just by the properties of the individual parts.

According to Rocha (1999) a complex system is:

> *"… any system featuring a large number of interacting components (agents, processes, etc.) whose aggregate activity is nonlinear (not derivable from the summations of the activity of individual components) and typically exhibits hierarchical self-organization under selective pressures." (Rocha 1999)*

According to Weaver (1948) a systems complexity can either be disorganized: *"It is a problem in which the number of variables is very large, and one in which each of the many variables has a behavior which is individually erratic, or perhaps totally unknown. However, in spite of this helter-skelter, or unknown, behavior of all the individual variables, the system as a whole possesses certain orderly and analyzable average properties."* or organized: *"…involve dealing simultaneously with a sizable number of factors which are interrelated into an organic whole."*

Because the focus of this thesis is the Austrian Healthcare system and its future demand for physicians, the next section will first give a short introduction into Healthcare systems and then focus on the Austrian Healthcare system.

2.1.1 Healthcare System

There are about 200 countries in the world having their own set of arrangements to reach the basic goals of a health care system: treating sick people, keeping people healthy, and protecting people from getting ruined by medical bills. In spite of the mass of systems they tend to follow four basic patterns.

(1) The Beveridge Model:

This model is named after William Beveridge, who designed Britain's National Health Service. This system is provided and financed through tax payments like the police force or the public library. The government controls what doctors can do and what they can charge, because in Britain doctors can either be government employees or private ones collecting their fees from government. The government also owns many but not all clinics. These systems tend to have a low costs per capita. Countries using the Beveridge Model or variations on it are: Great Britain, Spain, New Zealand, most of Scandinavia, Hong Kong and Cuba perhaps the most extreme application. (Reid 2008)

(2) The Bismarck Model:

This model is named after the Prussian Chancellor Otto von Bismarck, who also invented the welfare state during the unification of Germany in 19th century. This system provides health care through an insurance system. The insurers, called sickness funds, are usually financed by employers and employees through payroll deduction. This system has to cover everybody in a country and is not making profit. Although this is a multi-payer model tight regulations give the government much of the cost-control cloud as provided by the Beveridge Model. Doctors and hospitals are mostly private in Bismarck countries, like Japan that has more private hospitals than the U.S. countries using the Bismarck Model are: Germany, France, Belgium, the Netherlands, Japan, Switzerland and also in some countries of Latin America. (Reid 2008)

(3) The National Health Insurance Model:

This model inherits elements from both the Bismarck and the Beveridge Model, by having a governmental insurance program for the payment, that every citizen pays into and private-sector providers. These plans control the costs by limiting the medical services or increasing patient's treatment waiting time. This system is cheaper and much simpler in the administrative than the American-style for-profit insurance, because there is no marketing and no profit at all. Countries using the National Health Insurance Model are: Canada, Taiwan and South Korea. (Reid 2008)

(4) The Out-of-Pocket Model:

The last model is used in most of the countries around the world that are not developed and industrialized and have no established health care system at all. In this model the rich can afford medical care and the poor stay sick or die. In many countries millions of people will never see a doctor in their whole life or are not able to pay one. People that don't have enough money often pay a doctor in potatoes or milk or whatever they may have to give. They may have access to a so called "village healer" who provides people with home-brewed medicals which may or may not help cure the disease. The United States are the only industrialized country using all of the above described models. (Reid 2008)

2.1.1.1 The Austrian Health Care System

This section will just give a short introduction into the Austrian healthcare system and its payment. In Austria the state has the responsibility to provide healthcare for the population and therefore every citizen has access to medical and social services on the basis of legal compulsory insurance. The social security system is based on legal health insurance, accident insurance and pension insurance. The Federal Law on Nursing Allowance gives people in need of nursing care financial support. The healthcare system is financed by the social insurance entities and by various territorial bodies (Federal Republic, provinces and municipalities). Citizens may also insure themselves through additional private insurance. Approximately two third of the health care system is funded through social insurance contributions and general tax revenues. The other third is directly paid by private households. The health care services are delivered by public bodies, non profit organizations, for-profit private organizations and individuals. This organizational structure and the lines of accountability are shown in Figure 5. A detailed description of this structure will not be part of this thesis. The Austria's healthcare spending is about 8% of the domestic product and places it at mid-table amongst the OECD[2] states.

[2] OECD: Organization for Economic Co-operation and Development

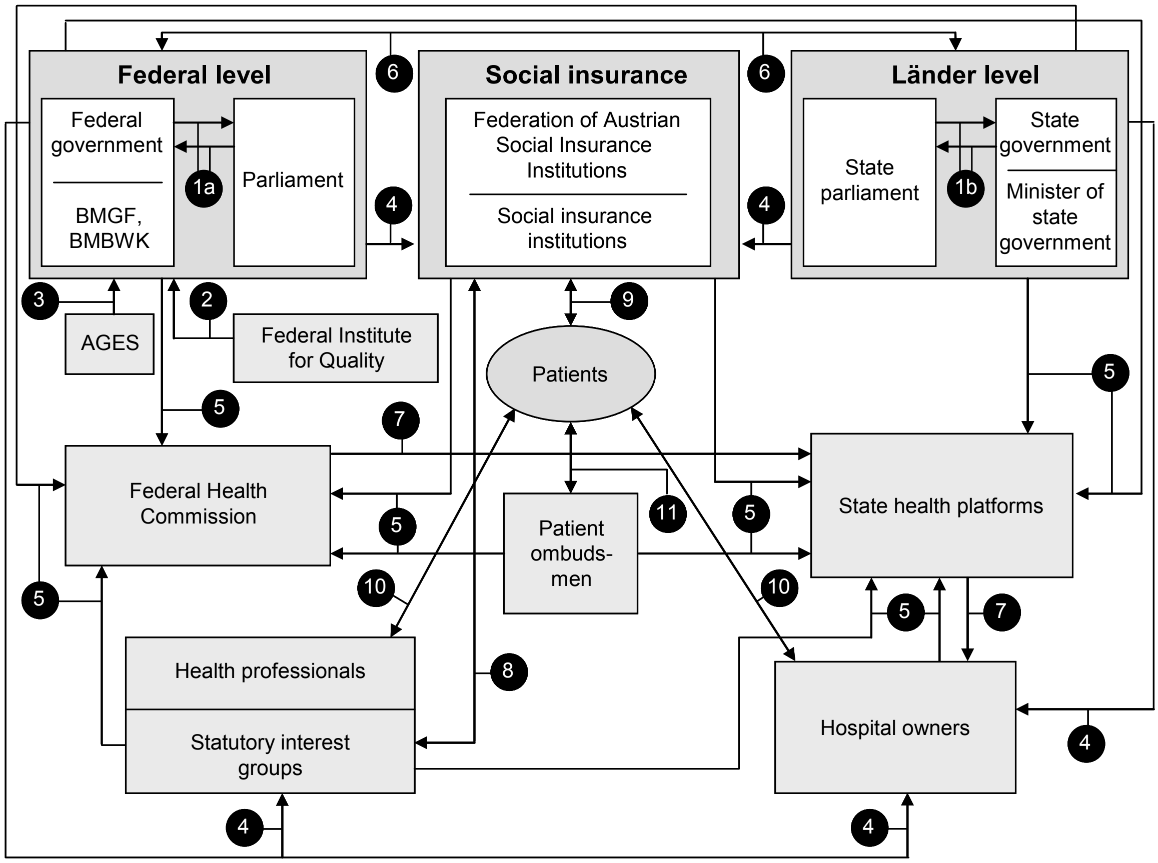


Figure 5: Organizational structure and lines of accountability in the health care system, according to Hofmarcher and Rack (2006)

Description of the numbers Figure 5 according to Hofmarcher and Rack (2006):

Notes: BMGF: Federal Ministry of Health and Women; BMBWK: Federal Ministry of Education, Science and Culture; AGES: Agency for Health and Food Safety.

(1) a) Bills proposed by the federal government (minister) to parliament or by the state government (member of the state government) to the state parliament;

b) Adoption of federal laws by parliament and of Länder laws by the state parliament.

(2) The Federal Institute for Quality in the health Care System (full name) support of the Federal Ministry of Health and Women (BMGF).

(3) Support of the BMGF within the framework of the licensing of medicines.

(4) a) Health care administration at federal government level (for example sanitary inspectors, sanitary supervision of hospitals, supervision of social insurance institutions and statutory representative bodies);

b) Health care administration at Länder level (for example in the field of hospital construction and operation permits, implementation of planning in the Land, investment financing; supervision of the social insurance institutions).

(5) Appointment of members to the Federal Health Commission and to the Platforms at Länder level.

(6) Consultation mechanism between the federal government and the Länder and/or local communities with regard to legislative activities (laws, decrees) which cause additional expenditure.

(7) a) Sanctioning mechanism: the Federal Health Agency (Federal Health Commission) can withhold funding for the respective State Health Fund (Health Platform) in the case of infringements against binding planning and instructions with regard to quality and documentation;

b) State Health Funds (Health Platforms) can provide for a corresponding sanctioning mechanism against hospitals.

(8) Negotiations on market entry, services and rates (general agreement and individual contracts).

(9) Mandatory membership in social institutions (compulsory insurance).

(10) a) Principal freedom of choice for patients regarding hospitals and health professionals in private practice;

b) Hospitals (both public and non-profit) and health professionals in private practice with health fund contracts are obliged to treat patients.

(11) Statutory patients' representation in each Land.

According to an agreement between the Federal Republic and the provinces in the year 1997 a global Austrian public health plan was developed and the performance-oriented hospital financing (the LKF schema) introduced. The core of this plan is the Austrian hospital and equipment plan, which is continuously developed to cope the demand of the future requirements and the medical progress of a modern healthcare system evolving from mere bed capacity planning to performance planning. The performance-oriented hospital financing system (LKF) as shown in Table 1 can be modified to meet each state's needs and permits the recognition of specific supply side factors and is a case fee payment system based on modified diagnosis-related groups (Austrian DRG system). Therefore it allows billing on the basis of actual services rendered in public hospitals. (MA-L 1998) (Hofmarcher & Rack 2006)

Table 1: Performance-oriented hospital financing system, according to Hofmarcher and Rack (2006)

Core area Nationally uniform	Points are allocated to inpatient stays on the basis of performance-oriented diagnosis-related case groups (LDF), including also all specific regulations for point allocation.
Fund control area Adjustable by the Länder	In addition, the following criteria may be considered in the LKF, taking into account Länder-specific requirements: - Hospital type - Personnel - Equipment - State of hospital buildings - Utilization of capacities - Quality of accommodation

The core of the DRG model is build by procedure- and diagnosis-oriented case groups (Leistungsorientierte Diagnosefallgruppen, LDF). Each group is given a certain amount of points (LDF flat rate) representing the median of the costs calculated. Each LDF flat rate consists of an activity-related component and a daily charge component. The activity related component is based on the costs determined in the reference hospital and allocated to specific medical services. Costs that could not be allocated to specific services are combined into the daily charge component, which depends on the length of the hospital stay where an upper and lower limit exists. (Hofmarcher & Rack 2001)

According to Hofmarcher & Rack (2006) there is a three stage algorithm which includes medical, economic and statistical criteria for the information of the individual procedure- and diagnosis-oriented groups.

Stage 1:

All patient cases from the reference hospitals were divided up on the basis of selected (existing) single medical service items into a group of cases based on single medical procedures (MEL-Gruppen) and a group of cases based on main diagnoses (HDG-Gruppen). To determine the case group based on single medical procedures, the surgical interventions listed in the benefits catalogue and a small number of no surgical services were used.

Stage 2:

In this stage consideration was given to the homogeneity of services and the medical categories of the procedures or main diagnoses, as well as to the homogeneity of costs within statistically significant groups. From the single medical service items, 209 single medical procedure groups were formed, and from the diagnoses 230 main diagnosis groups were formed.

Stage 3:

407 procedure- and/or diagnosis-orientated case groups (DRGs) were formed on the basis of structural characteristics in the single medical procedure groups, and 476 DRGs were formed based on the main diagnosis groups.

In the year 2005 a total of 883 DRGs based on either procedure- or diagnosis-oriented case groups were available.

2.2 Modeling

There are many definitions of what is a model. One of the earliest ones says a model is a representation of reality (Ackoff and Sasieni 1968). In general a model is a simplified clipping of the reality or possibility. From a model, scientists can gain useful information about the real system. Modeling is the process of trying to construct such a clipping of a real or imagined system. During the modeling process there will be many aspects from the real system that cannot be modeled or may not be present in the model and aspects in the model where the correspondent one is missing in the real system. The goal when modeling a system is to minimize those elements. A model and including the purpose of it is always a simplification of the real system. When the simplification reaches a sufficient level of correspondence in functionality, structure and behavior between original and model it is possible to gain useful findings and information. Consequentially the following definition of a model is used for this thesis:

A model is the simplified clipping of the real or imagined system recognized by a modeler that reaches a sufficient level of correspondence in functionality, structure and behavior for the intended purpose of the real system.

A model can be very useful to check existing theories by testing the hypothesis within a certain context. According to Pidd (1999) there are the following five principles of modeling:

***1. Model simple; think complicated**:*

This principle means that a relatively simple model can support complicated analysis. A simple model does not have to be a small model. Simplification requires considerable understanding of the system being modeled. When modeling social systems it is often not possible to determine the relevant variables and parameters before modeling, therefore simple models are not always better than complicated ones.

> *"The fact that complex outcomes can emerge from apparently simple systems does not mean that the complex phenomena we now observe is reducible to simple models. Even if a certain phenomena was generated using simple mechanisms, this does not mean the result we observe now are simple or could be usefully represented with a simple model." (Edmonds & Moss 2005)*

Simple models should be used when the purpose is set to understanding and explanation.

***2. Be parsimonious; start small and add**:*

The idea is that analysis should deliberately develop a series of models, each more complex than its predecessors. Through a series of prototypes the modeler gradually produces a model that is fit for its intended purpose. Increasing the complexity of a model should only be done when there will be a greater benefit for the indented purpose of the model.

3. Divide and conquer, avoid meg-models:

The idea is to divide a model into components that can be replaced if they are too simple, without the need to redevelop the entire model. Such an approach provides a modular structure that facilitates the testing and implementation of the model. Each of the developed components can be tested separately. The successful use of this principle of divide and conquer seems to depend on ensuring that assumptions are well documented and that all those doing the modeling understand these assumptions.

4. Use metaphors, analogies, and similarities:

The idea is to search for previous well-developed logical structures similar to the problem at hand. Analogies are most useful in the initial stages of modeling.

5. Do not fall in love with data:

Modeling should drive any data collection and not the other way around. The modeler should think about the type of model that might be needed before attempting large-scale data collection.

2.2.1 Modeling Process

The process of modeling can be separated into several discrete phases as shown in Figure 6. It is a nonlinear, iterative and feedback driven process.

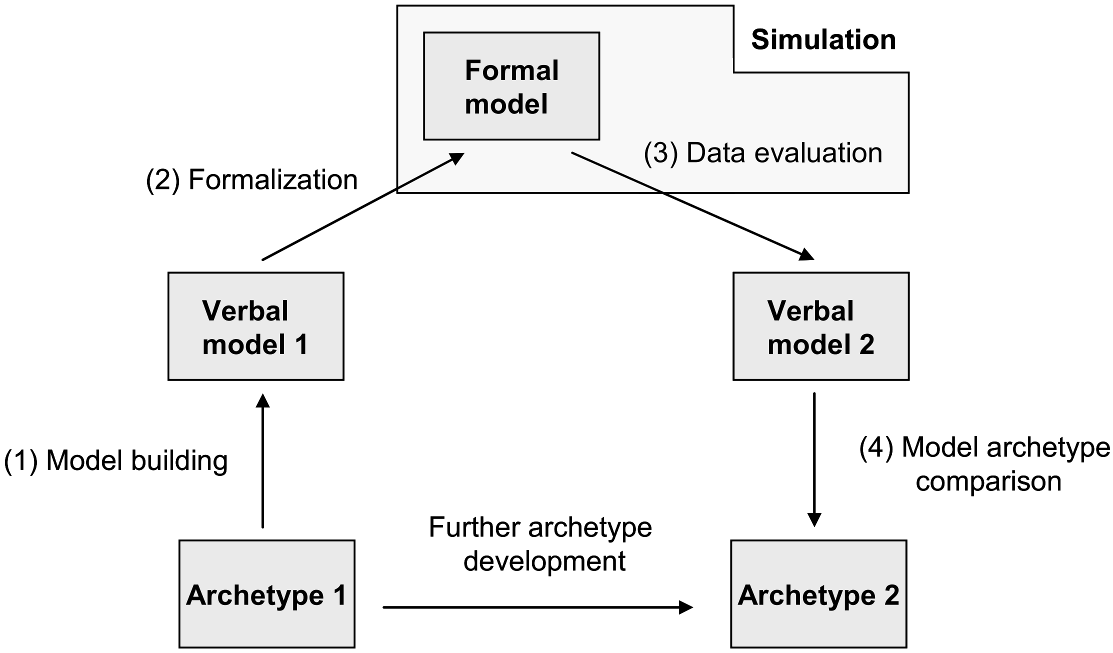


Figure 6: Modeling Process, according to Bandte (2007)

1. Model building:

Model building is only the process to develop the verbal model from the archetype whereas modeling is the whole process including the development of the verbal and formal model and their verification and validation. The verbal model must reproduce the reality for the indented model purpose, including variable influencing factors, outputs and all relevant relationships of the elements.

2. Formalization:

To simulate the developed verbal model it is necessary to transform this model into a formal one by using an appropriate programming language. Some programming languages can reduce the effort of formalizing by providing useful toolkits to develop a simulation model. Furthermore it is useful to use the Unified Modeling Language (UML), a generally, standardized and visualizing modeling language, to develop a universal formal model to improve the further use. With this standardized procedure it is possible to improve model comparison, maintenance and reuse.

***3. Data evaluation*:**

In this step many experiments are done with the model with several different sets of input parameters through many iterations. Depending on the model behavior conclusions are drawn that are used in verification and validation throughout the modeling process. For example robustness and sensitivity of the model to modified input parameters can be tested. Out of this collected data the verbal model can be adjusted to fit the intended purpose.

***4. Model archetype comparison*:**

The last step in the modeling process is to compare the results from the simulation and the conclusions obtained from the modified verbal model with the archetype. Within this step verification and validation is necessary to determine the applicability of the model.

2.2.2 Classification of models

The following classification schema of models, as shown in Figure 7, according to Troitzsch (1990) will also be part in the comparison of the modeling approaches.

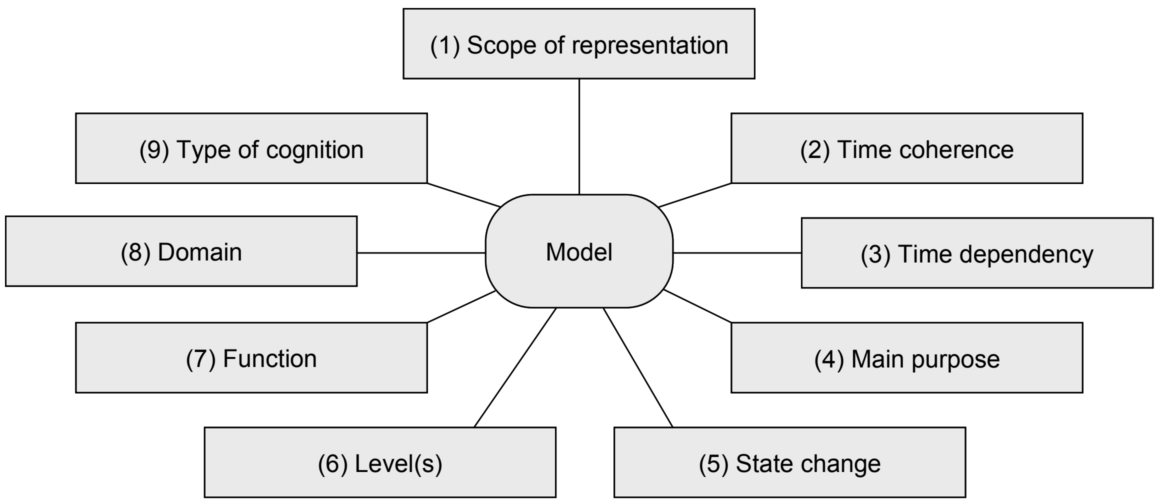


Figure 7: Classification criteria of models, according to Troitzsch (1990)

(1) Scope of representation:

Depending on the chosen range, the types of objects from reality, the purpose of the model and the context, models can be distinguished into real, iconic, verbal and formal models. The boundaries between those four categories are not clearly defined. In real models many features are represented by few like this is done within the animal model where effects of pharmaceuticals to humans are studied. Iconic models take a real object and represent it in a modified scale, like pictures, sculptures or drawings. Verbal models use the natural languages to describe the chosen part of reality whereas formal models use a formal language with a defined syntax to represent reality. Due to the tremendous rise of computing power over the last years it is now possible to build more and more formal models and use simulation to gain insight into systems.

(2) Time coherence:

Models can be distinguished by their time stability and structure namely static and dynamic ones. In static models the objects and their relations stay constant over the simulation time whereas in dynamic models they can change. Dynamic models can be distinguished into time discrete and time continuous. Time discrete means that changes occur to fixed time steps whereas changes in time continuous ones are floating.

(3) Time dependency:

Dynamic models can be distinguished into two groups those where the state of the elements depends only on the actual time and those where the actual state depends on past ones. The last ones are called process or reminiscent models.

(4) Main purpose:

There are three main purposes for models: description, explanation and prediction. Normally a model can be assigned to one of these purposes, because of the different perspective either ex ante or ex post. Description models are typically static iconic models just giving information of observations. Explanation models extend this type by adding the cause for the observation. Prediction models extend explanation ones by adding the ability to give information of possible future observations.

(5) State change:

According to a model's determinacy models can be classified into stochastic or deterministic ones. The output of deterministic models can be predicted and will always be the same for a given set of start values. In contrast to stochastic models where the next output can only be a probability value between 0 and 1. The choice whether using stochastic or deterministic elements for a simulation model depends on the level of abstraction.

(6) Level(s):

According to the type of represented objects a model can be classified into micro and macro models. Macro models consist of just one object having all explored attributes. It can be seen as a monolithic block where connections between the elements of the observed system are not addressed. Macro models always imply homogeneity of all attributes of elements in a system. Micro models try to go down to the individual level to model each existing element and its connections to others. The following example tries to demonstrate these two types of model paradigms when viewed from the edge of each paradigm. Let's assume a system consisting of two populations (predators and preys). A macro model would just exist of one object representing the system. Each time step the system knows two features the strength of preys and predators. A micro model would model each element of both types having different attributes. On the next level probabilities would be modeled to aggregate the populations. Emergent behavior can just be modeled with micro models by addressing individual attributes to the elements.

(7) Function:

Regarding the functions between elements and their attributes and their past state, models can be classified into linear and non-linear ones. Linear models consist of just linear functions. Those models are not trivial at all because attributes of linear dynamic models show exponential behavior. Non-linear models consist of at least one non-linear function having for example exponential or logarithmic progress.

(8) Domain:

Models can be distinguished into qualitative and quantitative ones depending on the operationalization of the used model variables. In a quantitative model the values of variables are empirical determined and the states are operationalized. That's why the results of the model can be evaluated qualitatively and quantitatively. If the quality of the database is limited only qualitative conclusions can be made. Hybrid models consist of discrete and continuous variables.

(9) Type of cognition:

Regarding the type of cognition a model can either be concept driven or data driven. Concept driven models have an existing theory, which should be modeled, as basis for the modeling process. Data driven models have no defined theory and use empirical values or rather the in-output behavior of reality.

2.3 Simulation

Simulation inherits both phases in the modeling process, before and afterwards, and therefore contains the whole process from developing the formal model to interpreting and evaluating of the gained data. According to Gilbert (2000) simulation means:

> *"…running the model forward through (simulated) time and watching what happens".*

Simulating is an activity to experiment with a system and observe the behavior. Figure 8 shows the logic of simulation as a method according to Gilbert and Troitzsch (2005).

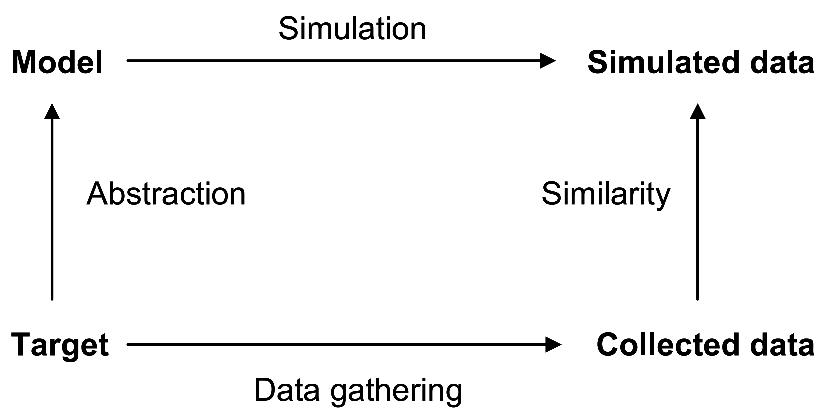


Figure 8: The logic of simulation as a method, according to Gilbert and Troitzsch (2005)

This logic is quite the same as of statistical modeling. First the researcher has to develop a model based on his knowledge, theories and assumptions of the real or imagined system. Then the model is transformed into a computer program to perform simulations to generate data of the designed model. This data is then compared with the collected data from the real system to check whether the outputs are similar to each other. If the check is valid for the intended purpose of the model this model can be used for explanation and prediction. Otherwise the modeling team has to adjust the model to generate needed data.

As shown in Figure 9 nowadays simulation can bee seen as the third pillar to gain scientific knowledge. A real systems problem can be solved, when available, with an applicable theory. If there is no theory available one can do experiments onto the real system. Simulation combines both strategies by using the theory to develop a model and then experiments are conducted to solve the problem.

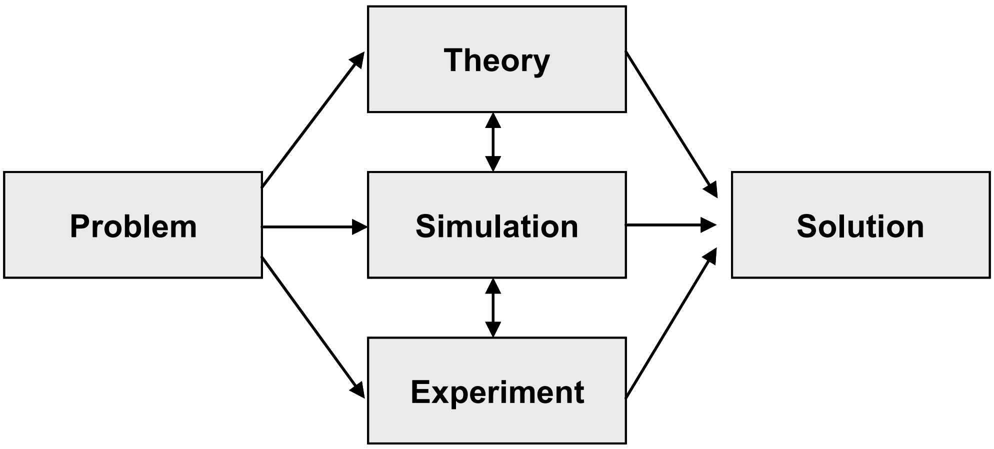


Figure 9: The three pillars of scientific knowledge gaining

Simulation has several pros compared to experimenting with the real system. Processes can be performed much faster than in reality and can be repeated several times by causing fewer costs. Simulation can also be used when there is no possibility to experiment with the real system when there are security reasons or laws. In contrast to pure mathematical models simulations are lesser abstract and more understandable.

This thesis focuses on social simulation, where computational methods are applied to study issues in the social science. This approach aims to close the gap between the descriptive and the formal one by focusing on the processes that build the social reality from the bottom up.

2.3.1 History of social simulation

Computer simulations in the social sciences range from sociology to economics, from social psychology to organization theory and political science, and from demography to anthropology and archeology and can be traced back to the fifties (Halpin 1998). In its early days, and up to the seventies, computer simulation was essentially used in mathematical modeling (Troitzsch 1997). The first use of computer simulation started within social research programs at universities and those models where based on discrete event and system dynamics as shown in Figure 10.

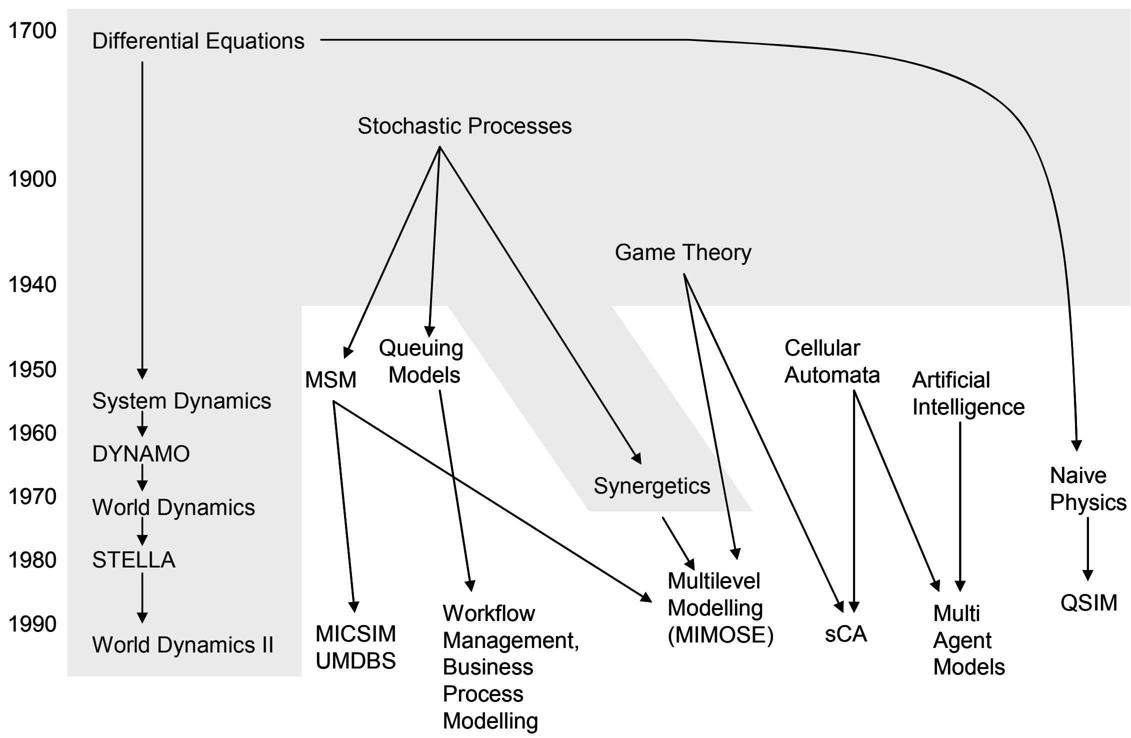


Figure 10: Development of simulation approaches in the social science, according to (Gilbert and Troitzsch 2005)

Legend: grey shaded area: equation based models
white shaded area: object, event or agent based models

Discrete event simulation, described in section 3.5, models units like customers that pass through queues and serving stations to simulate typical throughputs in for example a supermarket or an airport.

The System Dynamics (SD) approach, described in section 3.1, models large systems of difference equations and tries to predict the future behavior of these systems like the studies of the future of world economy by the Club of Rome (Meadows et al. 1972, 2004). With this first simulation of a global problem predicting a global environmental catastrophe this type of simulation became known worldwide. Unfortunately this model gave simulation an undeservedly poor reputation because the results depended heavily on the quantitative assumptions about the models parameters and didn't quite match reality. One problem regarding this model was the focus on prediction of a social system because social scientists where more concerned about understanding and explanation.

Another approach that had widespread recognition in the social science is rather misleadingly called Micro Simulation (Orcutt 1957). Described in section 3.4 this simulation approach is based on randomly generated individuals and households that form a population. Using transition probabilities each individual is aged during the simulation steps. Other probability tables are used to simulate deaths, births, marriage, and employment of the individuals. This kind of approach is well established in some parts of the world especially in Germany, Australia, United States, UK and Canada. The main goal when simulating with the Micro Simulation approach is to predict future distributions instead of explanations of the basic system. An important part compared to other approaches is that all elements are treated individually and there is no defined interaction between them. They only respond to the systems throw of the dice represented by a random number generator that is compared to available transition tables.

Another approach to simulate with individuals described in section 3.3 is called Cellular Automata. This technique was developed in the 1960's based on the Von Neumann machine. The basic idea is to simulate the emergent behavior of cells, which interact locally with their direct neighbors, situated on a grid. To understand the properties of large aggregates like magnetic materials, turbulent flow in liquids, soil erosion and other fields of science mathematicians and physicians developed this method (Toffoli and Margolus 1987). In these cases the properties can be modeled by interaction between the elements. The cells representing these elements can be one of some several defined states changing it due to rules that only depend on the immediate cells neighbor state.

In contrast to natural science where simulation is a basic methodological tool little was heard on simulation during the 1980's except for Micro Simulation. In the 1990's this situation changed due to the development of multi agent models. These models extend the abilities of Cellular Automata and Micro Simulation by modeling autonomous individuals with interaction. These modeling opportunities came from studies about nonlinear dynamics and artificial intelligence research. With the tremendous growth of the internet software agents, programs that can collect information from other computers and decide on past experience what action to perform became a research theme of artificial intelligence researchers (Doran 1997). Both fields developed models with interacting agents and therefore can be applied to simulate human societies.

Nowadays computer simulation of social phenomena can be considered as a well established field of research, because of a large number of publications, scientific events and the journal of artificial societies and social simulation. In the last two decades, the area of computer simulation benefits form a number of increasingly accessible facilities such as the development of high-level languages, the appearance of learning algorithms and systems, etc. (Conte et al. 1998)

2.3.2 Types of simulation

The universal simulation model can be split into two major parts the action area and the reaction area. The reaction area contains the formalizing part and the action area contains all human activities and actions. Due to the formalizing level a simulation model can be categorized into following three types. (Wordelmann 1978)

(1) Human to human simulation (role-playing)

The formalizing level of this type of simulation is quite low. In the action area there are several players personating different roles and the reaction area consists of several gaming rules controlled by the game master. The game master is the most important part of a role-playing simulation. He creates/describes the gaming environment and evaluates the possible decisions and actions performed by the players. A role-playing simulation is more spontaneous and less predictable than other types of simulation. This is a major problem, because of the unstructured form players sometimes overact in their actions and generate unrealistic behaviors. Due to these facts the comparability of individual runs is quite low. (Herrmann 1987)

(2) Human to machine simulation (business game)

Business games have a higher formalization compared to role-playing simulations. In the action area there are also players executing spontaneous behaviors but the reaction area consist of a formalized simulation model. Players involved in these simulations usually act in teams with different interaction intensity. After the start of a simulation the designer can not perform interventions. A simulation run consist of many time steps. In each step the team can react on the generated output by arranging their strategy and perform new moves.

The output usually consists of aggregated stocks. Due to the fixed frame of the simulation the options for new strategies are quite limited. (Herrmann 1987)

(3) Computer simulation

This type of simulation model has the highest formalization level. The action area consists just of some influence capabilities of the model user and the whole complexity is in the reaction area. Spontaneous human behaviors are completely impossible due to the structure and can just be simulated by randomly generated elements. A major benefit of computer simulation is to calculate large data sets with computationally intensive operations much faster and that's one can rerun a simulation very often. With the start of computer simulation mankind is able to simulate a much larger area of science that can not be analyzed just by imagination. The need of computer simulation is growing in all fields of science due to the complex world with all its dependencies. (Herrmann 1987)

2.3.3 Purpose of social science simulation

Social science simulation is more than just prediction or explanation of a system. According to Axelrod (1997) there are diverse purposes for social science simulation like, prediction, performance, training, entertainment, education, proof, and discovery. Although performance, training, entertainment and education may be discredited as little related to scientific research (Quinn 2000) there are at least three more valuable uses of simulation in addition to prediction, proof, discovery and these are explanation, critique and prescription according to (Blaschke 2007).

(1) Prediction:

From a formal model of a system, like world dynamics (Forrester 1971), simulation is able to predict a number of future scenarios which may or may not occur, limited to the models, initial conditions and random disturbances. The predictive power of simulation is not limited to basic research. Businesses frequently use simulation to predict future scenarios like Boeing did this in the late 1990s to seal a multi-billion-dollar contract with Ryanair. At that time Ryanair was a small airline company in Europe and Boeing was anxious about the credit-worthiness about this relative unknown partner. So they decided to simulate multiple scenarios with Ryanair's business model showing profitable earnings throughout all scenarios. (Bowley 2003)

(2) Proof:

Simulation validates the possibility of a theory or model to generate certain behavior by testing and demonstrating the feasibility of a theory or model and the connection of dynamics to specified conditions, in contrast to the rigorous mathematical proof like deduction of a theorem. Conway proves in his Game of Life, described in section 3.3.1.1, that simple rules may nonetheless produce complex system behavior.

(3) Discovery:

Another important part of social science simulation beside from prediction and proof is discovery. The major difference between natural science and social science is the ability to have a precise model to predict or prove system dynamics. The complexity in many fields like mass hysteria, the spread of epidemic diseases or organizational learning can't fully be accounted by modelers. However social scientists produce simple models to successfully discover connections, relationships and principles. Axelrod (1997) states that the simpler the model, the easier it is to understand and discover the subtle effects of the hypothesized mechanisms. Carroll’s and Harrison’s (1998) simulation of rival populations of organizations is a good illustration of the ability of a simple model, to gain insight to the process of competition. They discovered that sometimes weak populations win over competitively better ones due to path-dependent effects.

(4) Explanation:

Simulation helps to understand the origins of unexplained empirical phenomena. Indeed Explanation is qualitatively more than prediction, proof and discovery and typically extends beyond the mere demonstration of certain system dynamics. According to Waldrop (1992) predictions are nice when made, but the essence of science lies in explanation by showing the fundamental mechanisms of nature. A model developed by Waldrop to simulate thunderstorms gave deep insight and explanations about the cause of updrafts and downdrafts and the influence of temperature and humidity to the dynamics of a storm.

(5) Critique:

In opposite to proof simulation can also be used to criticize a theory by either uncovering the flaws or prove the correctness. Doing replication simulation can be used to critique other simulations. Replication confirms reliability and reproducibility of other results and is a test of the robustness of interferences from simulations (Chattoe et al. 2000). According-ing to Axtell et al. (1996) there are three levels of replication. The first when replication reproduces the exact same result of the original simulation. The second when the replication results are statistically indistinguishable and therefore achieves distributional equivalence. And the third when replication and simulation share the same internal dynamics and therefore having relational equivalence.

(6) Prescription:

When the dynamics of a theory or model are discovered and explained this theory or model can be modified to optimize a systems behavior. This modification is part of prescription, which eventually leads to a new and better definition. Discovery can be seen as the recognition of undetermined connections, principles and relationships in theory or model and explanation then adds the basic understanding of how these facts produce the system behavior. Therefore prescription can be seen as the next step after discovery and explanation.

2.4 Validation and Verification

The increasing use of simulation models to solve problems and aiding in the process of decision making makes it necessary to demonstrate that the model and its results are correct. This is done through model verification and validation of the primary processes for quantifying and building confidence or credibility. (Sargent 2007)(Thacker et al. 2004)

Verification is defined as ensuring that the computer program of the computerized model and its implementation are correct. (Schlesinger et al. 1979)

Validation is defined as to substantiate that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model. (Schlesinger et al. 1979)

Other definitions of validation as stated by different authors are:

- Substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model (Sargent 2003).
- Validation is the process of determining that the model on which the simulation is based is an acceptably accurate representation of reality (Giannanasi et al. 2001).

- Validation is the process of establishing confidence in the usefulness of a model (Coyle 1977).
- The process of determining the degree to which a model is an accurate representation of the real-world from the perspective of the intended uses of the model (DoD 2002).

The Verification and validation process's aim is to collect evidence of the correctness or accuracy of a model for a specific scenario. Therefore this process cannot prove that a model is correct and accurate for all possible conditions and applications. It can rather provide evidence that a model is sufficiently accurate for the intended application. The process is completed when sufficient confidence for a models validity is reached. A model can be considered to be invalid, if a test determines no sufficient accuracy for any of the experimental conditions. However, determining sufficient accuracy for the given experimental conditions is no guarantee for a models validity throughout the applicable domain. (Thacker et al. 2004)

2.4.1 Verification & Validation within the development process

Basically there are four approaches for checking the validity of a model:

- In the first approach the development team itself decides whether the model is valid or not, depending on the results of the various tests and evaluations throughout the development process.
- The second approach is very suitable when the development team is not very large and just adds another factor to the first one, by integrating the users of the model into the validation phase. Determining whether a model is valid or not is therefore shifted to the users and also adds model credibility.
- The third approach should be used when developing large scale simulation models by using several teams. This approach is often called "independent verification and validation", because it uses a third team (independent and outside of the development and user team) to decide on model validity. This can be done either concurrently or after the development of the simulation model. Because the second type can be extremely cost and time consuming it is better to perform validity throughout the development phase.

- The last approach determines the validity of a model by using a scoring model. Scores are subjectively set for different aspects and combined to category scores and an overall models score. A model can be considered valid if its overall and category scores are higher than a passing score. However, models that pass the scoring system need not to be valid at all.

There are two widely accepted paradigms (a simple and a complex view) relating validation and verification to the development process. First the simple version is presented because it more clearly illuminates model verification and validation (Banks et. al 1988).

Figure 11 shows the simplified version of the modeling process that consist of three big entities the problem entity representing the real or supposed system, idea, situation or phenomenon to be modeled, the conceptual model representing the mathematical/logical/verbal representation of the problem entity for a certain study and the computerized model representing the computerized implementation of the conceptual model. There are three different phases within the model development. While the conceptual model is developed through an analysis and modeling phase the computerized model is developed through a computer programming and implementation phase and inferences about the problem entity are obtained in the experimental phase by using computer experiments. Within these development steps the model validation and verification is done. In the conceptual model validation one has to determine if all theories and assumptions underlying the conceptual model are correct and that the model representation of the problem entity is reasonable for the intended purpose. In the computerized model verification one has to assure that the computer programming and implementation of the conceptual model is correct. And at last in the operational validation one has to determine that the model's output behavior is sufficiently accurate for the intended purpose. In all phases the validity of the data, that is necessary for model building, evaluation and testing has to be adequate and correct. (Sargent 2007)

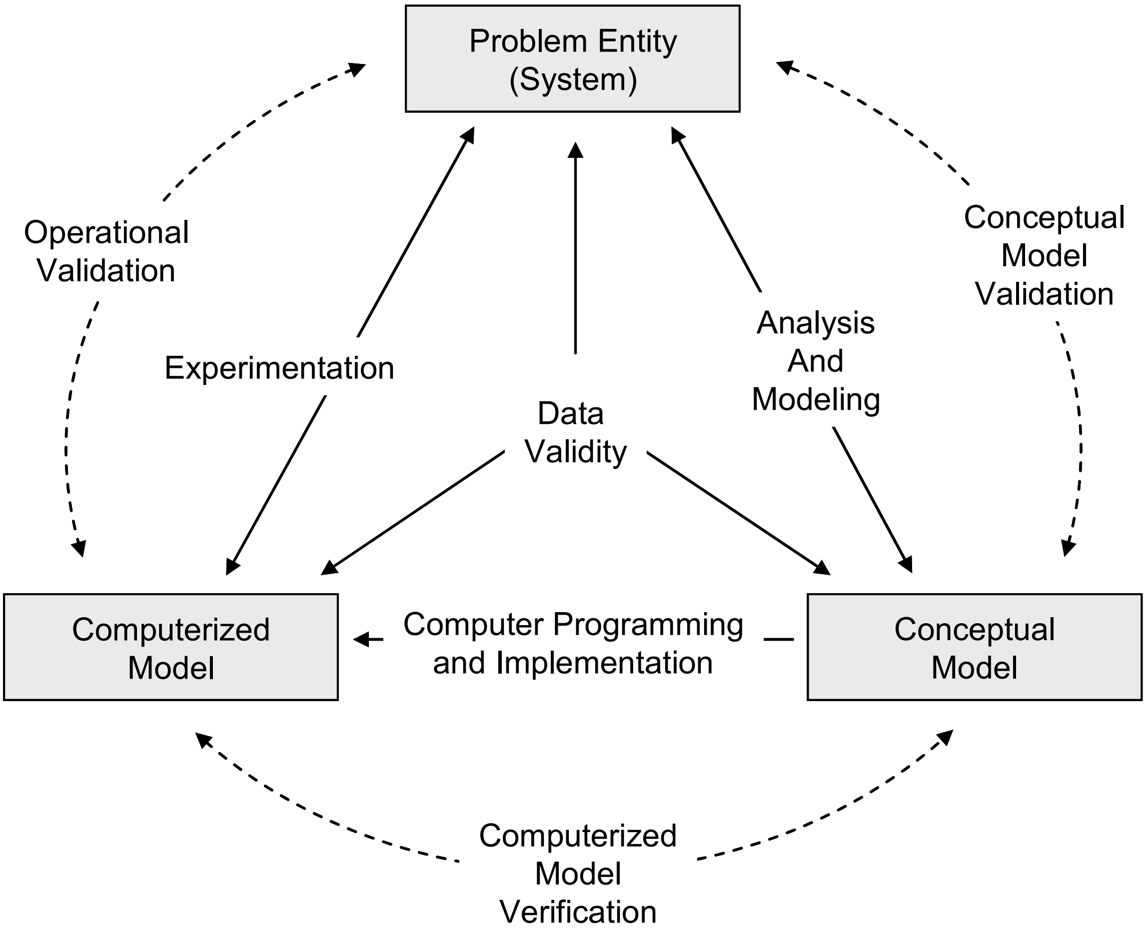


Figure 11: Simplified version of the modeling process, according to Sargent (1981)

A more detailed paradigm, than the simple one, of relating verification and validation onto the developing process and the theories is shown in Figure 12. This paradigm divides the process into a Real World and a Simulation World. First there is a system or problem entity that needs to be modeled. Systems data and results are obtained through experiments on the real system. System theories describe the primary characteristics and are developed through observation and by hypothesizing from systems data and results. These theories are validated by comparing them with systems data and results over the applicable domain by conducting several experiments on the real system. Within the simulation world the conceptual model is the mathematical/logical/verbal representation of the system and is developed by modeling the system using the system theories. The simulation model specification is a detailed description of the software design to implement the model on a computer. The implemented version of this document is the simulation model. Simulation model data and results are gathered through experiments with the simulation model. The validation of the simulation world starts with the conceptual model validation where the theories and assumptions underlying the conceptual model are checked on consistency with system theories. Specification verification is assuring that the software design and specification for the specified conceptual model is satisfying for the intended purpose. Implementation verification is assuring that the implemented simulation model fits the model specifications. In the operational validation one has to check if the model's output behavior has sufficient accuracy for the purpose over the intended application domain. This paradigm shows a more detailed process on developing system theories and valid simulation models. (Sargent 2007)

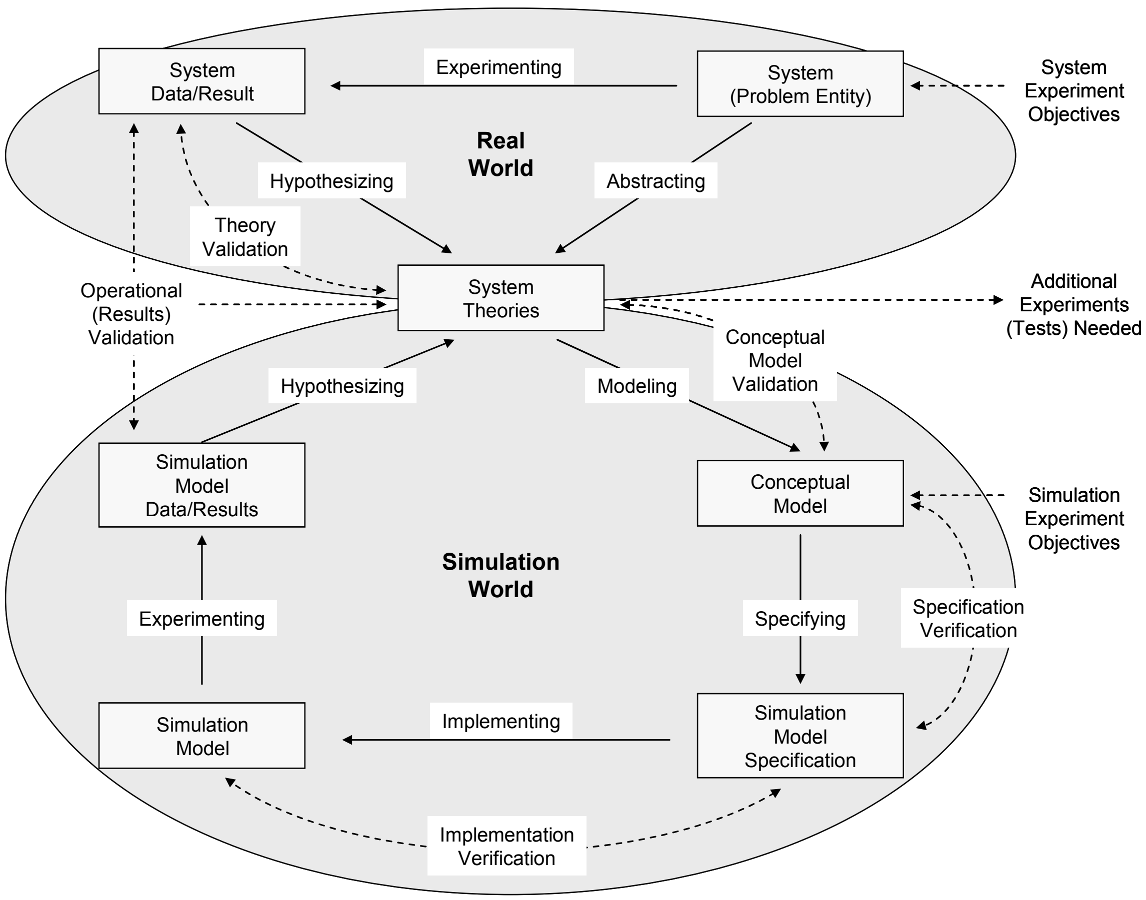


Figure 12: Real and simulation world relationship with verification and validation, according to Sargent (2001)

2.4.2 Validation Techniques

There are several techniques and tests to verify and validate the sub models and overall model that can either be used subjectively or objectively. In general a combination of those techniques should be used. Sargent (2007) describes various techniques, listed alphabetically, as follows:

Animation:

Giving a graphical evidence for the correctness of a models behavior, like movement of parts through a factory.

Comparison to Other Models:

Validated output results of the model are compared to other models validated results. This can be done by comparing simple cases of a model to a known analytical model or by comparing the simulation model to others that have been validated.

Degenerate Tests:

Models degeneracy is tested by picking appropriate values for the input and internal parameters, like looking at the average length of a queue when increasing the input amount above the service rate.

Event Validity:

Event validity means determining that the events occurring in the simulation must be similar to those of the real system.

Extreme Condition Tests:

Determining, that the simulation model's structure and output is plausible for any extreme and unlikely combination of levels in the system, like zero input should result in zero output.

Face Validity:

Face validation always means that a knowledgeable independent individual takes a look at the model and the behavior to argue if it is reasonable.

Historical Data Validation:

If historical data exists, part of it is used to build the model and the other part is used to test if the model can reproduce systems data.

Historical Methods:

There are three historical methods rationalism, empiricism and positive economics. Rationalism assumes that everyone knows if the assumptions of the model are true and logic deduction is then used to develop the correct model. In empiricism every assumption and outcome is empirically validated. In positive economics the model should be able to predict the future.

Internal Validity:

To test the internal validity of a stochastic model several replications are made to determine the variability. Depending on the amount of variability the model's results may be questionable or the appropriateness of the policy or the system.

Multistage Validation

Combining the three historical methods of rationalism, empiricism and positive economics leads to the multistage process of validation. This process consist of developing the assumptions on theory, observation and knowledge, validating these assumptions empirically where possible and comparing the in- output relationships of the model to the real system.

Operational Graphics:

Operational graphics means to visualize the values of various performance measures over the simulation lifetime.

Parameter Variability – Sensitivity Analysis:

To determine the effect of model's behavior and output compared to the real system the values of input and internal parameters are changed. This can be done either qualitatively (directions only of outputs) and quantitatively (both directions and magnitude of outputs). Parameters causing significant changes to a model's behavior or output are called sensitive parameters and should be made sufficiently accurate.

Predictive Validation:

Predictive validation compares the system's behavior, obtained from field tests, and models forecast of this behavior to determine the sameness.

Traces:

To determine the correctness of the logic of a model and the needed accuracy different types of entities are traced through the model.

Turing Tests:

Individuals that have the knowledge about the operations of the real system should determine the differences of model and real system.

2.4.3 Data Validity

One of the most important tasks before starting to develop the conceptual model or performing experiments is to assure the validity of the needed data. This task is usually difficult and time consuming but necessary to perform model validation. Developing theories and the conceptual model require sufficient data on the problem entity. To ensure data correctness one should develop procedures for collecting and maintaining data and perform several consistency checks. When handling with a large amount of data, a database should be used.

2.4.4 Conceptual model validation

A conceptual model can be considered being correct if both assumptions and theories of the model are correct and the representation of the problem and the structure and logic are reasonable for the intended purpose. Both theories and assumptions need to be tested by using linearity, data independence or stationary tests, fitting distributions to data etc. If there are sub models all of those need to be reasonable for the intended purpose too. To evaluate a model's structure, logic and mathematical relationships face validation and traces can be used. A face validation is primarily done by an expert of the problem entity that evaluates the graphical model, flowcharts and model equations of the conceptual model. Tracing means to track entities through all sub models and determine if the logic is correct and the needed accuracy is maintained. When finding an error in the evaluation phase the conceptual model has to be revised and conceptual model validation needs to be performed again. (Sargent 2007)

2.4.5 Computerized model verification

The computerized model verification assures the correctness of the implementation of the conceptual model. When using a simulation language, verification means: properly implementation of the language, a pseudo number generator and a correctly programmed model. Primary techniques to ensure correctness of a model are structured walk-throughs and traces. When using a higher level programming language one has to assure that the computer program is designed, developed and implemented with software engineering techniques and that the functions and the model are correctly being implemented. Basically there are two approaches to test simulation software: static and dynamic (Fairley 1976). Static testing of the correctness of a computer model is concerned with techniques like correctness proofs and structured walk-throughs whereas in dynamic testing the program is executed under different conditions to determine the correctness of the implementation by using internal consistency checks, in-output validation, traces, or reprogramming of critical elements. Nevertheless it is necessary to be aware of the fact that errors found during the tests can be caused by the data, the conceptual model or the implementation. (Sargent 2007)

2.4.6 Operational validity

In operational validation most of the validation testing and evaluation is done to determine a model's accuracy for the simulation output over the domain for the intended purpose. Deficiencies found within this process may be caused by any further steps developing the theories and the model or by invalid data. All validation techniques shortly described in section 2.4.2 are applicable for operational validation. What kind of techniques and in what combination and whether to use them objectively or subjectively is the decision of the development team, the sponsors and knowledgeable externals. The decision what methods to use depends whether the problem entity is observable (it is possible to collect data on the operational behavior) or not. Table 2 gives an operational validation classification based on the decision approach and system observability. (Sargent 2007)

Table 2: Operational Validity Classification, based on Sargent 2007

	Observable system	Non-observable system
Subjective approach	Comparison using graphical display Explore model behavior	Explore model behavior Comparison to other models
Objective approach	Comparison using statistical tests and procedures	Comparison to other models using statistical tests

To obtain a high degree of confidence in the simulation model and the results, what should always be the result of the operational validation, several comparisons of model's and system's output behavior with different sets of experimental conditions are required. In the case a system is not observable and therfore it isn't possible to get a high degree confidence in the model, the only possibility is to compare the model to other valid models whenever possible.

Explore model behavior

The behavior of a simulation model can be explored either qualitatively, where the directions and the magnitudes reasonability of the output behaviors are examined or quantitatively, where both directions and the precise magnitudes are examined. Experts to the real system often know these directions and magnitudes of the output behavior. Graphs of output data discussed later on can also be used as statistical approaches like metamodeling and design of experiments but usually parameter variability – sensitivity analysis should be used. (Sargent 2007)

Comparisons of Output behaviors

There are three basic approaches, which can be classified into subjective and objective decision making, to compare the simulation model's output behavior to either the system output behavior or another model output behavior. This can either be the use of graphs for a subjective decision, the use of confidence intervals for an objective decision and the use of hypothesis tests for an objective decision. In general it is wiser to use objective decision tests, however this is often not possible because of either insufficient quantity of systems data or the required statistical assumptions can't be satisfied. That's why graphs are commonly used in operational validation. (Sargent 2007)

Graphical comparison of Data:

There are three types of commonly used types for visualizing the comparison of the behavior from the system and simulation model: histograms, box plots, and scatter plots. To perform a reasonable comparison a variety of graphs using different types of measures and relationships are required. There are four ways to use this graphs in the validation of simulation models. First, the development team can use them to make a subjective judgment of a model's accuracy. Second, experts can use them in face validation to judge on the model's accuracy. Third, graphs can be used in Turing tests and fourth, graphs can be used in different ways in independent verification and validation.

Confidence intervals:

To validate a model's accuracy there are three possible range types: the confidence interval, the simultaneous confidence interval and the joint confidence regions that can be obtained for the differences between mean and variance for each set of experimental conditions. A statistical technique and a method of data collection must be developed for each set of experimental conditions to construct the range of a model's accuracy. Statistical techniques can be separated into univariate statistical techniques to obtain the confidence interval and with the use of Bonferroni inequality (Law 2006) the simultaneous confidence interval and multivariate statistical techniques to develop the simultaneous confidence interval and the joint confidence region. Parametric and non-parametric techniques can be used. The method of data collection must always satisfy the underlying assumption for the statistical technique.

Hypothesis tests:

Hypothesis tests are used to compare the means, variances, distributions and time series of the output variables of a model and a system to determine the accuracy of the model's output behavior. A model can either be valid or invalid for the acceptable range of accuracy under the set of experimental conditions. There are two different possible types of errors that must be carefully considered when using hypothesis tests. The first one is rejecting the validity of a valid model called model builders risk and the second is accepting the validity of an invalid model called model users risk. These two risks (errors) must be included into the calculation of the range of the operating characteristic. To determine a model's accuracy a validity measure, chosen that the amount of agreement between the model and the system decrease as the value of the validity measure increases and an acceptable range of accuracy are calculated. A detailed description of the methodology for using hypotheses tests is given in Balci and Sargent (1981). (Sargent 2007)

2.4.7 Recommended Procedure

As a minimum Sargent recommends following eight steps to be performed in model validation (Sargent 2007):

1. Before starting the modeling session the model developing team and the model sponsors should specify the basic validation techniques used in the process later on.
2. Specify the accuracy required for the model's output for the intended purpose prior or at least in a very early stage of the modeling.
3. Assumptions and theories underlying the simulation model should always be tested.
4. A face validation of the conceptual model should be performed in each iteration.
5. A Model's behavior should be explored in each iteration using the computerized model.
6. Perform output comparisons of system behavior and simulation model for some experimental conditions at least in the last model iteration.
7. Develop a documentation of the validation and include it into the global model documentation.
8. If a model is developed for a repeated use, develop a periodic validation schedule.

3 Approaches

In this chapter the main techniques available for modeling social systems are described. Each of these techniques has its own specific characteristics and area of application.

3.1 System Dynamics

3.1.1 History

System Dynamics (SD) was developed by Jay W. Forrester in the mid 1950s at the Massachusetts Institute of Technology (MIT).

Although having a scholarship to go to agricultural college, after spending his childhood at his parent’s ranch in Nebraska, he studied electrical engineering at the University of Nebraska. There he employed theoretical dynamics and had his first contact with systems behavior. After finishing the University he joined the MIT to become a research assistant of his mentor Gordon S. Brown, the founder of the Servomechanisms Laboratory and pioneer of "feedback control systems" military equipment. Years later he became the director of the newly founded MIT Digital Computer Laboratory, where the first general-purpose digital computer at the MIT, Whirlwind I, was designed. It was an experimental laboratory for testing the use of digital computers in military combat information systems. (Forrester 1992) (Forrester 1995)

By 1956, he felt the pioneering days in digital computers were over and joined the MIT related Sloan School of Management. This was in fact the important turning point towards management in his career. His background of science and engineering was helpful in examining the core issues of determining success or failure of corporations. He concluded, that the biggest impediment to progress does not come from the engineering side, but from the management side, because he reasoned that, social systems are much harder to understand and control than physical ones. (Radzicki 1997)

His work with General Electric (GE) in 1957 regarding employment instabilities and the result in the first inventory control system with pencil and paper simulation can be seen as the beginning of System Dynamics (Forrester 1995):

> *"Again chance intervened when I found myself at times in conversation with people from General Electric. They were puzzled by why their household appliance plants in Kentucky were sometimes working three and four shifts and then a few years later, half the people would be laid off. It was easy enough to say that business cycles caused fluctuating demand, but that explanation was not convincing as the entire reason.*
>
> *After talking with them about how they made hiring and inventory decisions, I started to do some simulation. This was simulation using pencil and paper on one notebook page. It started at the top with columns for inventories, employees, and orders. Given these conditions and the policies they were following, one could decide how many people would be hired in the following week. This gave a new condition of employment, inventories, and production. It became evident that here was potential for an oscillatory or unstable system that was entirely internally determined. Even with constant incoming orders, one could get employment instability as a consequence of commonly used decision-making policies. That first inventory control system with pencil and paper simulation was the beginning of system dynamics." (Forrester 1995)*

During Forrester's writing of article "Industrial Dynamics – A Major Breakthrough for Decision Makers" for the Harvard Business Review, he needed computer simulations, and therefore Richard Bennett, a co-worker and computer programmer, developed SIMPLE ("Simulation of Industrial Management Problems with Lots of Equations") a compiler that automatically creates code for a given set of equations to perform computer controlled simulations. This compiler served as the basis for DYNAMO ("DYNAMic MOdels") and the System Dynamics language developed by Phyllis Fox and Alexander L. Pugh. (Forrester 1995)(Radzicki 1997)

After publishing his first book "Industrial Dynamics" that served as the first presentation of the philosophy and methodology of system dynamics, Forrester joined the board of the Digital Equipment Corporation. There he took system dynamics out of physical simulation by modeling the cooperate growth of a high technology company. (Forrester 1992)

Until the end of 1960's System Dynamic was primarily used for corporate modeling and then extended to social systems when John F. Collins, who had been mayor of Boston for eight years, moved to MIT to become Visiting Professor of Urban Affairs. They combined their efforts, taking Collins experience in cities and Forrester's background in modeling to look for interesting insights about the problems of large cities. The subsequent discussions evolved the book "Urban Dynamics" (Forrester 1969) that illustrates the use of System Dynamics to urban problems. The book produced strong emotional reactions, because it showed that policies that were used to increase the economy were ineffective and rather detrimental, like low-cost housing. (Forrester 1992)

> *"Our examination of urban behavior showed that the most damaging policy was to build low-cost housing. At that time, building low-cost housing was believed essential to reviving the inner cities. But the construction of low-cost housing occupies land that could have been used for job-creating structures, while at the same time the added housing draws in people who need jobs. It creates a social trap that increases unemployment, and reduces the economic vitality of both the city and the individual residents." (Forrester 1992)*

The second major non corporate application of system dynamics came in 1970 where Forrester joined the Club of Rome after a meeting with the founder Aurelio Peccei concerning the various problems of the world.

> *"The Club of Rome is an organization devoted to solving what its members describe as the "predicament of mankind" -- that is, the global crisis that may appear sometime in the future, due to the demands being placed on the earth's carrying capacity (its sources of renewable and non renewable resources and its sinks for the disposal of pollutants) by the world's exponentially growing population". (Radzicki 1997)*

Forrester developed a model of the socioeconomic system of the world (WORLD1). He refined the first model naming it WORLD2 and published the book "World Dynamics" (Forrester 1971). This model showed the important interrelationships between world population, industrial production, pollution, resources depletion, and agriculture. (Forrester 1992) Because of the prognoses, published in the book, of rising environmental pressures that will progressively restrain growth of population and industrialization over the next fifty years, it became attention by global media. But the model was also used to identify policies for achieving a sustainable quality state for global environment. (Radzicki 1997) In response of this global attention the Club of Rome initiated a second study concerning the predicament of mankind. This led to the publication “The Limits to Growth” (Meadows et al. 1972) in 1972. The presented model was updated in 1991 in the “Beyond the Limits” and recently in “Limits to Growth: the 30-Year Update” (Meadows et al. 2004).

The book “Urban Dynamics” led to the creation of the System Dynamics National Model, a model of the United States economy. The model generates the major kinds of behavior of a capitalistic economy: business cycles, inflation, stagflation, growth, and the economic long wave or Kondratieff cycle. It showed that economic crises are recurrent within a 50 to 70 year cycle. (Forrester 1992)

> *“The National Model supplies for the first time a theory for the economic long wave, which we believe accounts for the great depressions that occurred around 1830, 1890, and in the 1930s. The long wave arises from major interactions among capital investment, saving, monetary policy, real interest rate, and speculation. It generates severe economic downturns at five-to-seven-decade intervals.” (Forrester 1992)*

This approach came with a new and different way of looking at the study of economic systems and it helped people to understand large macroeconomic systems.

As a consequence, that adults already have an established point of view of their environment and that understanding of dynamic behavior takes time, Forrester’s last attention was the extension of system dynamics training to kids. With the help of his mentor Gordon Brown it was integrated in the entire school district from kindergarten to 12th grade (K-12). (Forrester 1992) (Forrester 1996)

Nowadays the concept and definitions of Forrester’s System Dynamics (SD) approach are widely accepted and used in many fields of applications from economics, physics, biology, medicine, social systems and so on. Many companies use the approach to get recommendations for the policy makers in strategy and operational business.

3.1.2 The Basics

System Dynamics (SD) is a so called “top-down” approach where the point of view to describe and model a system is set to an aggregate level. When we talk about System Dynamics the philosophy System Thinking is always related to it. System Thinking shows the dependencies between systems structure and the result of the systems process by describing feedback structures, complexity and non linearity of a system with the Causal Loop Diagram. Figure 13 shows how different the term System Thinking can be seen in relation to System Dynamics. To Forrester System Thinking is just a part of the whole System Dynamics process by showing the global system coherences. Whereas Richmond defines System Thinking as an aura around the System Dynamics term, concerning the connection to practical work. For him it is a learning method and paradigm at the same time. He says:

> *"… the art and science of making reliable inferences about behavior by developing an increasingly deep understanding of underlying structure". (Richmond 1994)*

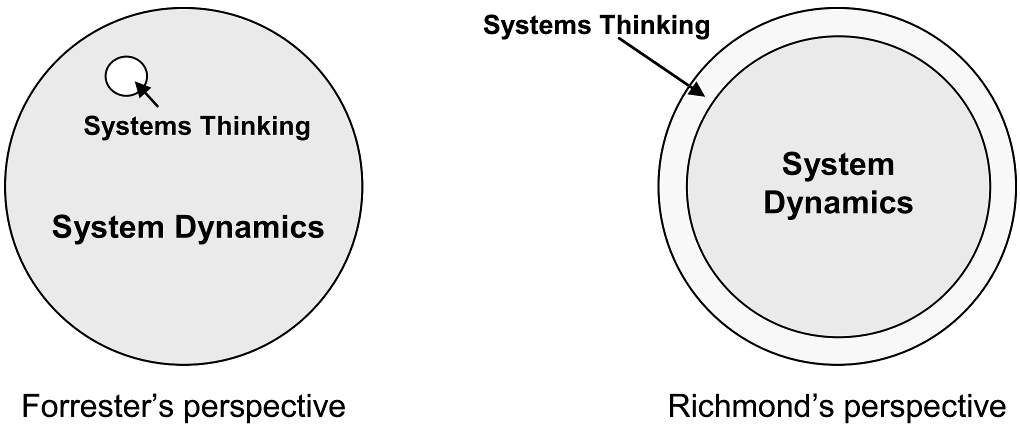


Figure 13: Different perceptions of the term Systems Thinking, according to Richmond (1994)

Regardless from which point of view, the System Dynamics simulation approach can be seen as the practical application of System Thinking, where the Causal Loop Diagram is transformed into a Stock and Flow Diagram to simulate the modeled system.

John D. Sterman, Professor of Management at the MIT Sloan School of Management and Director of the MIT's System Dynamics Group describes the main issue of SD modeling to discover and represent the feedback processes of a system by means of a Causal Loop Diagram. With the addition of stocks and flows, time delays and nonlinearities the dynamics and therefore the systems behavior can be determined and this leads to the understanding of the system. (Sterman 2000)

3.1.3 Modeling Process

As shown in Figure 14 the System Dynamics modeling process is a permanent feedback process and consists of the following five key elements as described by John D. Sterman (2000):

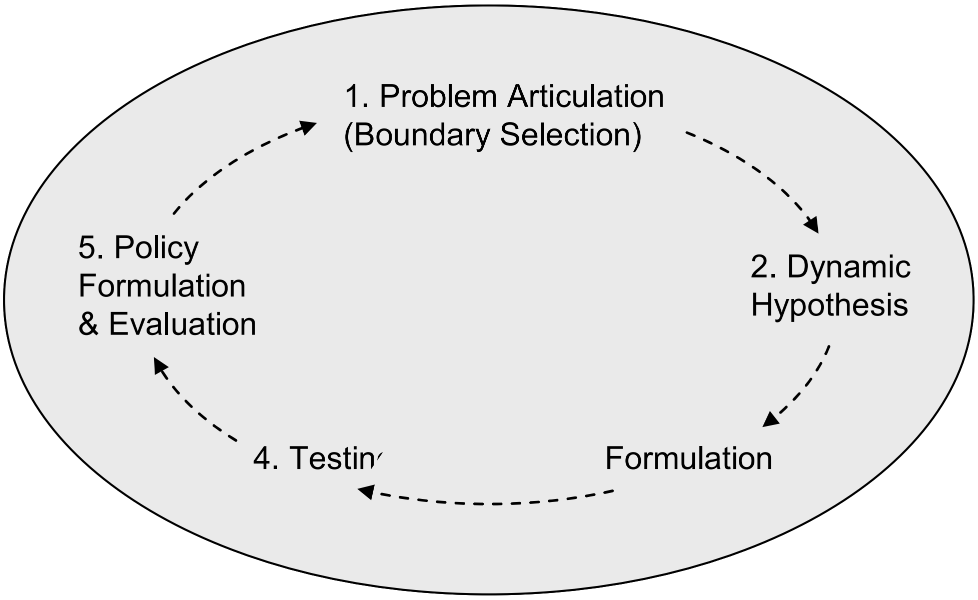


Figure 14: System Dynamics modeling process, according to Sterman (2000)

1. Problem Articulation (Boundary Selection)

- Theme selection: What is the problem? Why is it a Problem?
- Key variables: What are the key variables and concepts we must consider?
- Time horizon: How far should we look into the future? How far back in past lie the roots of the problem?
- Dynamic problem definition (reference modes): What is the historical behavior of the key concepts and variables? What might their behavior be in future?

2. Formulation of Dynamic Hypothesis

- Initial hypothesis generation: What are current theories of the problematic behavior?
- Endogenous focus: Formulate a dynamic hypothesis that explains the dynamics as endogenous consequences of the feedback structure.
- Mapping: Develop maps of causal structure based on initial hypotheses, key variables, references modes, and other available data, using tools such as
- Model boundary diagrams
- Subsystem diagrams
- Causal loop diagrams
- Stock and flow maps
- Policy structure diagrams
- Other facilitation tools

3. Formulation of a Simulation Model

- Specification of structure, decision rules.
- Estimation of parameters, behavioral relationships, and initial conditions.
- Tests for consistency with the purpose and boundary.

4. Testing

- Comparison to reference models: Does the model reproduce the problem behavior adequately for you purpose?
- Robustness under extreme conditions: Does the model behave realistically when stressed by extreme conditions?
- Sensitivity: How does the model behave given uncertainty in parameters, initial conditions, model boundary, and aggregation?

5. Policy Design and Evaluation

- Scenario specification: What environmental conditions might arise?
- Policy design: What new decision rules, strategies, and structures might be tried in the real world? How can they be represented in the model?
- "What if …" analysis: What are the effects of the policies?
- Sensitivity analysis: How robust are the policy recommendations under different scenarios and given uncertainties?
- Interactions of policies: Do the policies interact? Are there synergies or compensatory responses?

Modeling is not a linear sequence of steps it is rather an iterative cycle of steps and models go through iterations, continual questioning, testing and refinement. In the System Dynamics modeling process results from any step or iteration phase can yield insights that lead to revisions in any earlier step or iteration phase. (Sterman 2000) Each step of the modeling process is described below. The major tools used in these steps are described in the following section.

3.1.3.1 Problem Articulation (Boundary Selection)

Having a clear purpose is the most important ingredient when starting modeling. Although models with a clear purpose can still be misleading or difficult to understand they allow questioning to reveal if that model is useful in addressing the problem or not. A model should always address a relevant problem and be a simplification of the real system rather than mirroring it. A Clear purpose helps to identify the relevant features and aspects and those that can be excluded.

Key variables as the second major part of problem articulation form the edges for the system to be modeled. Adding the interconnections between them will give it a first body. Gathering all necessary variables can be a quite hard work, because everyone could have a different understanding and mental image of the system to be modeled. Techniques like brainstorming, information research, direct observation, or interviews can help extract the real relevant variables and summarize identical ones.

Considering the time horizon is the third major part of the problem articulation part. Time horizon should always extend far enough back in time to address the symptoms and show how the problem emerged and examine the changes of the key variables and their interdependencies. On the other hand it should also extend far to the future to capture the delayed and indirect effects of potential policies. (Sterman 2000)

3.1.3.2 Formulation of Dynamic Hypothesis

After addressing the Problem over an appropriate time horizon, modelers must develop a theory about the problematic behavior the so-called dynamic hypothesis. John D. Sterman describes it as:

> *"Your hypothesis is dynamic because it must provide an explanation of the dynamics characterizing the problem in terms of the underlying feedback and stock und flow structure of the system. It is a hypothesis because it is always provisional, subject to revision or abandonment as you learn from the modeling process and from the real world." (Sterman 2000)*

Meaning, that this theory shows how the problem arose and focuses the modelers on certain structures. Because each member in the team has its own theory about the source of the problem, all theories must be jumbled together in conversations to extract the real relevant ones. The goal of these conversations is to create an endogenous explanation, the arising from within, for the problematic dynamics:

> *"An endogenous theory generates the dynamics of a system through the interaction of the variables and agents represented in the model. By specifying how the system is structured and the rules of interaction (the decision rules in the system), you can explore how the behavior might change if you alter structure and rules." (Sterman 2000)*

System Dynamics offers a variety of tools to represent these dynamics and causal structures of a system like, model boundary diagrams, subsystem diagrams, causal loop diagrams and stock and flow diagrams. A short description of these tools will be given now but a more detailed description of the two major tools, the causal loop and the stock and flow diagram will be given in section 3.1.4.

Model boundary chart:

This chart shows the scope of a model by summarizing and listing all the key variables and their correlation to the model, either being endogenous, exogenous or excluded.

Subsystem diagram:

This diagram shows the overall architecture of a model by aggregating and describing all major subsystems and connecting them to show the whole system. Each subsystem's flow like material, money, goods, information and so on is shown in the big graph. Multiple subsystem diagrams can also be used to represent the hierarchical structure of large systems. Considering that these diagrams are just overviews they should not contain too much detail.

Causal loop diagrams:

The first two tools just show the boundary and the architecture of the modeled system but don't show the correlation between the included variables. Causal loop diagrams show the links between variables from cause to effect and therefore emphasize the causal relationship within them. They also show the important feedback structures within the model.

Stock and flow maps:

Causal loop diagrams can be seen as a pen and paper model. Transforming these diagrams to a computer simulation one gets the Stock and flow maps. They emphasize the underlying physical structure by tracking the accumulation of the flows (material, information, money etc.). Stocks characterize the state of the system and flows are the rates to increase or decrease these stocks.

3.1.3.3 Formulation of a Simulation Model

After developing the initial dynamic hypothesis, model boundary and conceptual model it is time to test them. Doing this means moving from the conceptual realm towards a fully specified formal model, complete with equations, parameters and initial conditions. Formalizing a conceptual model often leads to better understanding and gain more insight even before the model is ready to be simulated. During the formulation stage one can perform a variety of test to identify flaws in proposed formulation and hypothesis. (Sterman 2000)

"Formalization helps you to recognize vague concepts and resolve contradictions that went unnoticed or undiscussed during the conceptual phase. Formalization is where the real test of your understanding occurs: computers accept no hand waving arguments." (Sterman 2000)

3.1.3.4 Testing

One thing in testing is to compare the simulated behavior of the model to the actual behavior of the system. But it is more than just a simple replication of historical behavior. All variables must correspond to a meaningful concept of the real world and all equations should be dimensionally consistent. A model should be tested with extreme conditions even if they never occur in the real world. (Sterman 2000)

"What happens to GDP of a simulated economy if you suddenly reduce energy supplies to zero? What happens in a model of an automaker if you raise the price of its cars by a factor of one billion? What happens if you suddenly increase dealer inventories by 1000% ?" (Sterman 2000)

Even if these conditions could never be observed in the real world, the possible behavior is no doubt. Applying extreme condition tests along with other tests of model behavior onto the developed model help to determine flaws and set the stage for improved understanding. (Sterman 2000)

3.1.3.5 Policy Design and Evaluation

After finishing the model and simulation process it is time to use the model to evaluate policies for improvement. This is much more than just adjusting values of parameters:

"Policy design includes the creation of entirely new strategies, structure, and decision rules. Since the feedback structure of a system determines its dynamics, most of the time high leverage policies will involve changing the dominant feedback loops by redesigning the stock and flow structure, eliminating time delays, changing the flow and quality of information available at key de-

cision points, of fundamentally reinventing the decision process of the actors in the system." (Sterman 2000)

Within a wide range of scenarios the robustness of policies and their sensitivity to uncertainties in model parameters and structure must be assessed. The last thing in policy design is trying to combine policies because the impact might not just be a sum of its parts. Sometimes they interfere and sometime they might reinforce one another and generate substantial synergies. (Sterman 2000)

3.1.4 System Dynamic Tools

3.1.4.1 Causal Loop Diagram

The Causal Loop Diagram (CLD) is an important pen and paper tool for representing feedback structures of a system. With a CLD one is able to: (Sterman 2000)

- Quickly capture the hypotheses about the root of dynamics,
- Visualize the mental models of individuals and teams included in the modeling process,
- Identify the major feedback structures that are responsible for a problem.

In general a CLD consists of variables connected by arrows that denote the influence among the variables. There are only a few but necessary conventions when drawing a CLD as shown in the simple CLD of a Population in Figure 15.

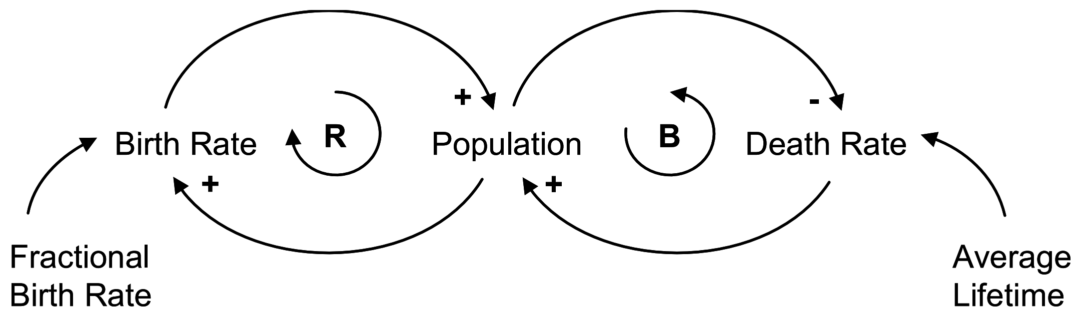


Figure 15: Causal loop diagram notation, according to Sterman (2000)

In the CLD each causal link is assigned a polarity, either positive (+) or negative (-) to indicate the change from dependent to the independent variable. The loops are highlighted by a loop identifier indicating the general feedback of this loop being either positive (reinforcing) or negative (balancing). This identifier circulates in the same direction as the loop it corresponds to. Sterman describes the polarities as:

> *"A positive link means that if the cause increases, the effect increase above what it would have been, and if the cause decreases, the effect decreases below what it would otherwise have been. In the example in Figure 15, an increase in the fractional birth rate means the birth rate (in people per year) will increase above what it would have been, and a decrease in the fractional birth rate means the birth rate will fall below what it would have been. That is, if average fertility rises, the birth rate, given the population, will rise; if fertility falls, the numbers of births will fall. When the cause is a rate of flow that accumulates into a stock then it is also true that the cause adds to the stock. In this example, births add to population.*
>
> *A negative link means that if the cause increases, the effect decreases below what it would otherwise have been, and if the cause decreases, the effect increases above what it would otherwise have been. In the example in Figure 15, an increase in the average lifetime of population means the death rate (in people per year) will fall below what it would have been, and a decrease in the average lifetime means the death rate will rise above what it would have been. That is, if life expectancy increase, the number of deaths will fall; and if life expectancy falls, the death rate will rise." (Sterman 2000)*

Table 3: Link polarity of the Causal loop diagram, according to Sterman (2000)

Symbol	Interpretation	Mathematics
$X \xrightarrow{+} Y$	All else equal, if X **increases (decreases)**, then Y **increases (decreases)** above (below) what it would have been. In the case of accumulations, X **adds** to Y.	$\frac{\partial Y}{\partial X} > 0$ In the case of accumulations, $Y = \int_{t_0}^{t} (X + \ldots)ds + Y_{t_0}$
$X \xrightarrow{-} Y$	All else equal, if X **increases (decreases)**, then Y **decreases (increases)** below (above) what it would have been. In the case of accumulations, X **subtracts** from Y.	$\frac{\partial Y}{\partial X} < 0$ In the case of accumulations, $Y = \int_{t_0}^{t} (-X + \ldots)ds + Y_{t_0}$

Link polarities don't describe what actually happens they describe what would happen if there were changes and therefore they describe the structure of the system and not the behavior of variables. When labeling link polarities of single links, assume all others are constant.

These links always form loops, that can either be positive (reinforcing) or negative (balancing). Peter M. Senge states that the two distinct types of feedback processes are the reinforcing and the balancing loop (Senge 1994):

The reinforcing loop

The reinforcing loop is a process that leads either to accelerating growth (positive reinforcing) or decline (negative reinforcing). Most of these reinforcing loops are exponential.

The balancing loop:

The balancing loop in contrast tries to reach equilibrium and generates stability. Balancing loops always try to reach a certain goal or objective.

There are two ways to determine the polarity of a loop (Sterman 2000):

(1) The fast way: Count the number of negative links

With this method to tell if a loop is positive or negative one just has to count the number of negative links in the loop. If the number is even, the loop is positive, and if the number is odd, the loop is negative. Positive loops reinforce change and negative loops are self correcting. This method always works except in complex diagrams. Here you have to carefully trace the effect of a disturbance around the loop, that's why the second way can help you save time and get the correct polarities. (Sterman 2000)

(2) The right way: Trace the effect of change around the loop

Tracing the effect of a small change in one of the variables as it propagates around the loop is the right way how to determine the polarity of a loop. Positive loops reinforce the original change and negative loops oppose the original change. The starting point can be every variable in the model. This method works no matter on how many variables there are in a loop and no matter concerning on the starting point. (Sterman 2000)

For a better understanding of model and to help the audience navigate the network of loops try to name your loops.

CLD don't distinguish between stocks and flows, they just show the system variables and their correlation to each other.

3.1.4.2 Stock and Flow Diagram

To be able to simulate the developed model using the CLD one has to transform this model to a Stock and Flow Diagram (SFD).

Stock and flows, along with feedback are the main concept of System Dynamics modeling. Stocks represent the state of the system and generate the information upon which decision and actions are based. They are the system memory and accumulate the difference between inflow and outflow. There is always a continuous change even when the rates change discontinuously.

Flows represent rates that directly add or subtract from a stock. Values don't depend on a previous state of the rate but they directly depend on the connected stock and exogenous variables.

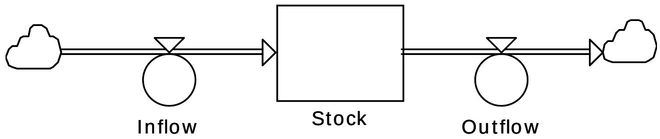
The stock and flow conventions were originated by Forrester (Forrester 1961) based on a hydraulic metaphor (the flow of water in and out of a reservoir) and therefore Sterman suggests thinking of stocks as bathtubs of water:

> *"The quantity of water in your bathtub at any time is the accumulation of the water flowing in through the tap less the water flowing out through the drain (assume no splashing or evaporation)." (Sterman 2000)*

There are four equivalent representations of the general stock and flow structure as shown in Figure 16. The bathtub and stock and flow diagrams are precisely equivalent and contain the same information as the integral or differential equation. From any system of integral or differential equations one can generate corresponding stock and flow diagrams and vice versa. The integral equation represents the value of the Stock at any time, by integrating over the inflow and outflow. The differential equation represents the net rate of change of the stock with its derivative being the inflow minus the outflow. (Sterman 2000)

Hydraulic Metaphor:

Stock and Flow Diagram (SFD):



Integral equation:

$$Stock(t) = \int_{t_0}^{t} [Inflow(s)\text{-}Outflow(s)]ds + Stock(t_0)$$

Differential equation:

$$d(Stock)/dt = Net\ \ Change\ \ in\ \ Stock = Inflow(t) - Outflow(t)$$

Figure 16: Four equivalent representations of the general stock and flow structure

The notation of the Stock and Flow Diagram (SFD) as shown in Figure 17 is described below:

- Stocks or levels are represented by a rectangle that displays a container for holding content.
- Flows or rates are represented by an hourglass.
- Auxiliaries are represented by a circle. They calculate intermediary values.
- Sources or sinks are represented by clouds and denote variables outside the boundary of the model.
- Constants are represented by diamonds. They represent numerical values.
- Flow arcs represent the connection between the flow and the stock.
- Cause and effect arc show the connection between a stock and an auxiliary/constant or between auxiliaries.

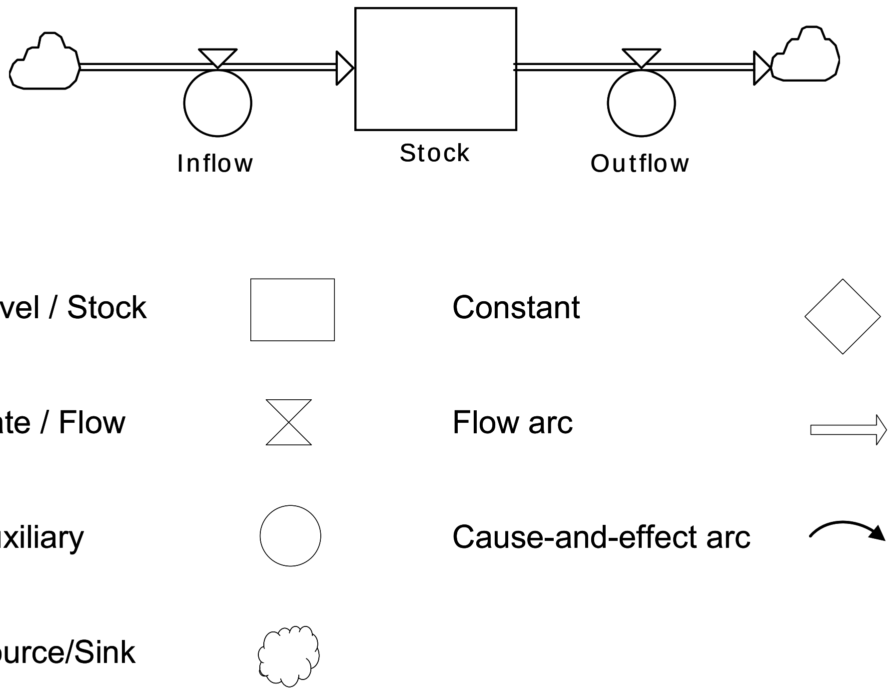


Figure 17: Stock and flow diagram notation

Considering this notation and the conventions above, Figure 18 shows the SFD from the original CLD in Figure 15.

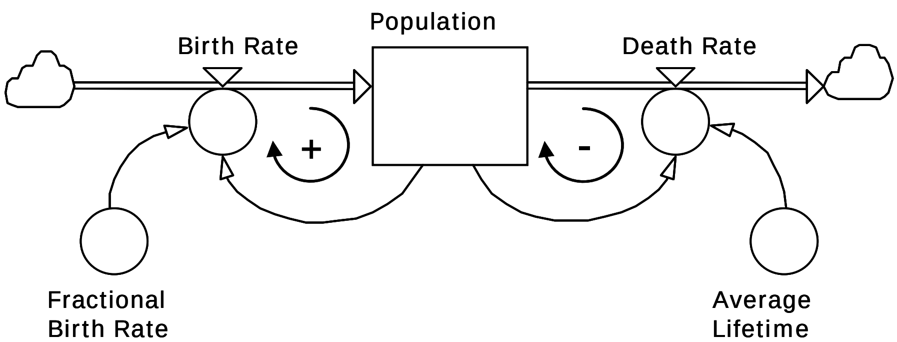


Figure 18: Stock and flow diagram example

3.1.5 Software-Tools

The common System Dynamics environments are intuitive graphical software tools that allow even inexperienced users to be able to build their first models within a few steps introduced through the available tutorials. The most representative ones are:

- Powersim Studio website: http://www.powersim.com
- STELLA/iThink website: http://www.iseesystems.com
- Vensim websites: http://www.vensim.com

3.2 Micro Simulation

The Micro Simulation (MS) approach was developed parallel to the SD one. The main goal is to forecast dynamic effects as a result of modified conditions. Individual reactive elements are modeled to simulate system behavior that can not be reproduced at an aggregate level. There is no interaction between the entities of a model and no reaction on the behavior of other entities. Because of the ability to model individual properties and different heterogeneous entities the quantitative model output with this approach is significantly higher than with macro simulation approaches like SD.

This is the main difference when we compare SD to MS. This difference can best be described by a population where SD always models the target system as individual wholes not distinguishing between, age groups, gender, regions, etc. Although Meadow's WORLD 3 was a step forward by implementing some age groups and the corresponding death and birthrate, the final system doesn't distinguish genders. The output of a system modeled at the individual level is, when having access to all the needed data, always a better version of the reality than an aggregated average building system.

3.2.1 History

Guy Orcutt developed this method in 1957 to illustrate economic systems. The problem with population models based on aggregated data is that there is an inevitably information loss in the distribution. That's why Orcutt suggested a model with various interacting units. The model works in a probabilistic manner generating the effect that identical units with the same inputs may produce different outputs. The proposed model included birth, death, marriage and dissolution. The model was implemented in 1961 with the help of his students and upgraded in the 1970s to a more sophisticated version called DYNASIM2. This model was used to model the financial situation of retired people in the United States. The latest update to this work remodeling the transition probabilities yielded in DYNASIM3. (Orcutt 1957)(Orcutt et al. 1961, 1976)(Favreault and Smith 2004)

Influenced from the work of Orcutt's DYNASIM other MS models all over the globe arose. CORSIM developed at the Cornell University in 1987 supported the United States Social Security Administration in their Social Security Reform Analysis. (Zaidi and Rake 2001)

Directly derived from CORSIM, DYNACAN, written in programming language C, was developed in Canada to model social security and retirement schemes. The model contains a set of demographic, education, income and social security modules. (Morrison and Dussault 2000) Another model developed in Canada is LifePaths allowing simulation of pregnancy, birth, cohabitation, marriage, divorce and mortality. (Zaidi and Rake 2001)

To model student loans in Australia DYNAMOD-2 was developed and then extended to address a wider range of policy debates about education and student earnings. It is a very flexible model allowing the user to specify fertility and mortality rates. (King et al. 1999)

To assist in Norway's policy development for financing public expenditures MOSART was developed in 1988. The model simulates the life course of a representative sample of the Norwegian population with respect to demographic events, education, labor supply and public pension benefits. (Fredriksen 1998)

Models like PENSIM and PENSIM2 have been developed to model and forecast the income of elderly people in the UK. (Hills 2006) Another important UK MS model initiated at the London School of Economics in 1999 is SAGE (Simulating Social Policy in an Ageing Society). It is designed to provide projections to inform the development of social policy in Britain for the twenty-first century, focusing on the implications of population ageing for pensions and issues regarding health and long-term care needs. SAGE is a full population model, and covers demographic processes, education, earnings, pension accumulation, health and disability. (Cheesbrough and Scott 2003)(Scott 2003)

Worldwide many other MS models have been developed and new ones seem to arise in an exponential rate. All these models are complex and resource intensive to develop and take years to complete. (Harding 2007) However today there is no generally applicable toolkit for MS modeling.

3.2.2 Process

The process when modeling with the Micro Simulation approach, as shown in Figure 19, starts with selecting a target population with all its properties. Because a population has many properties with lots of dependencies the first step is to create an abstraction of the target population. This abstraction consists of just some selected or probably needed properties to create all the effects of the target population. This abstraction is named representative sample. This sample is then simulated to get a predicted hypothetical sample, by applying transition probabilities to the individual cases. In each simulation step this simulation yields a predicted hypothetical sample. After a defined number of steps the generated samples are projected to get an estimation of the structure of the target population.

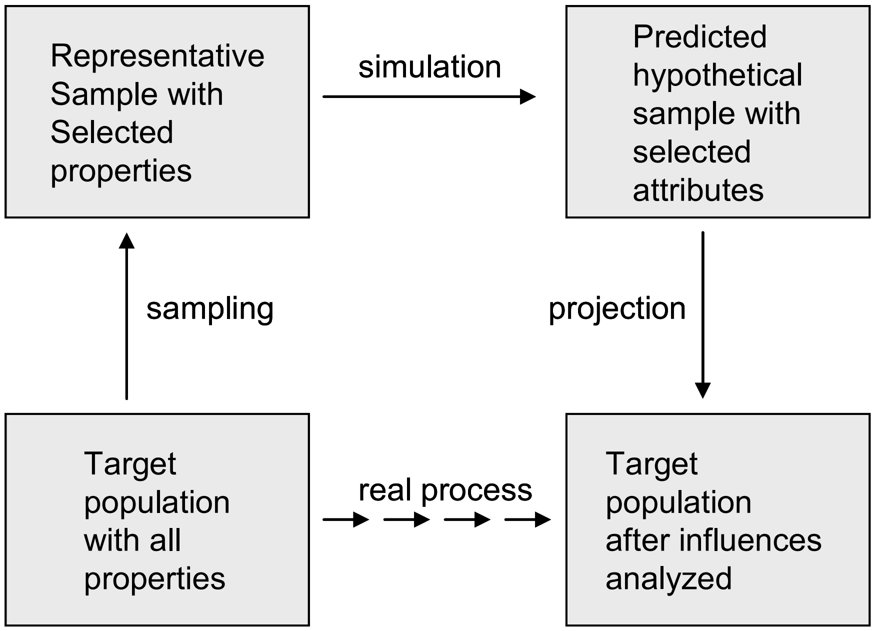


Figure 19: General procedure of Micro Simulation, according to Gilbert and Troitzsch (2005)

MS models consist not only of the individual level but also of an aggregate level. Because of the detailed information needed to simulate the populations this models are very data-based or data-driven. The most important point when modeling with MS is not only the collection of the data at the level of individuals but also the storing of it in the simulation. Because of the fast progress of computing power and with the availability of grid computing it is nowadays much easier to simulate large-scale populations.

The initialization of MS models is done by reading a micro data file and generating the starting population with all its characteristics contained in that file.

If we consider a population we can state that the typical properties of individuals are age, gender, employment, family state. In addition to this primary attributes there are some necessary ones that are needed to simulate a population like birth, death and migration. Each time step in the simulation contains several sequential or parallel processes. The simplest process that needs to be modeled is ageing. Each living individual's age is increased each time step. If an individual dies during a time step it is deleted from the data basis. Within the death process, death probabilities for each age group are applied onto the individuals to decide whether one will survive or die. These death tables can change during simulation. The same process is then applied to female individuals by applying birth tables to the age group from 15 to 45. When modeling births one should perhaps consider also following properties like nationality, social state of the mother, employment or education level. Next process would be immigration and emigration which can also be modeled by age dependent tables. With this primary processes a given population can be extrapolated. Because of the rapid changes in birth tables and death rates due to medicine and social improvements it is necessary to adjust these tables for each year or otherwise the model output will not truly reproduce reality. Even the central bureau of statistics in each country can't exactly predict future population distributions with their statistical methods.

During the simulation individuals will change their educational and employment status. They will enter and leave different schools and work in different jobs, earn a different amount of money and retire at different probabilities depending on their age.

These probabilities available in age dependent tables can be constant or can change over the simulation period. Considering the fact that a birth rate depends on the educational, employment and martial status or age it is impossible to extract all information just out of a birth statistic, because these statistics just show age dependent life bearings. Real dependencies of the properties can therefore not be completely adjusted. The same problem arises with death rates that can change over time due to medicine, technological and cultural changes and improvements. Adjustments to the model behavior when compared to reality are therefore very hard and time expensive.

3.2.3 Methodologies

There are several different methodologies for MS as shown in Figure 20 according to (Merz 1994).

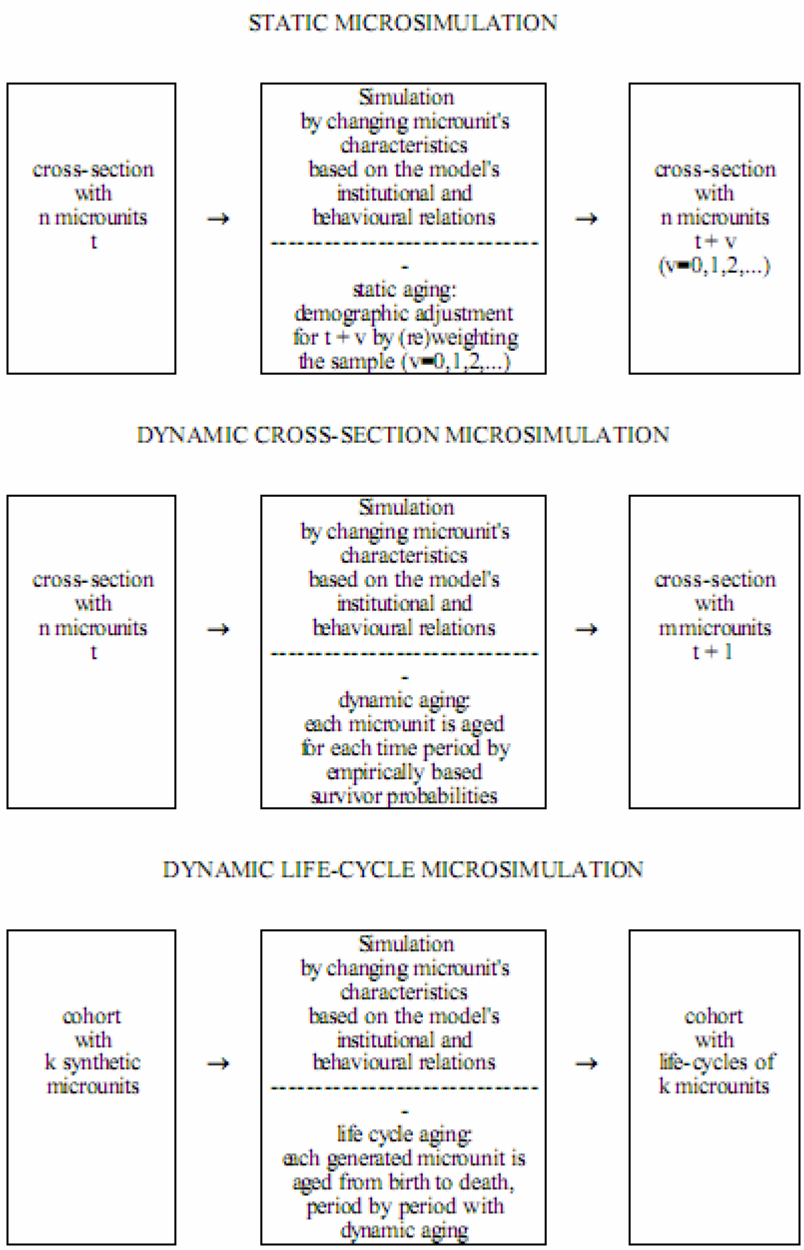


Figure 20: Types of Micro Simulation, according to Merz (1994)

3.2.3.1 Static Micro Simulation

In Static Micro Simulation (SMS) populations are changed by reweighing the distribution with external information for each available time step.

> *"…each individual data record in the micro data file is given a different weight for different years, so that the weighted file displays the age structure for all years." (Gilbert and Troitzsch 2005)*

This can be done to all available classifications for the distribution.

The main aim for this type of methodology is short term prediction to see the immediate impact of a policy change in populations. When doing these predictions only the direct influences concerning the policy question are rearranged and all others are kept equal. Sometimes hypotheses are formulated due to the behavior of the system like: Because of the sharp increase of the tax on luxury goods people won't buy those goods and government's revenue will decrease instead of increase.

3.2.3.2 Dynamic Micro Simulation

In Dynamic Micro Simulation (DMS) populations are changed by ageing the individuals individually each time step. New entries to the distribution are modeled by individual birth rates according to the age of women and deaths are modeled with individual death rates according to the age and gender of the individual. These death and birth rates are normally available through tables that can also be changed throughout the simulation. Therefore the demographic structures of the micro data file changes endogenously.

The main aim for this type of methodology is long term prediction of demographic changes in populations.

3.2.3.3 Longitudinal Micro Simulation

Longitudinal Micro Simulation (LMS) sometimes named dynamic cohort can be seen as a part of Dynamic Micro Simulation because this type of simulation is just applied to a specific age cohort and over the whole life of just this cohort. Children generated by this cohort can also be simulated. Starting with the selection of the specific age group a life cycle of this group is simulated to address just policy changes addressing this group. The Results of this simulation can then be seen as direct impact on policies if the mean individual is a winner or loser for this decision.

3.2.4 Software-Tools

For a long period of time general purpose language programs written by specialists served as simulation base for MS models. The big problem concerning these programs was they could only be changed and maintained by programming specialists. In recent years more and more MS models have been developed that are more suitable for average users. Some examples are listed below:

- MICSIM
- STINMOD
- DYNAMOD
- CORSIM

Because of the definition of both approaches, toolkits available for Agent BasedModeling (ABM) can be used to model MS models. Figure 21 shows the toolkits described in the ABM and MS section on a continuum. On the left end there are the MS models written in native language code such as C, C++ and Java like DYNASIM and SAGE. In the next abstraction level there are frameworks like SWARM and Java Agent-based Simulator (JAS) providing Java classes that can be altered to create new models. Then there are MS environments like ModGen. At the end of the continuum there are the scripting languages like NetLogo, Steve and Python.

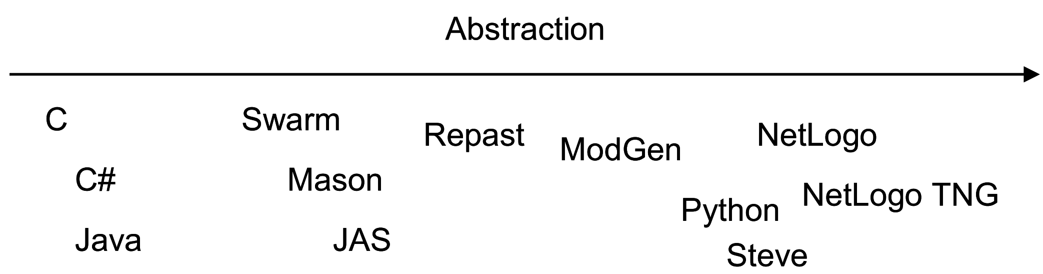


Figure 21: Micro Simulation and Agent Based modeling methods

3.3 Cellular Automata

Developed in the late 1940’s to model emergent behavior of cells situated on a grid, Cellular Automata (CA) are the simplest models of spatially distributed processes. Space, time and the states of the system are discrete. A cell can have any one of a finite number of states that are updated synchronously over all cells at each time step according to a local rule. These rules determine the next state of the cell that only depends on its own state one time step previously, and the states of its nearby neighbors at the previous time step.

This is one of the main differences when we compare CA to MS where the next state of an individual of a population does not depended on the neighborhood but on given probabilities.

3.3.1 History

The Cellular Automata (CA) approach was developed in the 1940’s at the Los Alamos National Laboratory in northern central New Mexico by the mathematicians John von Neuman and Stanislaw Ulam. The basic idea is to simulate the emergent behavior by cells, which interact locally with their direct neighbors, situated on a grid. Each cell is therefore a reactive element with a fixed amount of possible states that emerge from the predefined rules. Possible one and two-dimensional setups are shown in Figure 22. The type of neighborhood can be either a Von Neumann, just the direct neighbors count (left, right, above, underneath), or a Moore one, where all eight possible neighbor cells count like shown in Figure 23. All cells are homogenous and actualized simultaneous within a discrete period of time. (Hegselmann 1996)

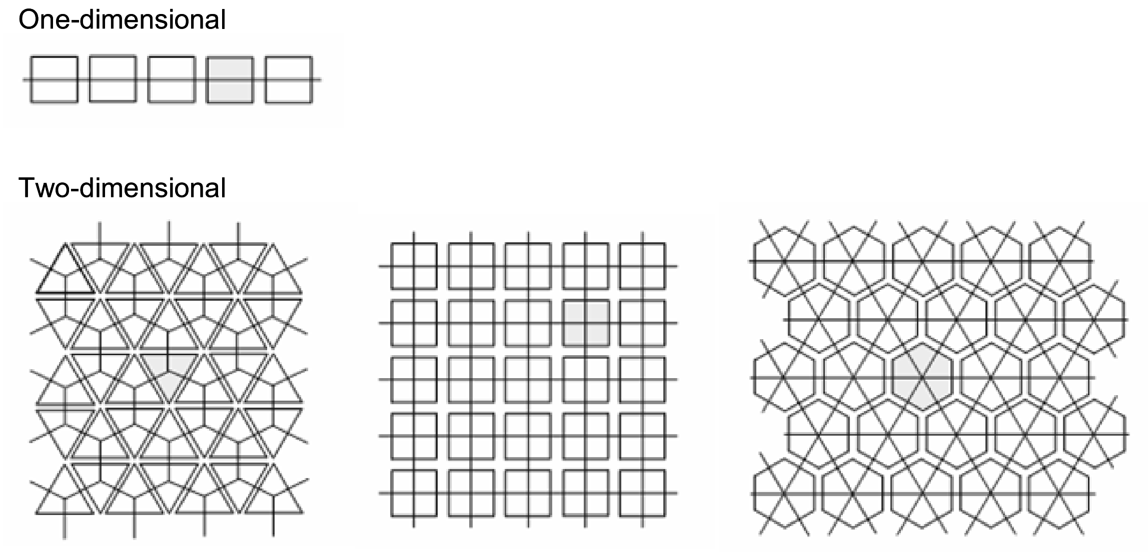


Figure 22: Possible one and two-dimensional setups for a Cellular Automata

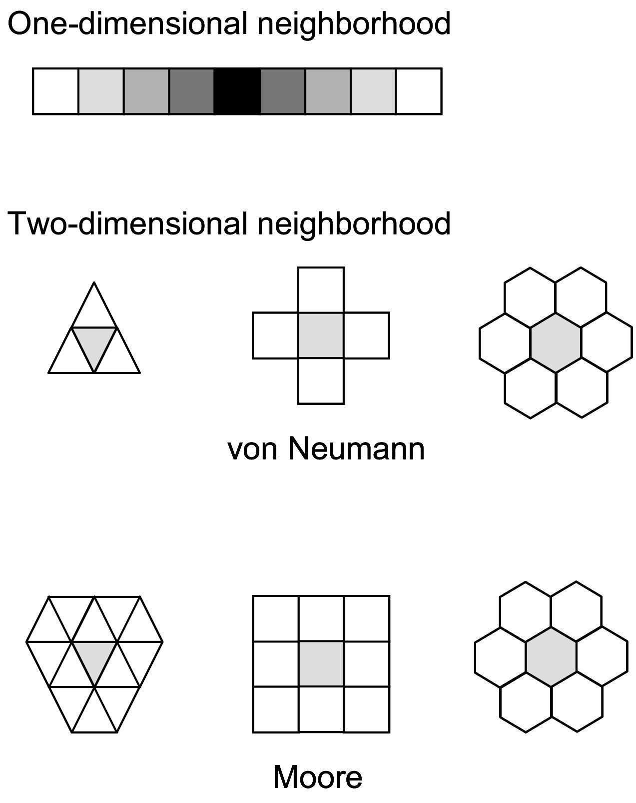


Figure 23: Types of neighborhood in Cellular Automata's

“A typical CA is a two-dimensional grid or lattice consisting of cells. Each cell assumes one of a finite number of states at any point in time. A set of simple rules determines the value of each cell based on the cell’s previous state. Every cell is updated each period according to the rules. The next value of a cell depends on the cell’s current value and the values of its immediate neighbors in the eight surrounding cells. Each cell is identical in terms of its update rules. A CA is deterministic in that the same state for a cell and its neighbors always results in the same updated state.” (Macal and North 2005)

According to Gilbert and Troitzsch a CA has the following features (Gilbert and Troitzsch 2005):

- It consists of a number of identical cells arranged on a grid. The number of used cells is not limited and can even extend to millions. The grid can be one, two or even three dimensional, either being a long line, a rectangular array or a cube.
- The cells evolve in discrete time steps according to the predefined rules and therefore can change their state each time step.
- There is a finite set of possible values for the cells. For example this can be on or off, alive or dead.
- The value of each cell evolves according to the same deterministic rules. These rules specify the next value of a cell depending on the previous state and the values of the cell’s immediate neighbors. They are computed simultaneously for all cells of the grid and therefore the model is homogenous.
- Rules for the evolution of a cell only depend on the local neighbors and therefore CA’s are best used to model situations where the interactions are local.

“With these characteristics, cellular automata provide rather general discrete models for homogeneous systems with local interactions. They may be considered as idealizations of partial differential equations, in which time and space are assumed discrete, and dependent variables taken on a finite set of possible values.” (Farmer et al. 1984)

3.3.2 Models

Till now CA's have been used in a variety of areas like physical science, biology, mathematics and social science. The two most popular examples of a CA are the Game of Life (GOL) from Conway and the simulation of human migration behavior from Schelling.

3.3.2.1 The Game of Life

Using all neighbors the GOL is an example of the Moore neighborhood. A cell in the GOL can only survive if there are either two or three active neighbor cells. With this given rules a cell either dies from overcrowding or from loneliness. There are three rules that define the next state of each cell in the GOL (Macal and North 2005):

1. The cell will be on in the next generation if exactly three of its eight neighboring cells are currently on.
2. The cell will retain its current state if exactly two of its neighbors are on.
3. The cell will be off otherwise.

Figure 24 shows a snapshot of a randomly generated grid with the GOL. The eight neighbor per neighborhood assumption can be seen as an agent interaction with just local available information and the ability to update the own state. Although the GOL has just simple and locally based information rules repeated simulations reveal a world of endless creations and led to the research of collective intelligence or swarm intelligence.

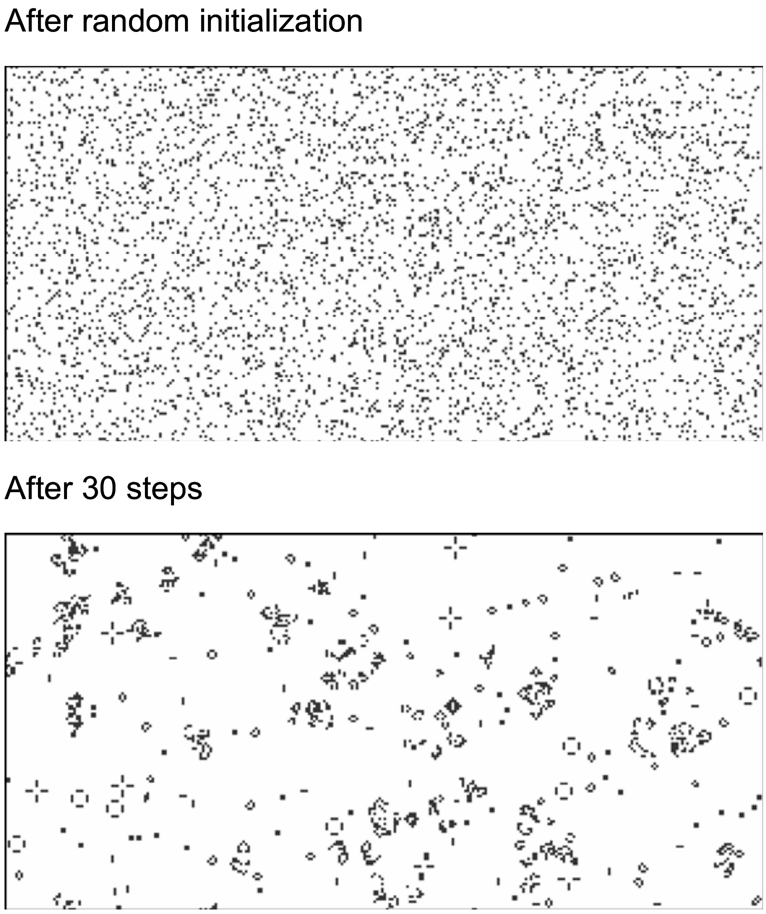


Figure 24: GOL snapshots with random initialization

To get an impression of how the GOL works an evolution over twelve time steps Figure 25 shows this evolution starting from a fixed pattern. If the sequence is continued to the fifteenth step the pattern will be the same as the first one. Therefore this sequence repeats every fourteen steps.

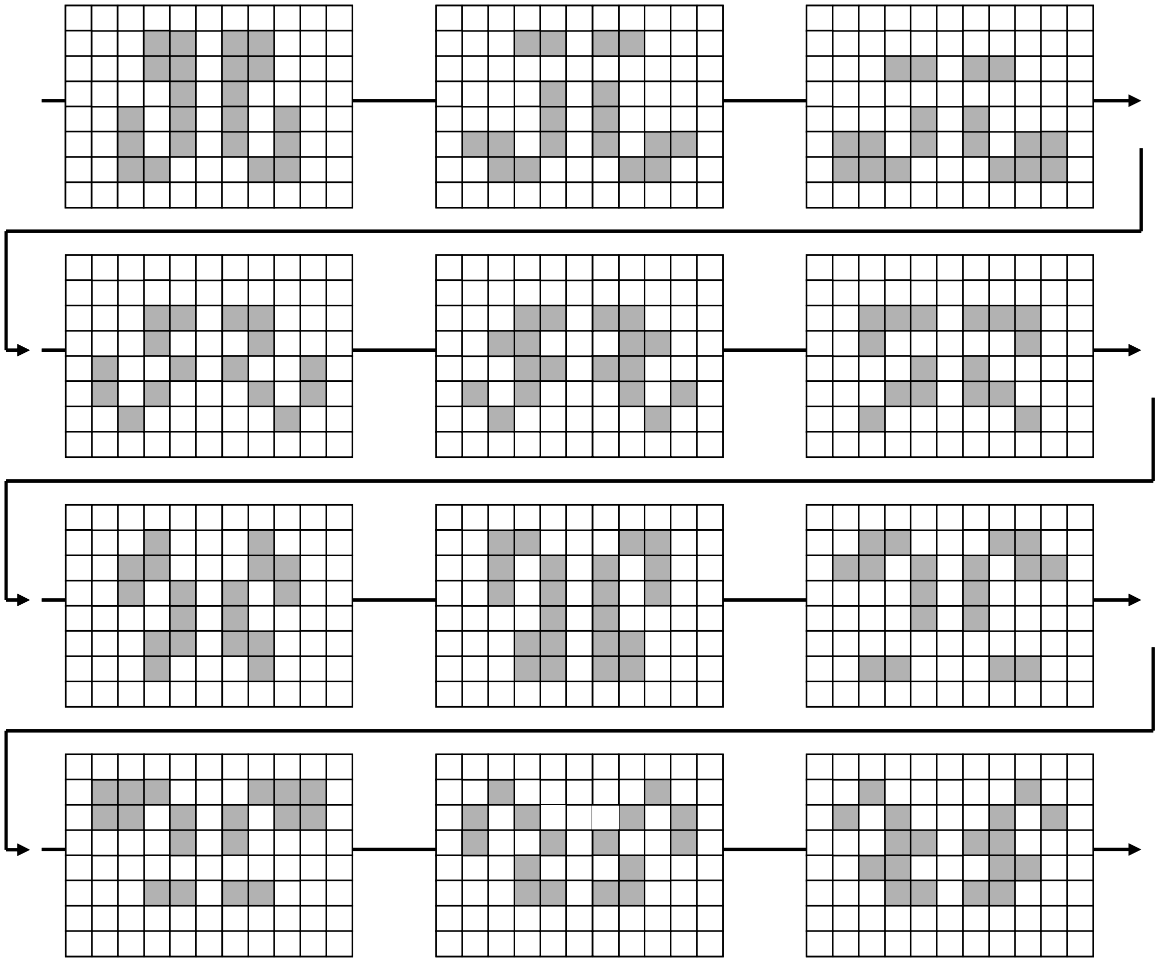


Figure 25: GOL evolution, according to Gilbert and Troitzsch (2005)

3.3.2.2 The parity model

Using only the four direct neighbors the parity model is an example for the von Neumann neighborhood. This model is used to model physical systems by using only one rule:

1. The cell becomes active if the sum of the active von Neumann neighbors plus itself is odd and it will become deactivated if the sum is even.

Figure 26 shows the evolution of this model from the starting pattern to the 119th time step. The evolution of this model is quite astonishing. After the start the pattern expands reaching a complex arrangement before collapsing into the starting pattern plus four copies, one at each corner of the starting block. Some steps later the complex pattern is created once again, until it collapses once more into the starting pattern plus 25 copies. The regularity of these patterns is due to the properties of the parity rules. (Gilbert and Troitzsch 2005)

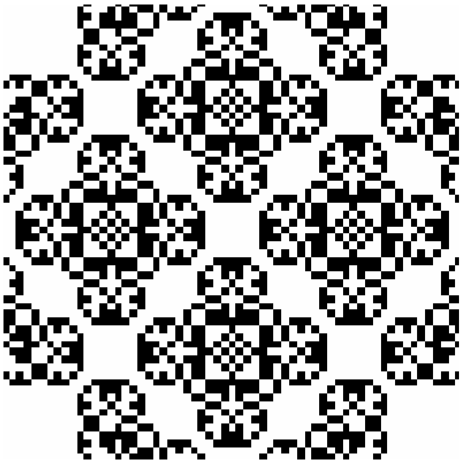


Figure 26: The parity model from starting after 119 time steps

3.3.2.3 One-dimensional models

The CA method is not limited to two or more dimensions. It is also possible to create one-dimensional models, where the cells are arranged along a line. According to (Wolfram 1986) there are only 32 different rules for a one-dimensional CA. Figure 27 shows a pattern emerged from only a single cell at time 0 at the top and moving down to step 120 at the bottom using rule number 22: A cell becomes active if and only if one of following four situations applies:

1. The cell and its left neighbor are active but the right neighbor is deactivated.
2. The cell and its right neighbor is deactivated but the left neighbor is active
3. The left neighbor is deactivated but the cell and its right neighbor are active.
4. The cell and its left neighbor are deactivated but the right neighbor is active.

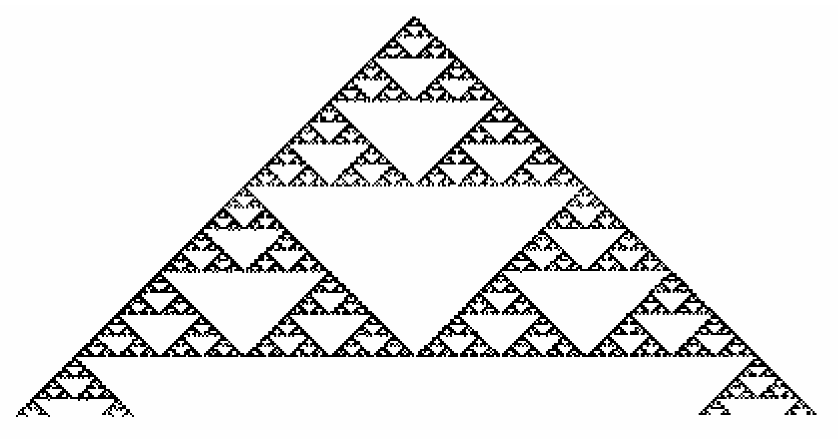


Figure 27: One-dimensional model emerging from rule number 22

CA's are able to simulate qualitative and quantitative issues and reproduce simple communication between the entities. The behavior on the macro level is simulated through the emergent behavior on the micro level. The structure, grouping and arrangement result out of the rules and form the basis for self-organization which can be verified in experiments. Due to the simplicity of cells (all are homogenous) and the global rules the ability to reproduce social system's behavior is quit marginal. Regarding feedback of cells Anderson states:

> *"each cell is constrained to interact with the same number of neighbors as every other cell; clearly, in social systems some individuals have many more ties than others do". (Bandte 2007)*

Because of this simplicity CA are quit limited in reproducing social systems.

3.3.3 Software-Tools

There are no widely available packages to run CA models except from the variations of the Game of Life. Because of the limits of this model to social simulation it is therefore not suitable for modeling. In order to experiment with CA one needs to have some programming skills for creating models, either by using a programming language like C, C# or Java or by using a specialized product like NetLogo. Although programs written in C or C++ would probably run much faster it is much easier to create and debug models in NetLogo.

3.4 Agent Based Modeling

3.4.1 History

Agent based modeling (ABM) has many connections to other fields like, system science, complexity science, System Dynamics, management science, social science and traditional modeling and simulation. The roots of ABM can be traced back to Cellular Automata (CA) and the field of Complex Adaptive Systems (CAS) with the underlying notation to build a system from the ground-up in contrast to the top-down view of System Dynamics (SD). The field of CAS concerns itself with the question of how complex behaviors arise in nature among myopic, autonomous agents.

Based on the concept of the Von Neumann machine the physicist Stanislaw Ulam developed a model represented by cells on a grid. This was the first notation of CA. A simple game developed by the mathematician John Conway, the Game of Life (GOL) based on CA was the next improvement. (Macal and North 2005)

Although ABM and CA share the same characteristics simulating complex systems behavior there are a few important differences:

Time:

Agent’s actions need not to be performed synchronously because there is no fixed schedule for entity actions.

Environment:

Agent based modeling is not necessarily bound to a grid environment.

Mobility:

In CA the cells are total immobile and attached to their neighbors whereas agents can either be mobile or immobile.

Properties:

In CA the cells all share the same set of properties whereas in ABM the agents can have different properties within a system.

Knowledge about CA and the field of CAS can help one build an agent based model. The development of agent based models is also linked to the vast progress in hardware and software technology, because large models take a long time to simulate even with simple rules. Since the early 1990s ABM is being used within social sciences especially in economics, political science and sociology. Therefore there are various fields where ABM is used like, biology, ecology, medicine, geology, politics and sociology. Macal and North mentioned the range of applications from modeling stock markets, supply chains to predicting epidemics and bio-warfare and from consumer behavior to the fall of ancient civilizations. Schieritz and Milling added the analysis of traffic flow and the study of animal behavior. Billari et al. mentioned interdisciplinary fields such as economic-physics and sociophysics that deal with problems like traffic systems, moving crowds or environmental planning.

There is a wide range of definitions and understanding of agent based modeling in the literature and they are quite different. Following terms are addressed to the ABM term in literature: agent-based modeling (Epstein and Axtell 1996), agent-based simulation modeling (Judson 1994), multi-agent simulation (Ferber 1999)(Bousquet 2001), multi-agent-based simulation (MABS) (Edmonds 2001), agent-based social simulation (ABSS) (Doran 2001)(Downing 2001), individual-based modeling (Gilbert and Troitzsch 2005) and multi-agent systems (Downing 2001). Throughout these definitions there are two important conceptual distinctions, which derive from the three heritages of ABM: (Epstein and Axtell 1996)(Doran 2001)

- Interactions are the most important phenomena to be modeled.
- Deliberative social cognition is the most important phenomenon to be modeled.

(1) Individual-based modeling (IBM):

Populations of organisms are simulated through discrete unique individuals.

(2) Artificial life (A-life) simulation:

Lifelike behaviors at the macro scale are modeled by simple interactions at the micro scale.

(3) Distributed Artificial Intelligence (DAI) / multi-agent systems:

Many autonomous, social, communicative, reactive, pro-active agents form a system. Agents use their abilities to interact and/or change the environment.

Figure 28 summarizes how the terms would fit along a continuum according to the interaction.

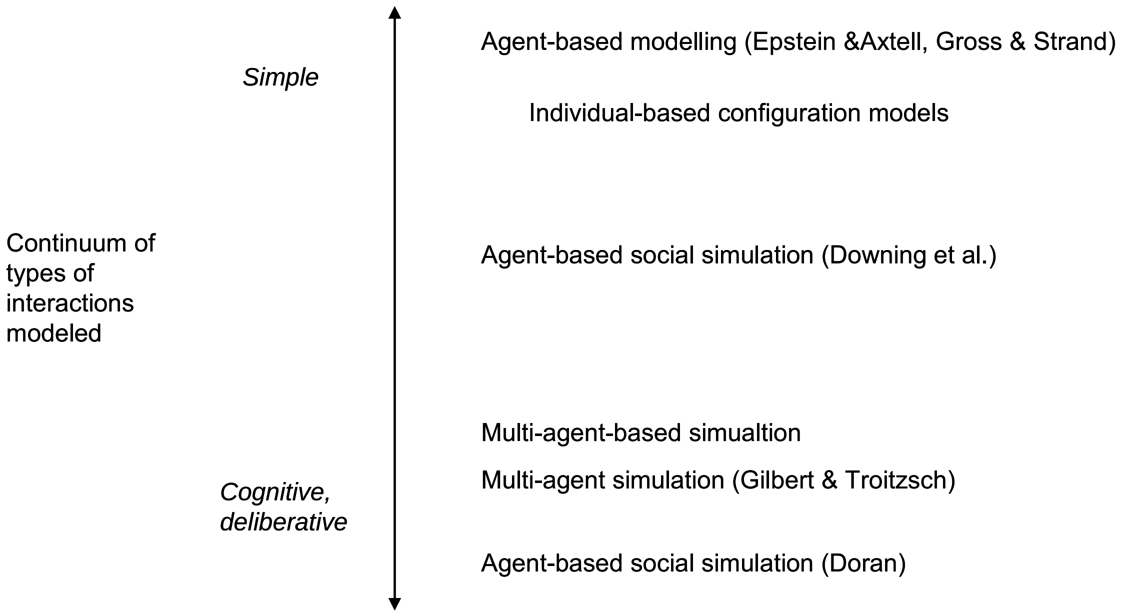


Figure 28: Agent based continuum, according to Hare and Deadman (2004)

3.4.2 The Basics

Agent Base Modeling (ABM) is a so called “bottom-up” approach where the point of view to describe and model a system is set to lowest level. The individual entities situated at this level are called agents and build the basic building block of this approach. The global system's behavior emerges from the behavior of the agents, their rules and interactions. This process is called emergence and is a major benefit over other modeling approaches. (Schieritz & Milling 2003)

> *"Emergent phenomena result from the interactions of individual entities. By definition, they cannot be reduced to the system's parts: the whole is more than the sum of its parts because of the interactions between the parts. An emergent phenomenon can have properties that are decoupled from the properties of the part. For example, a traffic jam, which results from the behavior of and interactions between individual vehicle drivers, may be moving in the direction opposite that of the cars that cause it. This characteristic of emergent phenomena makes them difficult to understand and predict: emergent phenomena can be counterintuitive." (Bonabeau 2002)*

Generating this behavior is the most complicated part when modeling with agents.

Although there is no unique definition of the term agent section 3.2.3.1 gives a summary over the agent term used in literature.

3.4.3 Modeling Process

The process of modeling an agent based system is quite similar to other modeling approaches although there are no standard formalisms or procedures for model development and agent representation such as those in System Dynamics. There is also no scheme for representing an agent based model. Agent based modeling can benefit from the Unified Modeling Language (UML), a visualization for representing object oriented models, to represent models and help in designing within the communication phase. A short description of UML is given in 3.2.4. (Macal and North 2006)

In addition to standard modeling tasks one has to consider some extra steps when modeling an Agent Based Modeling System (ABMS) like Macal and North identified: (Macal and North 2006)

1. Agent identification

   Identify the agents and get a theory of their behavior. Agents can be simple individual or complex entities and generate the emergent behavior of the system and can therefore be seen as the basic building block.

2. Agent relationship

   Define the agent relationships and their interactions and get a theory of agent interaction.

3. Agent data

   Get all the needed agent-related data.

4. Agent behavior validation

   Validate the agent behavior in the models in addition to the model as a whole.

5. Analyze output

   Analyzing the output from the standpoint of linking the micro-scale behavior of the agents to the macro-scale behavior of the system is essential after each simulation run.

In general an agent based simulation runs through several stages. First the concept development and articulation stage define the global project goals. Specifying these goals is done in the requirements definition stage. Model structure and functions are defined in the design stage. Using this design the model is build in the implementation stage. At last the operationalization stage puts the model into use. A typical agent based simulation iterates over these stages several times, to get more insight and detailed models. (Macal and North 2006)

3.4.3.1 Agent

There is no unique meaning or definition for the term agent in literature at all. In business economics literature the agent term is used to describe transactions between actors. In the last years the term software agent emerged in internet applications. Those agents (so called soft bots) are used for the information retrieval like searching for products and their prices on different internet shops. In artificial intelligence science the term agent can be found in different areas. The perception goes from the robotic point of view where agents are reactive systems that can perform task in an environment to stay alive (Brooks 1991, to cooperating problem solvers whose behavior can be triggered from a higher abstraction layer (Bamberger 1999). Jennings and Wooldridge state an agent based system as a system whose basic concept is that of an agent. Every multi agent system is therefore an agent based system but not vice versa. Although the lack of a unique definition of what makes a system to become an agent Franklin and Graesser stated (Franklin and Graesser 1997):

> *"An agent is a system situated within and a part of an environment that senses that environment and acts on it, over time, … and so as to effect what it senses in the future" (Franklin and Graesser 1997)*

This definition is neither quite specific nor meaningful and so Wooldridge demanded to describe the agent term via its attributes like it is done with complex systems.

Following properties of an agent can be found in literature:

Identification:

An agent is an individual with a set of characteristics and rules that describe its behavior. There should be no problem to identify an agent and its resources within an Agent Based Model.

Autonomy:

A task assigned to an agent is always executed autonomous within the given environment. For Russel and Norvig an agent can then be considered as autonomous when his behavior depends on experiences learned through past processes (Russel and Norvig 2004). For Castelfranchi autonomy can be stated even when there is only a weak specification of self steered actions (Castelfranchi 1998). For Henning the ability to learn from behavior of the past is not a necessity to describe autonomy. So we can consider that an agent acts neither fully autonomic nor complete addicted.

Communication:

To be able to perform tasks an agent uses a protocol to interact with its surroundings. The communication protocol provides a formal language for the interaction with other agents and the environment. An agent has therefore the ability to sense and change his environment through sensors and effectors. The agent must be able to cope with the changes in his environment. (Wooldridge and Jennings 1995)

Situation:

An agent can only exist in a defined environment. As mentioned before an agent must be able to cope with changes within the environment performed by him or other agents.

Knowledge:

Actions performed by an agent are based on knowledge. An agent has the ability to store appropriate data in a memory and adepts his behavior based on experience or available information. When information is incomplete or faulty an agent may create a defective opinion and this leads to a wrong behavior. (Gilbert and Troitzsch 2005)

Goals and Strategy:

Agents try to reach self defined goals by using strategies to reach these desired objectives. They create sub goals and decide on their own which path to take to fulfill their requirements. The selected path needs not to be the best or optimal one and must be adapted over time according to the constantly changing environment. (Billari et al. 2006)

Emotions:

From today’s point of view it is not quite clear if emotions can be illustrated with a computer. Agents may be equipped with variables that correspond with human properties such as joy, fear or rage. Those variables are adapted with psychological rules and correspond directly to the agent’s behavior.

Anthropomorphisms:

Agents can have human behaviors by trying to reconstruct the mental mindset like visions, wishes, loyalty or fidelity. This denotes a high potential for simulations of social systems and is therefore a highly discussed theme in social science. (Gilbert and Troitzsch 2005)

Intelligence:

Franklin and Graesser identified three influencing variables for the intelligence of an agent like, the amount and quality of knowledge, the ability drawing consequences on previous experiences and the ability to learn. The learning ability can be seen as the ability to adept its reactions to the environment. (Franklin and Graesser 1997)

This list is not exhaustive but gives a good overview to possible attributes of agents. Considering the diverse nature of agents makes modeling with this approach particularly interesting:

> *" ... agents are diverse, heterogeneous and dynamic in their attributes and behavioral rules. Behavioral rules vary in their sophistication, how much information is considered in the agent decision (cognitive "load"), the agent's internal models of the external world including other agents, and the extent of memory of past events the agent retains and uses in its decisions. Agents also vary by their attributes and accumulated resources" (Macal and North 2005)*

3.4.3.2 Agent classes and architectures:

In literature the term agent class or agent architecture is used to describe the agents and their behavior in the model. For this aspect Brassel et al. gives a summary of possible agents and differs between three different classes (Brassel et al. 1997):

(1) Reactive agents:

They react on messages from their environment by sending messages to others and actualize their inner state. The message rules are fixed and can't be modified by an agent.

(2) Intentional agents:

In addition to reactive agents, intentional agents can change and set their own goals. They are able to plan new goals and ways by recognizing conflicts.

(3) Social agents:

In addition to intentional agents, social agents have the ability to recognize the way other agents act so they can predict their behavior.

Similar to the term agent class Ferber identified three different types of agent architectures to describe the internal organization of an agent (Ferber 2007):

(1) Reactive architectures:

Reactive agents have no explicit representation of their environment and of other agents and behave in terms of stimuli-response loops. Agents have no developed cognitive function and the conative one is reduced to simple response operations on perceived input. There are three known architectures in this domain: *subsumption architecture* where tasks in competition are arbitrated along predefined priorities, *competitive task architectures* where tasks weight is modified through a reinforcement process and *connectionist architectures* which are based on neural nets. Some approaches try to combine these architectures.

(2) Cognitive architectures:

These architectures are based on the metaphor that agents reason from knowledge, that explicitly represents their environment and other agents, described with a symbolic formalism. The BDI (Belief-Desire-Intention) architecture is the best known one, where agents are characterized by beliefs, goals and intentions. Cognitive agents are intentional in the way that they intend to perform their actions to satisfy their goals. BDI agents act rationally on their beliefs about world states, their knowledge and their intentions to achieve the desired goals. This architecture has been used in several applications of military simulation like modeling a combat pilot or the tactical rules of a terrestrial control team. Another application was the game Black & White where the interactive aspect of the game characters was modeled through a BDI.

(3) Hybrid architectures:

A combination of the above architectures results in a hybrid one to build more flexible architectures. Agents are composed of modules which deal independently with the reactive and cognitive aspects of agent behavior. Ensuring the systems balance is the most difficult aspect when using such models.

3.4.3.3 Rules

To describe procedural aspects of behavior one has to define rules on how agents have to act in certain situations. There is always a condition and a concerning action. The condition has to be fulfilled before the dependent action with its activities is performed. We can state for each agent, that if the condition is true an action has to be performed.

Literature differs between two major types of rules, local and global ones. The global rules act on the macro level. On the other hand local rules are on the micro level to reach global optima's. (Haslett et al. 2003)

3.4.3.4 Environment

The environment is the "world" for the agents and describes the properties and processes for the agents within they can act and can therefore be considered as fundament for their existence. Following specification of environments can be distinguished: (Russel and Norvig 1995)

Accessible vs. Inaccessible

In an accessible environment all information concerning the behavior and goals of the entities is available for the agents.

Deterministic vs. Non-deterministic

A deterministic environment is characterized by a fixed sequence of actions and objects, like in a supply chain.

Discrete vs. Continuous

An environment can be considered as discrete when there is a fixed amount of actions and objects.

Static vs. Dynamic

A static environment never changes during the simulation process. In a dynamic environment the amount of agents and their properties can vary during the simulation for example when modeling populations.

Homogenous vs. Inhomogeneous

In homogenous environments the agents have the same properties, goals and rules.

3.4.3.5 Interaction

The term interaction is described by separating it from communication and transmission. In case of transmission an agent sends information to a second one, that doesn't receive it, whereas in communication the second agent receives the information without reacting on it. An interaction takes place when an agent sends information to another one that receives it and responds onto it. This is defined as feedback and the key concept in complex systems. These concepts are illustrated in Figure 29. (Wooldridge 2000)

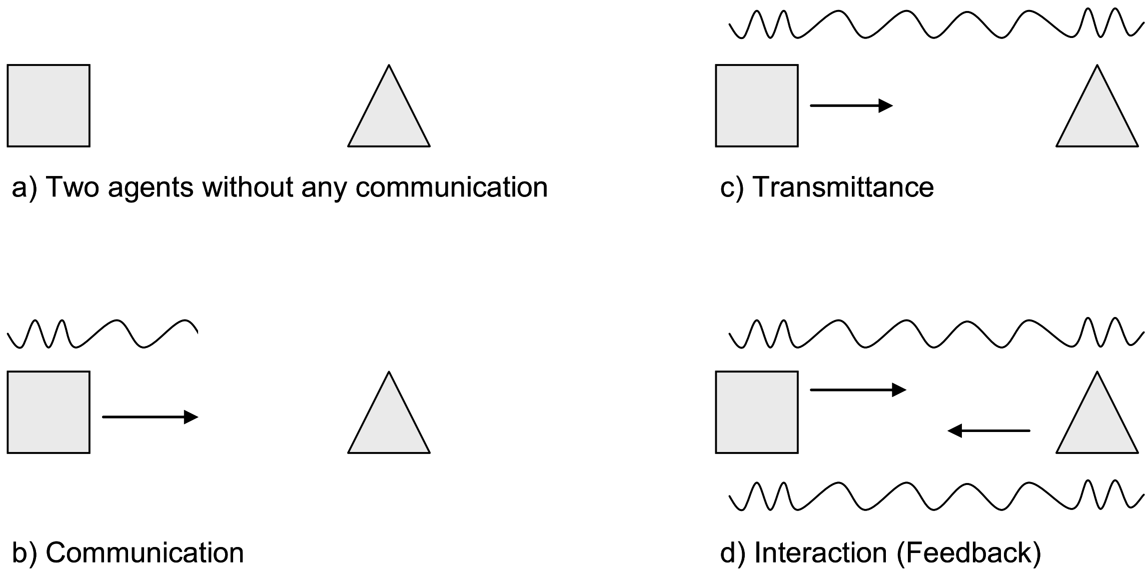


Figure 29: Agent interaction, according to Bandte (2007)

3.4.4 Agent Based Modeling Tools

There is no global modeling tool available for agent based modeling but Unified modeling language (UML) can be considered as a helpful toolset as mentioned above. UML is the accepted standard in industry for the object oriented methodology.

> *"Contrary to objects which systematically invoke a method when they receive a message (which is usually not a "message" in the standard meaning of the world but a method invocation), agents attempt to improve a satisfaction function or to achieve a goal, thus triggering an action on their own and, conversely, agents may refuse to answer requests. But, as an agent may be seen as the evolution of objects, it is interesting to see how standard object oriented methodologies such as UML may be used within the agent oriented paradigm." (Ferber 2007)*

There are a set of diagrams: static diagrams that describe classes, properties and methods and dynamic diagrams like the activity, sequence or states diagram model evolution and interaction. For the agent based formalism the class diagram, that describes classes and their relations, seems to be the most suitable diagram to describe entities and their relation. UML describes objects and not agents per se, and so does not allow the designer to remain at the right conceptual level. The dynamic diagrams and within these the sequence and the collaboration diagram can be used to describe the behavior of entities. (Ferber 2007)

> *"One of the main qualities of the UML notation is to be very expressive, and above all to offer a common language, which can be easily understood by both computer scientists and modelers. This is the reason why this formalism tends to develop in the domain of multi-agent modeling and simulation. However, there is a major downside in UML: the confusion between modeling and implementation, by mixing together in a same diagram both aspects" (Ferber 2007)*

3.4.5 Software-Tools

There are various development environments and software kits for agent based modeling. In general following requirements for agent based software can be summarized: (Bandte 2007)

- Independence from a specific social theory.
- Transparent visualization of processes and rules.

- Supporting the identification, manipulation and documentation of the selected abstraction.
- Ability to verify and validate the simulation model and support due to the interpretation of the simulation output.

Three different types of implementing an agent based model can be differed: (Bandte 2007)

(1) General-purpose languages:

These languages like JAVA, C++ or C# are widely accepted in the software development community but there is no preferred one when creating simulation models. The object oriented programming (OOP) paradigm and the ability to create dynamic models is the major benefit of these languages. The big disadvantages are the needed programming skills even when creating simple models and the need of redevelopment of the basic algorithms for each application.

(2) Class libraries:

Based on general-purpose languages libraries like Ascape or SWARM have been developed to solve the problem of redeveloping the basic routines. Nevertheless appropriate programming skills are still essential.

(3) Software packages:

In the last years software packages and toolkits increased their importance in developing agent based models and today there is a large number of proprietary and non-commercial development environments available. The goal of such packages is to alleviate the work of modelers by supplying a standard development environment and graphical user interfaces with known elements or parameter editors. Small and not to complex models can be build very fast without special knowledge.

When modeling large and complex social models with the agent based modeling approach one must be able to develop his own simulation framework by using a general-purpose language in combination with some class libraries. It is also advisable to use high performance computing systems or even clusters when simulating large scale models. Some of the most popular software toolkits are described below.

Ascape:

A Java based Swarm like agent based simulator. Java skills are required to build advanced models but some complex models can me modeled without the need of specific programming skills.

Breve:

Available under the GNU public license (GPL) source code it is a 3D simulation framework for artificial life and decentralized systems based on Python's scripting language. It is designed for modelers with no or limited programming skills.

Cormas:

Based on Visual Works programming environment, Cormas is designed for applications in ecological and natural resource interactions.

MadKit:

Free for non-commercial applications and licensed under GNU General Public License MadKit provides a Java framework for developing multi-agent simulations based on the concepts of observer, group and agent.

Mason:

Developed for multi-agent simulation this framework provides Java libraries and features like Swarm. Opposite to Swarm it is designed for execution speed.

NetLogo:

Used in the area of modeling natural and social phenomena NetLogo provides a Java framework to build models with static or mobile agents situated on a visual grid. The good documentation, the ease of use and lots of library models make this one of the more accessible platforms.

Sugarscape:

Used to simulate emergent behavior of economic systems this social science simulator simulates moving agents on a grid consuming simulated sugar and food.

SWARM:

This system is used to simulate swarm behavior of moving agents. Today available in Java this original agent based simulator was originally written in Objective C. Good Java skills are needed when extending given or modeling new models.

3.6 Comparison of the approaches

All the technique described above will now be compared to each other. To characterize the approaches, the major differences are summarized in Table 4 according to the classification of Troitzsch (1990) and Marietto et al. (2003, 2004) the following comparison of the approaches in social science simulation is based on Bandte (2007), (Gilbert and Troitzsch 2005) and (Martischnig et al 2008).

Table 4: Comparison of social simulation approaches

	System Dynamics	Micro Simulation	Cellular Automata	Agent Based Modeling
Time Dependency	reminiscent	reminiscent	reminiscent	reminiscent
Time Coherence	approximately continuous	discrete	discrete	discrete
Solution procedure	simulation	simulation	simulation	simulation
Level(s)	macro	micro and macro, without feedback	micro	micro
Main Purpose	explanation, prediction	prediction	explanation, prediction	explanation, prediction
Function	non linear	non linear	rule based	rule based
State Change	deterministic	stochastic	deterministic	deterministic, stochastic
Model output	qualitative, quantitative	qualitative, quantitative	quantitative	qualitative, quantitative
Number of modeling levels	1	2	2	2+
Communication between agents	no	no	yes	yes
Complexity of agents	low	high	low	high
Number of agents	1	many	many	many
Adaptation	weak	strong	strong	strong
Perspective	Top-down	Bottom-up	Bottom-up	Bottom-up
Mathematical formulation	Equation based	Equation based	Equation based	Equation & Logic based

The main elements for model classification are described in section 2.2.2. For model display format and model perception no explicit grading of the approaches could be achieved. The number of modeling levels considers the amount of capable modeling levels (individuals and aggregate ones) and their interaction. Emergent behavior can just be modeled with techniques capable of modeling two or more levels. When interaction and language are a considered part for modeling some approaches offer the ability to model this kind of communication. Most techniques are able to handle the large amount of agents that are needed to simulate social systems, except for SD that is oriented to develop models for a whole system being the only agent. The adaptation represents the ability of adding details to the simulation without redeveloping the structure of the model. This is quite hard when thinking of adding more and more information or details to a SD model compared to a MS or AB model. Another part concerned with adaptation is the ability to change a model's structure over the simulation process. SD models have a fixed structure and therefore can not be modified during the simulation process but by nonlinearities shifts of loop dominance can be generated. When simulating with agents, adaptation of their properties and behavior can easily be implemented. Such a change in structure can be achieved by using evolutionary or genetic algorithms. The model perspective can either be Top-down like in SD or Bottom-up like in all other approaches. Top-down means to look at the system as a whole and model the structure of it whereas a Bottom-up approach models each individual element and gains information about the system when all individuals are aggregated. Thus emergent behavior can just be modeled with Bottom-up approaches. Models based on Equations like differential equations or probability tables are precise and have an unambiguous mathematical meaning. Let's consider SD where the inflow minus the outflow of a stock is defined by differential equations. For AB models there is usually no formalism provided for the mathematical description and therefore most ABM formalisms are logic-based.

Based on the level of modeling the techniques can be separated into macro and micro level modeling approaches. MS, CA and ABM operate at the micro level whereas SD operates on the macro level.

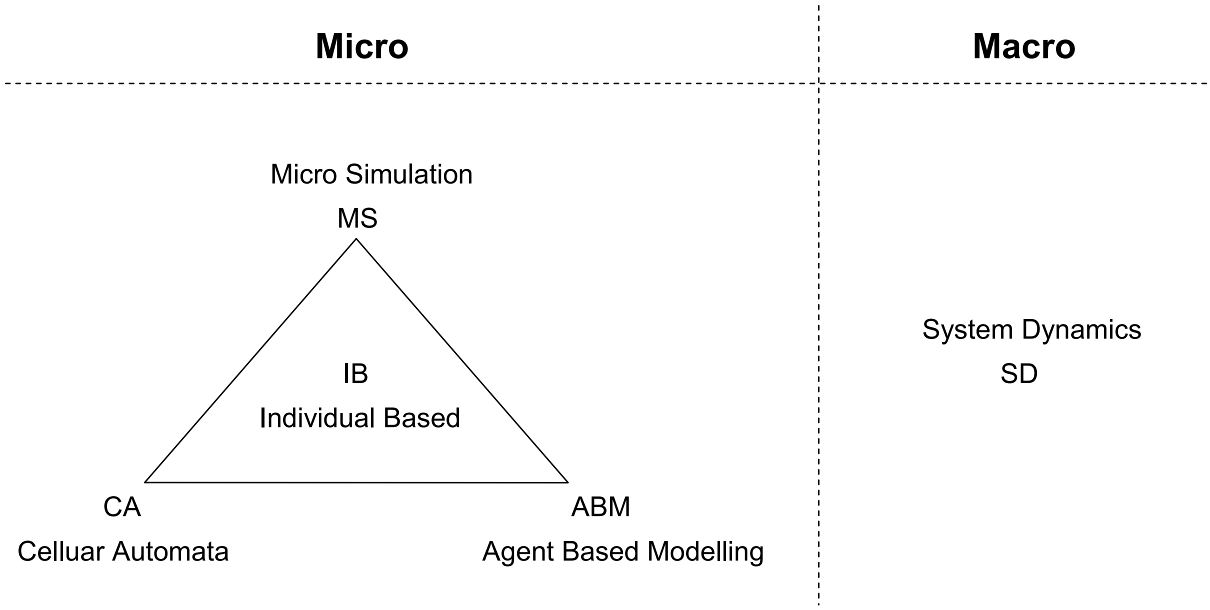


Figure 30: Micro (Individual Based) versus Macro Simulation

Individual Based (IB) and in this case MS and ABM can best be compared to SD when considering a population based model. Several variables would form our model like sex/age groups. To simulate deaths and births sex and age-group-specific death and fertility rates would be applied onto those groups. If the interest is just the age structure of a population, this deterministic macro model might be sufficient because, with a very large number of persons, all random influences on individual births and deaths (and other events that might be of interest) would be averaged out. Using additional information, for example different fertility rates for different education levels, the model would get very complicated in system dynamics with a large number of level and rate variables that could not be decomposed or otherwise simplified.

The IB simulation approaches overcome this problem by going to the individual level, modeling individual persons with a number of attributes like sex, age, martial status or education and a number of transition probabilities and or interaction. This makes up a stochastic micro model, as opposed to the deterministic macro model of the system dynamics approach. In simple cases, especially in demography, both approaches will produce approximately the same result. There would be the same prediction for age structure, given that the birth and death probabilities of the macro model are compatible with the respective probabilities of the micro model. (Gilbert and Troitzsch 2005)

In today's literature it is sometimes not quite clear what authors mean when talking about an agent based model, because Micro Simulation models are also considered being agent based ones. To differentiate between the three IB modeling approaches Table 5 shows a detailed comparison according to Bandte (2007).

Table 5: Comparison of Individual Based simulation approaches

	Micro Simulation	Cellular Automata	Agent Based Modeling
Dynamic	yes	yes	yes
Path dependency	yes	no	yes
Variety	yes	partial	yes
Feedback	no	no	yes
Non linearity	yes	yes	yes
Candidness	no	yes	yes
Self organization	no	yes	yes
Emergence	no	yes	yes
Autopoiese	no	no	yes

4 Healthcare Modeling

4.1 Reductionism Hypothesis

One of the most valued and successful methods of science is analysis, trying to dissect a process or phenomenon into its components and dissecting this components into its components until the point is reached where one cannot go any further. (Mayer 1988)

Derived from his work Mayer states:

> *"… after having studied the function of the liver as a whole, I learn a great deal more by studying what goes on in individual liver cells, and finally by determining which molecules play which role in the different organelles of the liver etc." (Mayer 1988)*

This analytic process is referred to reductionism, which refers to the classical Newtonian assumption to understand the dynamics of any complex system by studying the properties of its parts. Therefore complex systems are broken down into their components and each piece is studied individually. The challenge is to find the entry points from where to address the particulars of the system, because after knowing the parts, the dynamics of the whole can be derived. (Østreng 2004)

The limits of reductionism:

The limits of the old term of reductionism can be addressed when system cannot be understood just by examining their parts, because of the behavior or interconnecting behavior of the parts. Thus breaking down complex systems into their individual components by the method of reductionism can sometimes only be a first approximation and makes it necessary to use the holism way to put the pieces together. Weinberg also states:

> *"… as one goes to the higher and higher levels of organization, new concepts emerge that are needed to understand the behavior at that level." (Weinberg 1987)*

Holism:

This term was originally introduced 1926 by the South African statesman Jan Christian Smuts. He wanted to argue against reductionism by stating, that a unity of parts could be so

> "*… close and intense as to be more than the sum of its parts; which not only gives a particular conformation or structure to the parts, but so relates and determines them in their synthesis that their functions are altered; the synthesis affects and determines the parts, so that they function towards the whole" (Smuts 1926)*

The theory of holism is concerned with the phenomenon or process and with complex interactions within it rather than with the study of isolated parts. The assumption underpinning this approach is that the properties of the parts contribute to our understanding of the whole, but the properties can only be fully understood through the dynamic of the whole. Therefore the research focus in holism is on the relationship between the components, i.e. on their interconnectedness, interdependencies and interactions. Holistic interpretation proceeds from the whole and relationships are presented as non-directional or non-linear. It is therefore holistic to assert that the whole is more than the sum of its parts. (Østreng 2004)(Chandler 1995)

Including holism:

Holism is neither a contrary nor an opposing theory but it is adding value to the reductionism theory and this concession has been done by adding the existence of emergent behavior to the new term of reductionism. So these two theories are rather supplementing than conflicting each other. Østreng states:

> "*The one focuses on the properties of parts, the other on the relationship between them. Put together, they stand out as supplementary rather than conflicting, as inclusive rather than exclusive." (Østreng 2004)*

In analogy when thinking of the GOL in section 3.3.2.1 it requires a kind of holistic viewpoint to recognize the patterns of emergence, but however without a reductively viewpoint the nature of the appearance of those patterns would remain concealed and you might only find a superficial pattern without understanding the system. And vice versa when looking at the system reductively you just will understand how the system works but not the larger consequence it entails.
This is like Einstein's stated on a symposium of science, philosophy and religion in 1941: *"Science without religion is lame, religion without science is blind"*.

Reductionism enables us to see the static connections between parts of larger things, and sometimes to understand how they work together dynamically also. (Adams 2006)

Holism enables us to see the patterns of behavior among collections of objects whose larger thing is unknown or may even not exist. (Adams 2006)

Based on this thesis the global model for a healthcare system is described below.

4.2 Global Model

In order to make the model not uncontrollable by the large number of dynamic influences as drafted in Figure 1, but nevertheless integrating all necessary influences to generate valid outputs and explainable phenomena, the developed model consists of three main exchangeable modules and a fourth one to compare simulated scenarios from both sides as shown in Figure 31.

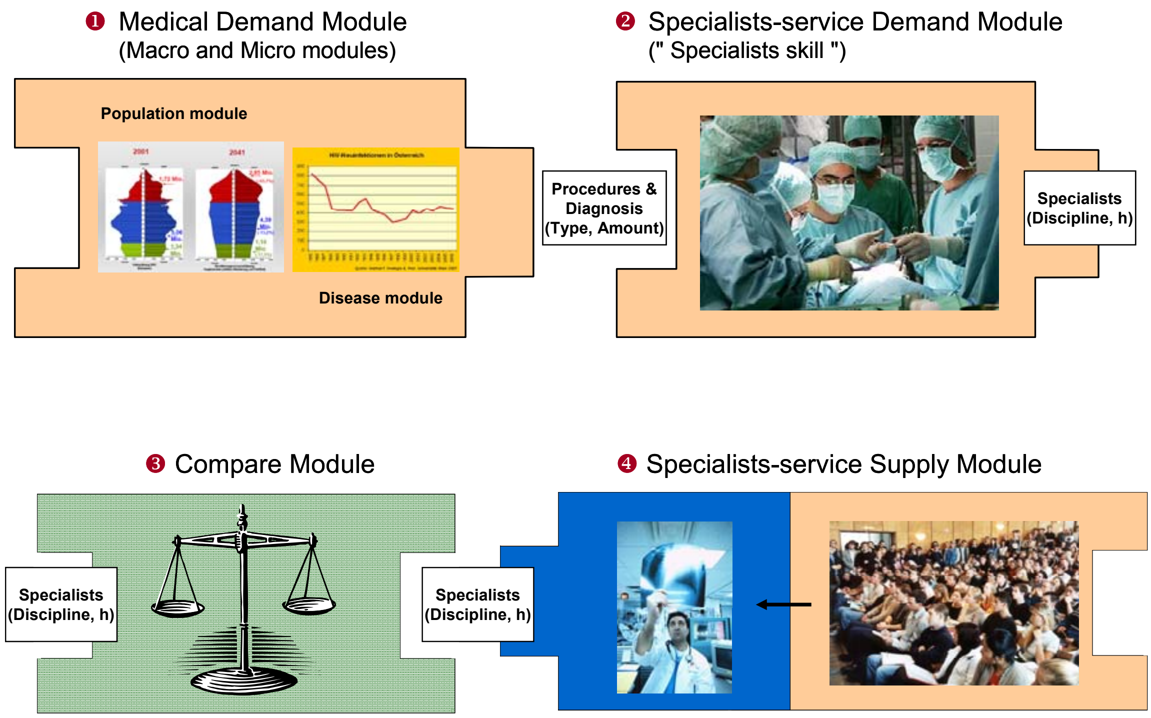


Figure 31: Global Healthcare Model

4.2.1 Medical Demand Module

Basically the Medical Demand Module (MDM) consists of two major modules: a population module and a disease module. Both contain macro and micro modules. The output of the MDM is defined by the amount of classified accomplished or to be accomplished procedures or diagnosis per year. This classification is based on the LDF classification described in section 2.1.1.1. Macro models contain trend models that can give a fast approximation of population or disease developments. It is possible to extract a trend of an industrial country and apply it onto a developing one to determine the local diseases development. Micro models are used to get specific detailed answers on the level of individual diseases. On the micro level it is possible to model specific influences for a given disease whereas macro models only use global influences over the whole spectrum of the classified diseases. A detailed description for both will be given in the next chapter.

4.2.1.1 Population module

There are two possible simulation types: macro and micro, as shown in Figure 32 that can be performed with the population module. The output as well as the input to the simulation is defined as a population distribution of both men and women for all classified age groups. Due to this definition the generated simulation output can be used as an input for the next simulation.

(1) Macro:

With the macro modules it is possible to apply mathematical computations on an entire population distribution or to individual age groups of it to generate new distributions. The mathematical computations used are: scaling, interpolations as well as trend computations. It is therefore possible to for example adapt the population distribution of a country to the size of another country and afterwards use the trend of another country onto this distribution for future development.

(2) Micro:

With the micro module it is possible to generated new population distributions on the level of each individual. Different age-dependent mortalities, birth rates and migrations are assigned to each individual to calculate the influences at each time step. The assigned values and the underlying distribution functions are changeable over the simulation time.

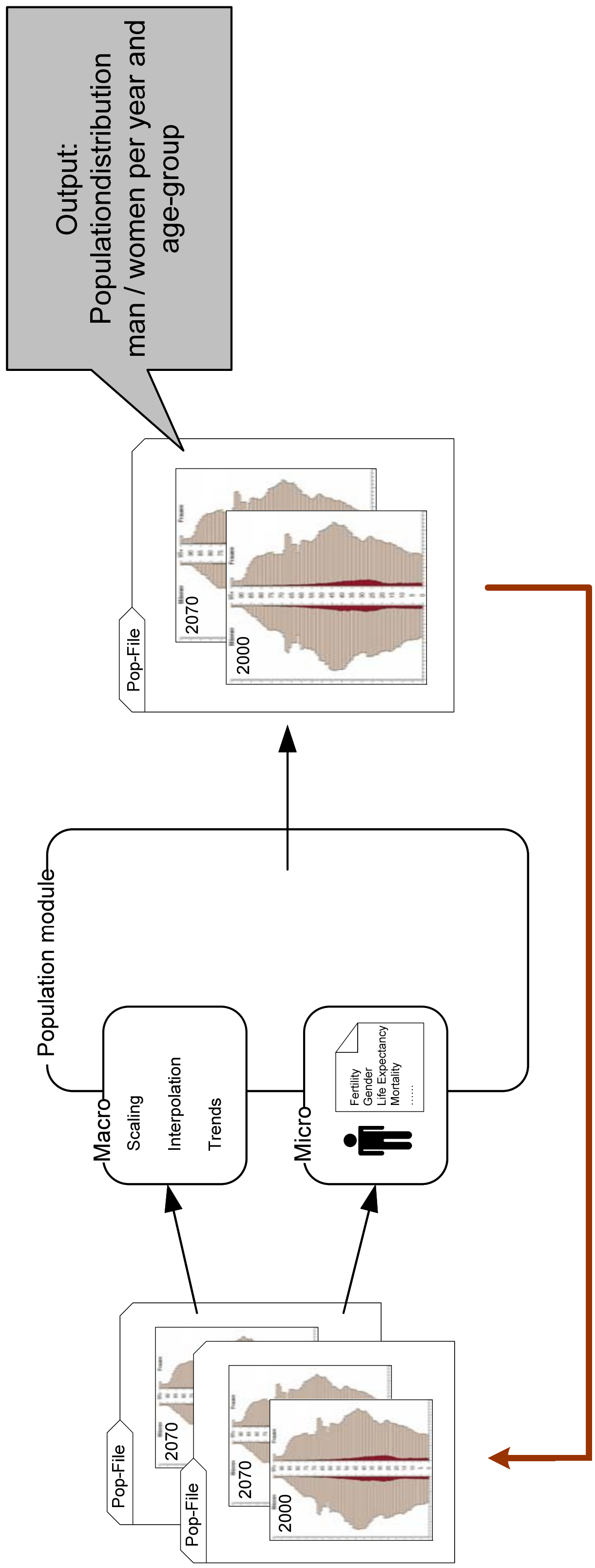


Figure 32: Population module

4.2.1.2 Disease module

There are two possible simulation types: macro and micro, as shown in Figure 33 that can be performed with the disease module. The output as well as the input to the simulation is defined as a population distribution both man and women for all classified age groups and a procedures and diagnosis distribution. Due to this definition the generated simulation output can be used as an input for the next simulation.

(1) Macro:

With the macro modules it is possible to apply mathematical computations for the whole distribution over all defined procedure and diagnosis. The mathematical computations used are: scaling and several selectable trend computations. It is therefore possible to for example calculate procedures and diagnosis for the future, based on the trend of the past years when combined with an extrapolated population distribution.

(2) Micro:

With the micro module it is possible to generated new procedure or diagnosis distributions based on the parameters and behavior of each individual. It is also possible to include new models like a preventive checkups model as described in chapter 4.4 to generate different output behaviors for each individual disease.

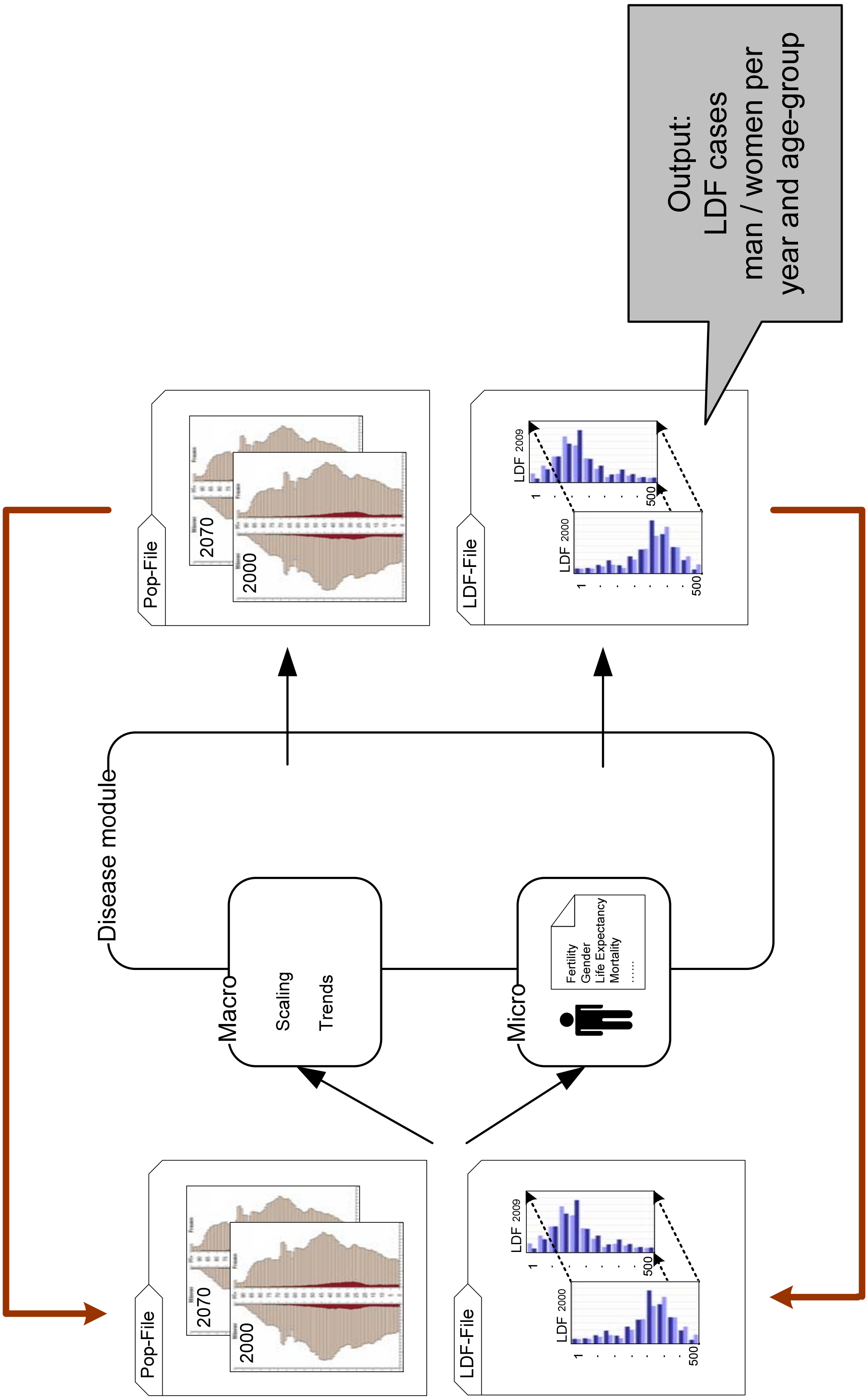


Figure 33: Disease module

4.2.2 Specialists-service Demand Module

The Specialists-service Demand Module (SDM) contains two different modules to calculate the needed specialist's hours for a given set of procedures and diagnosis as shown in Figure 34. The first module uses a specialist's matrix and the other uses a specialist's distribution.

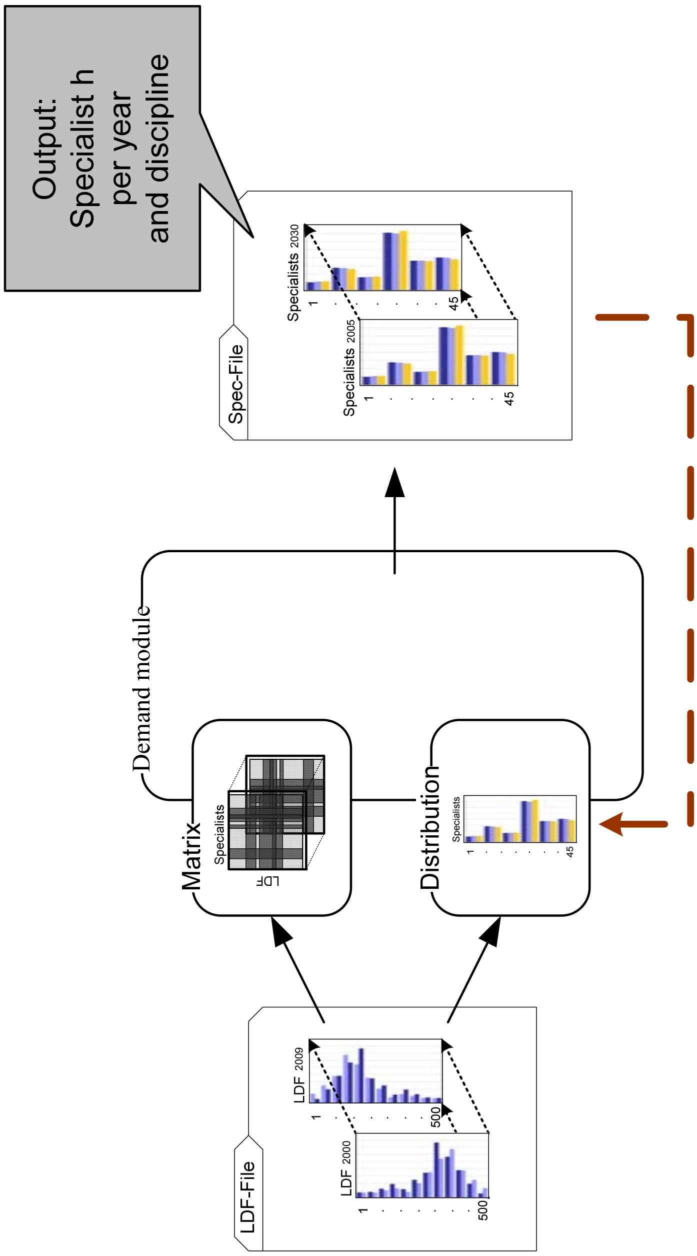


Figure 34: Specialists-service Demand Module

(1) Specialist's matrix:

A specialist's matrix contains the needed duration for each classified procedure and diagnose for each specialists discipline for a given year. The medical improvement is included in two ways.

1. Medical treatment:

To capture changes in methods of treatment the matrix can be adjusted for each year as shown in Figure 35. In the past years medical and technical improvements have lead to a shift in many disciplines. For example the big shift towards minimal invasive surgeries nowadays performed with endoscopies. In such shifts sometimes different disciplines are involved in treatment and the duration of treatment can be decreased. These two types of changes can be integrated into the matrix.

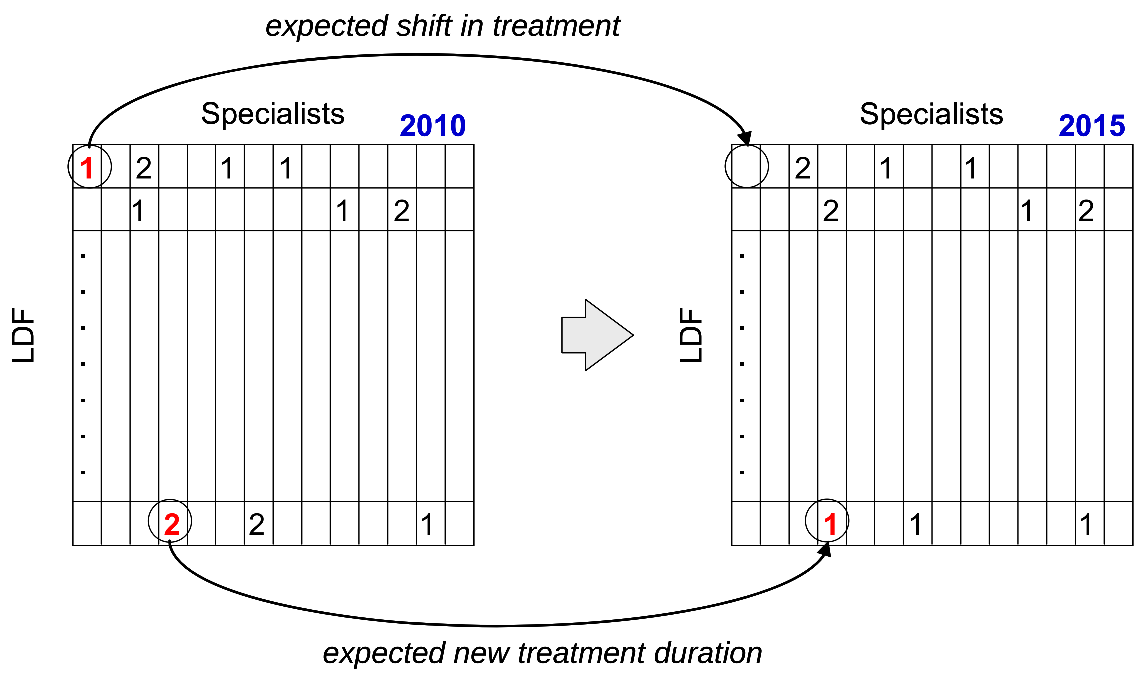


Figure 35: Specialist's matrix adjustment for two years

2. Productivity:

To capture the productivity in each procedure a percentage parameter can be selected as shown in Figure 36. This productivity will be calculated for each year until a certain threshold. This threshold can either be a new entry in the specialist matrix for a later year or cero. Thus each entry in the matrix is decreased by the productivity percentage each year towards a new entry or it reaches cero.

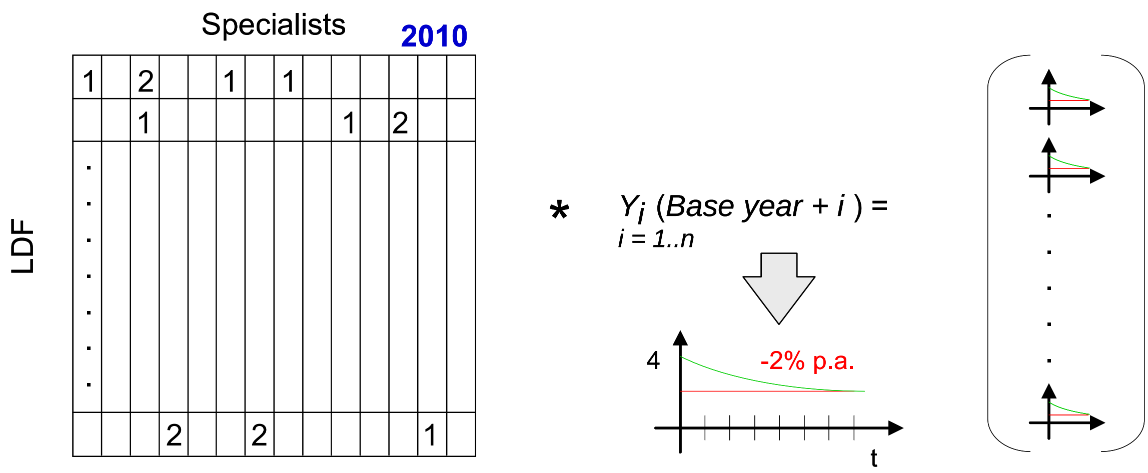


Figure 36: Specialist's productivity for each year and LDF group

Depending on the matrix‘s level of detail the future demand for specialists can be approximated. Thus based on a matrix calculated from a given calibration year where all performed procedures and diagnoses are equally weighted to the different specialists disciplines for the overall sum of all accomplished work hours of this year, this matrix can be improved either by classifying several blocks or refine it towards certain procedures and diagnoses or to refine it towards certain specialists disciplines or a combination out of this three possibilities to get more accurate as shown in Figure 37. Regardless which refinement is done the amount of specialist hours for the whole matrix stays the same for the given calibration year and can just increase or decrease for a new matrix in a later year.

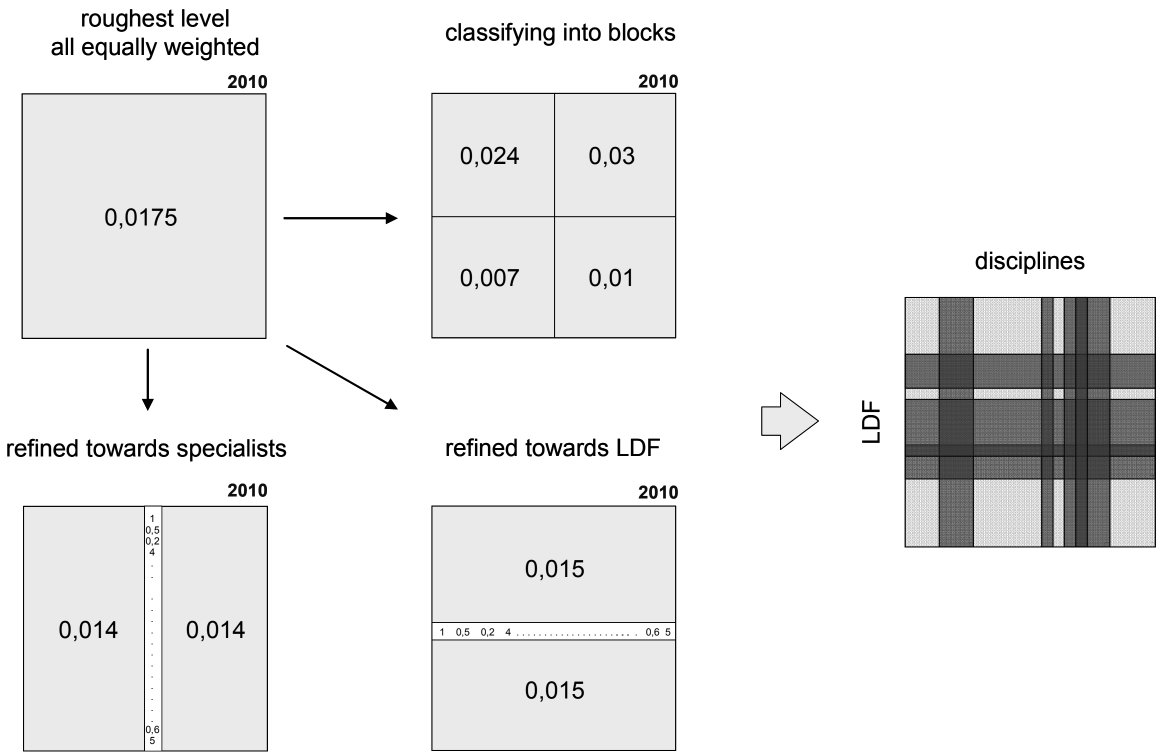


Figure 37: Specialist's matrix adjustment types (block, specialists, LDF)

(2) Specialist's distribution:

A specialist's distribution contains specialists with different disciplines for a given year. The ratio between the active specialists in each discipline and the performed procedures and diagnosis for a selected year, taken from the selected LDF-projection, builds the value for future projections. The medical improvement in this module is included within a productivity parameter that changes the productivity for each discipline for each year. The projection of the specialists needed to perform the procedures and diagnoses selected from the LDF-file is calculated by multiplying the ratio with the LDF-cases for each year minus the productivity factor.

This calculation inherits the assumption that the selected specialist can perform all procedures and diagnoses at full workload without considering the effectiveness of the treatment or other work like administrative ones.

4.2.3 Compare Module

The Compare Module (CM) serves to oppose simulated demand and supply scenarios and to derive recommendations for steering actions due to this variance comparison.

4.2.4 Specialists-service Supply Module

The Specialists-service Supply Module (SSM) as shown in Figure 38 consists of a micro model containing an integrated physician workforce and education model. Healthcare institutes always bear a kind of double role being employers and instructor at once and must therefore give sufficient availability of educational places for junior house officers and specialists to immediately compensate losses or persons leaving. Due to the long educational period of approximately nine years from a graduate to becoming a specialist it is necessary to react on changes far in advance. Therefore this module allows simulating trendsetting decisions to recognize critical effects by now.

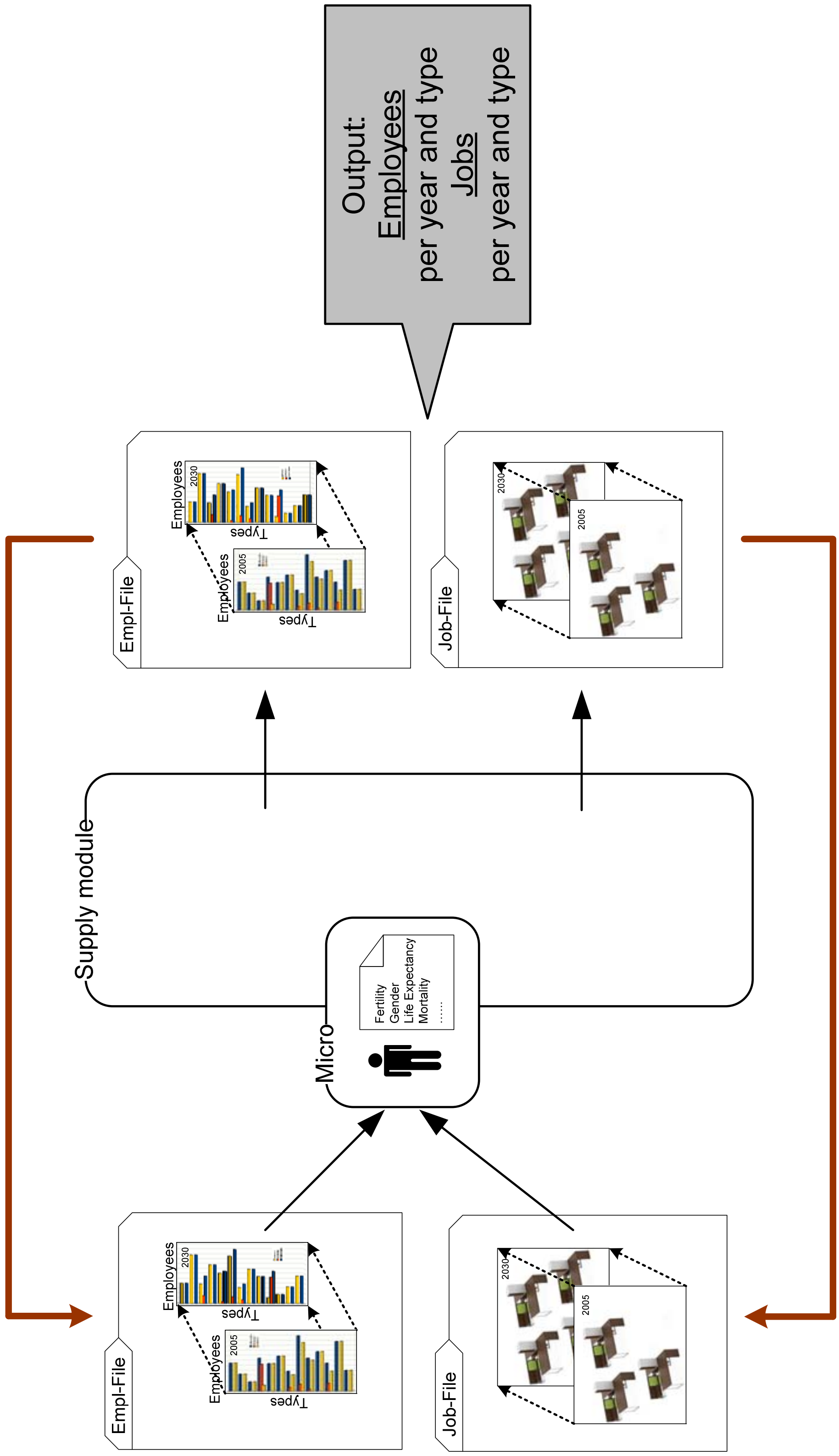


Figure 38: Specialists-service Supply module

4.3 Macro models

Macro models act as their name indicates on the macro level of simulations thus using all individuals as a whole to simulate systems behavior. This section will first describe the population model (4.2.1.1) using mathematical computations like scaling, interpolations as well as trend computations to simulate populations, and then the disease model (4.2.1.2) using mathematical computations like scaling and several selectable trend computations to simulate all classified disease for a given population.

4.3.1 Population module

The population module generates based on a starting population and mathematical computations possible future population distributions. This can be done either by interpolation between two given population distributions for the given simulation years or by calculating a trend within a population and applying it onto a starting population for the given simulation years.

4.3.1.1 Input and Output

Due to the modularity of the model the simulation output- and input files have the same structure. The first step in the population simulation is to acquire an initial population distribution. This can either be done by selecting a prior simulation or statistical data. There is at least one annual population distribution required to perform a simulation run. The population data is always loaded from plain text files on the local file system. A proper population distribution consists of two files:

Population file:

The population file contains at least one annual population distribution. The population data is denoted for males and females in one-year age-groups for the corresponding year. There is a total number of 96 age-groups (from 0 until 95 years of age). Furthermore, the data is divided into three blocks namely the male distribution, the female distribution and the sum of both distributions.

Information file:

The information file is associated with the respective population file. It is generated automatically in the course of the simulation process. The file contains the properties of the respective population distribution by means of descriptive entries. The basic information includes *username, date, simulation start year, simulation end year* and *type of simulation*. Furthermore, a number of parameters for the used simulation type are added.

4.3.1.2 Interpolation

In this type of simulation a linear interpolation between a selected start population and a selected goal population is calculated as shown in Figure 39. The calculation as shown in Equation 1 takes all age groups from the selected start population and calculates the difference to the respective age group in the goal population and divides it through the simulation years. This generated value is then added each year to each respective age group to get a new population distribution.

Equation 1: Interpolation between two populations for each age group

$$I(agegroup) = x_i + (x_{start} - y_{goal}) / n \ \forall i\{1..n\}$$

x_{start} … start population distribution
y_{goal} … goal population distribution
n … amount of available data rows (years)

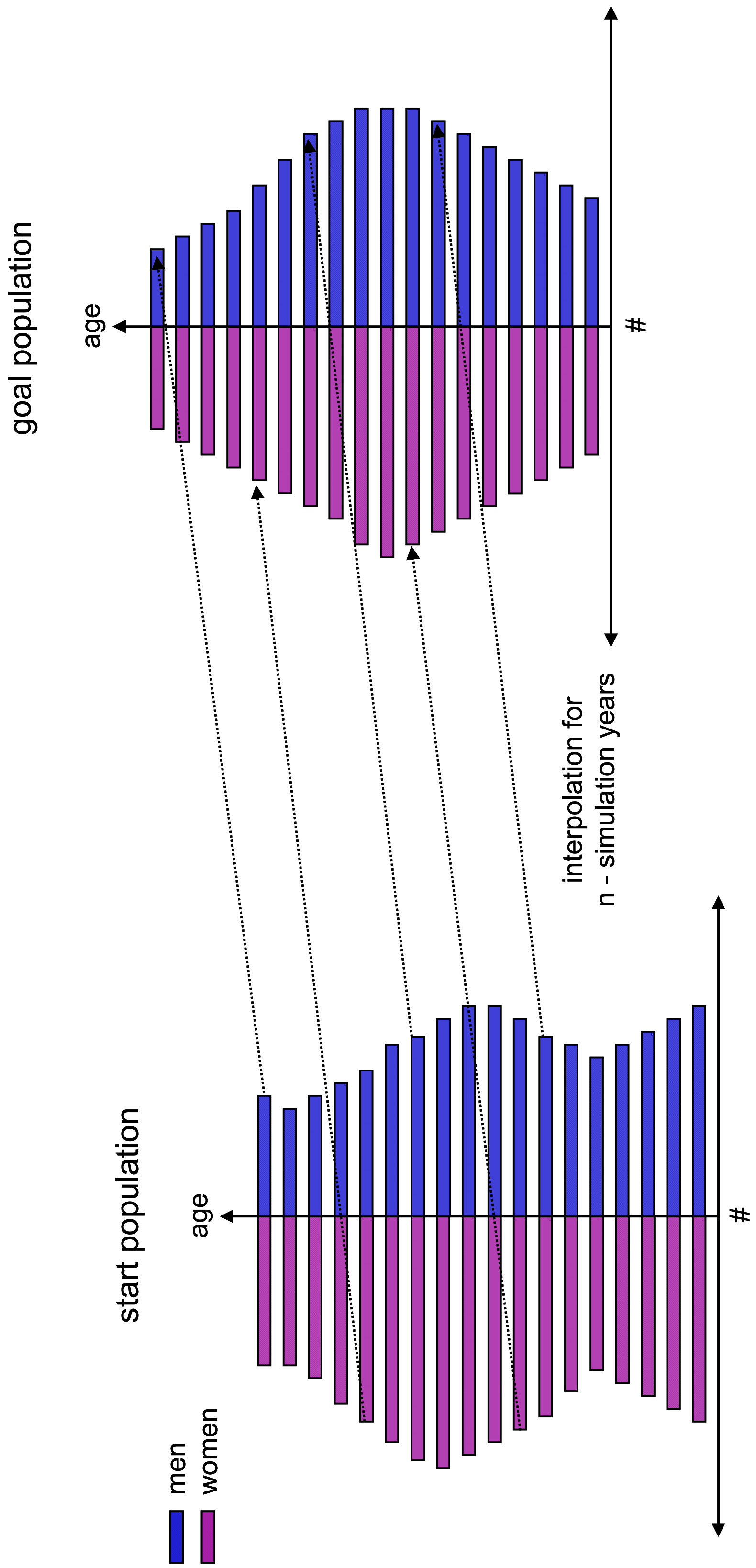


Figure 39: Macro population simulation – Interpolation between two population distributions

The selectable start population distribution can either be:

1. Statistical data (data gathered by a local statistical department).
2. Simulations file (prior generated population distribution).
3. An individual distribution (rectangle or triangle distributions are selectable).

The selectable goal population distribution can either be:

1. Statistical data (data gathered by a local statistical department).
2. Simulations file (prior generated population distribution).
3. An individual distribution (rectangle or triangle distributions are selectable).

Before starting the simulation both start and goal population can be transformed in:

1. Size (by entering a new sum amount a scaling over all age groups and gender is being calculated)
2. Shape (trapezoid or conus transformations can be applied onto the selected population).

4.3.1.3 Trend

In this type of simulation a trend from a selected population distribution is being applied onto a selected start population for the amount of simulation years as shown in Figure 40. The calculation as shown in Equation 2 takes the trend population and calculates the difference for each age group to the next year as a percentage. This percentage is added for each year to generate the new population distribution. Furthermore a goal population can be selected to shift the calculated trend into a direction. When selecting a goal population a linear interpolation as shown in section (4.3.1.2) is being applied to the calculated new population distribution.

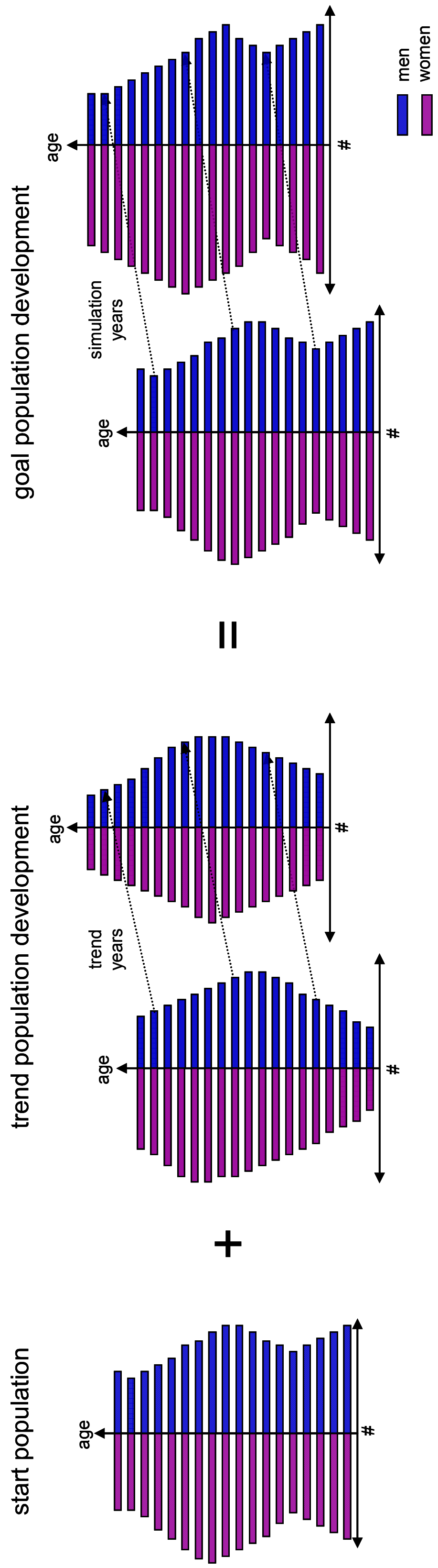


Figure 40: Macro population simulation – Trend applying onto a start population

Equation 2: Population trend calculation for each age group

$$T(agegroup) = x_i + x_i * (100 / Trend_i * Trend_{i+1} - 100) / 100$$

Trend … trend population distribution

The selectable start population distribution can either be:

1. Statistical data (data gathered by a local statistical department).
2. Simulations file (prior generated population distribution).
3. An individual distribution (rectangle or triangle distributions are selectable).

The selectable trend population distribution can either be:

1. Statistical data (data gathered by a local statistical department).
2. Simulations file (prior generated population distribution).

The selectable goal population distribution can either be:

1. Statistical data (data gathered by a local statistical department).
2. Simulations file (prior generated population distribution).
3. An individual distribution (rectangle or triangle distributions are selectable).

Before starting the simulation both start and goal population can be transformed in:

1. Size (by entering a new sum amount a scaling over all age groups and gender is being calculated)
2. Shape (trapezoid or conus transformations can be applied onto the selected population).

To demonstrate the population module a trend calculation for Styria's population for the next thirty years will now be given by taking the trend of Styria's population from 1970 – 2000 and apply it onto the starting year 2000 as summarized in Table 6.

Table 6: Macro population trend simulation parameters

Parameter	Value
start population	Styria 2000
trend population	Styria 1970 - 2000
goal population	-
simulation start year	2000
simulation end year	2030

The first step is to calculate the trend within the trend population in this example from Styria from 1970-2000 as illustrated in Figure 41. This is done by calculating the difference ratio between two years and aggregating them to a new series.

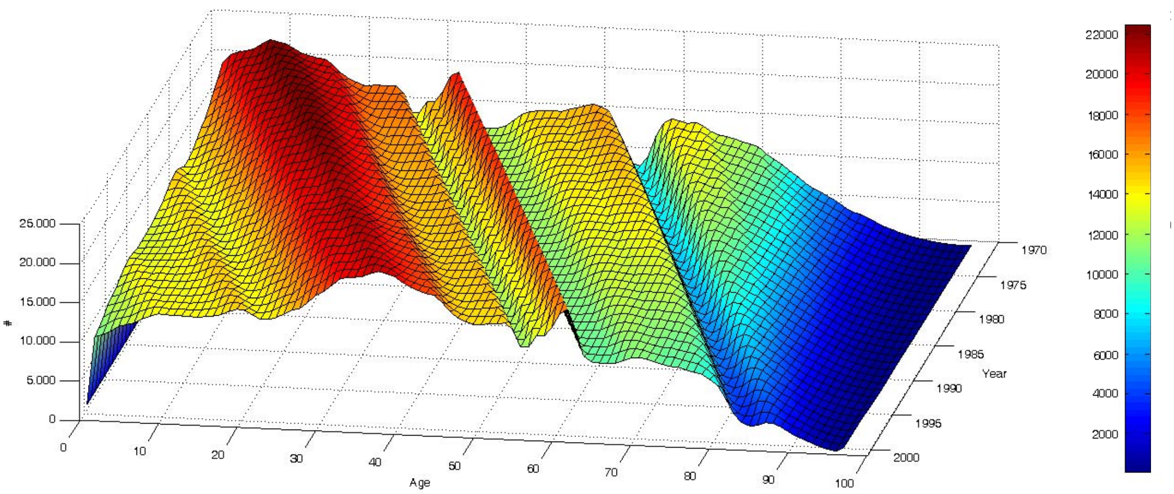


Figure 41: 3D view of Styria's population from 1970-2000

This generated series is then applied onto a given start population distribution, in this example Styria's population from the year 2000 as shown in Figure 42, for the given simulation years.

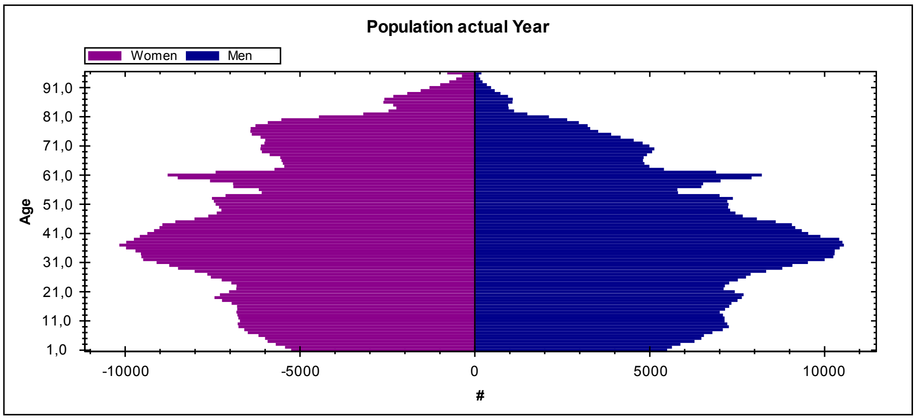


Figure 42: Styria's population distribution for the year 2000

The output for the population trend calculation for the start and end year is shown in Figure 43 and in a 3D diagram in Figure 44.

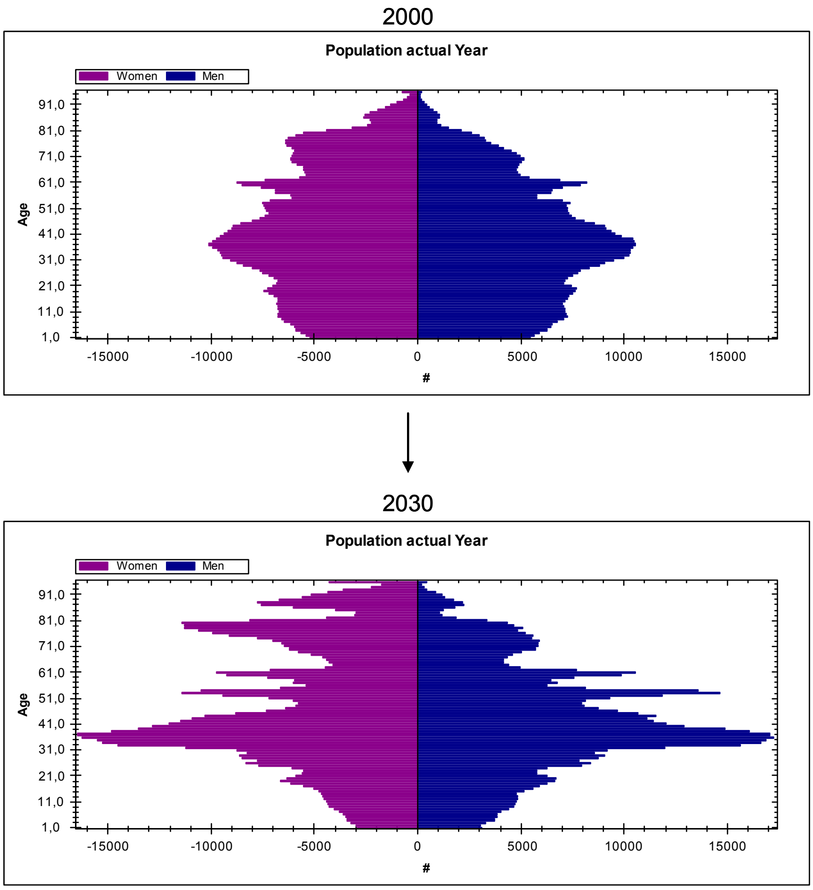


Figure 43: Start and end year of the extrapolated Styria's population from 2000-2030

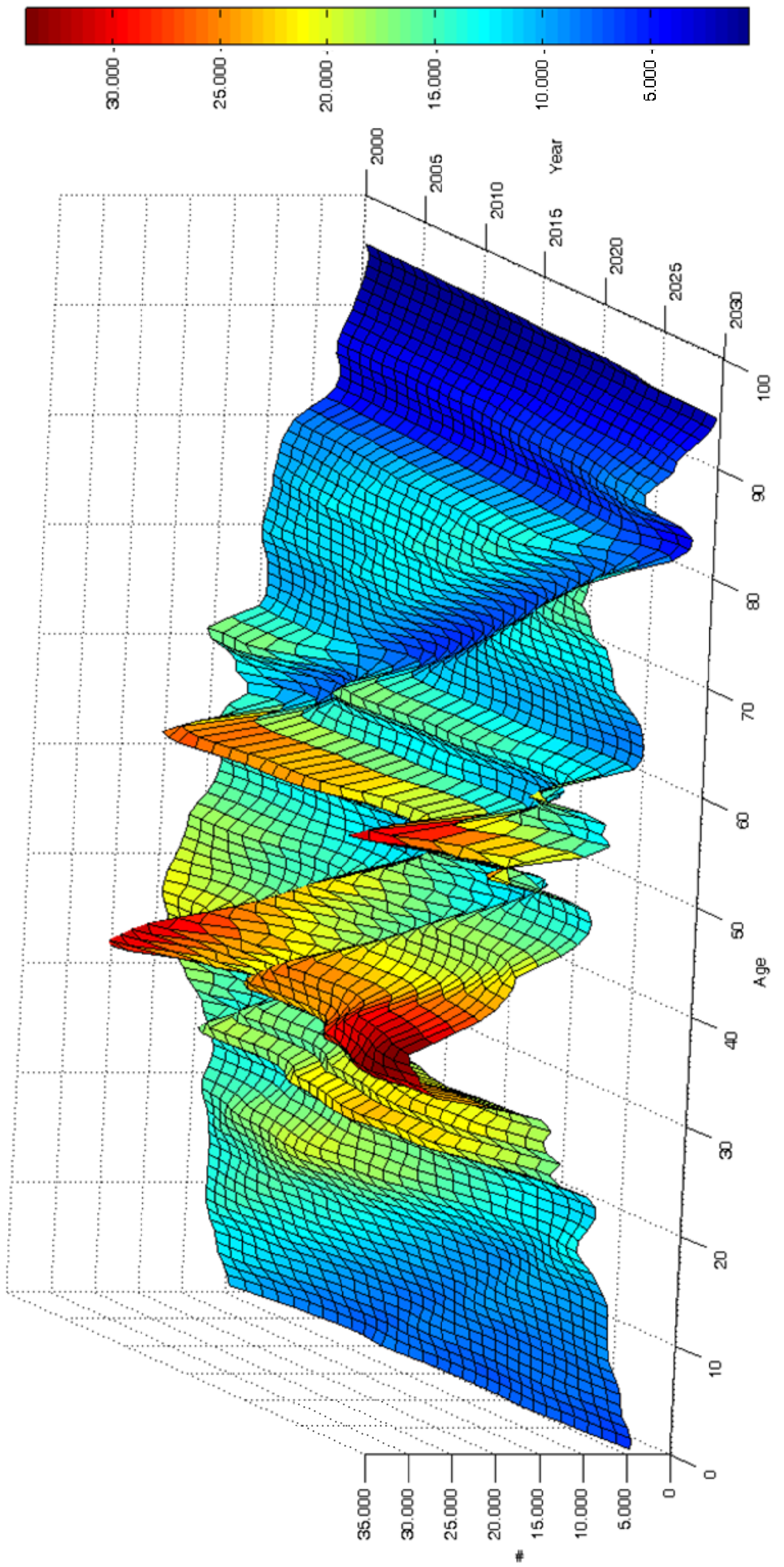


Figure 44: 3D view of the extrapolated Styria's population from 2000-2030

4.3.2 Disease module

The diseases module uses a population and a disease distribution to calculate possible future disease distributions. This can either be done by scaling a disease distribution for a selected year to a selected start population and then compute future diseases with this ratio and an extrapolated goal population distribution, or by calculating the trends from a given disease distribution and the selected start population distribution for all diseases and apply this trend onto an extrapolated goal population distribution to compute future diseases.

4.3.2.1 Input and Output

Due to the modularity of the model the simulation output- and input files have the same structure. The first step in the disease simulation is to acquire an initial disease and population distribution. This can either be done by selecting a prior simulation or statistical data. There is at least one annual population and disease distribution required to perform a simulation run. The population and disease data is always loaded from plain text files on the local file system. A proper disease distribution consists of two files:

Disease file:

The disease file contains at least one annual disease data record. The cases of the diseases are denoted for each gender in one-year age-groups for the corresponding year. There is a total number of 96 age-groups (from 0 until 95 years of age). The measure of the spread of a disease case about the mean is given by the respective standard deviation value.

Information file:

The information file is associated with the respective disease file and is generated automatically. The file contains the properties of the respective disease record by means of descriptive entries. The basic information includes *username, date, simulation start year, simulation end year* and *disease record filename* and a number of parameters of the selected simulation type.

4.3.2.2 Scaling

In this type of simulation an extrapolation of diseases is calculated by using a scaling function. The calculation as shown in Equation 3 weights a disease distribution to a selected start population and applies this ratio onto a selected goal population distribution as shown in Figure 45. The underlying assumption for this simulation is that all diagnoses and procedures from the selected scaling year stay the same for whole simulation period and are just influenced by the amount of people in the respective goal population age group.

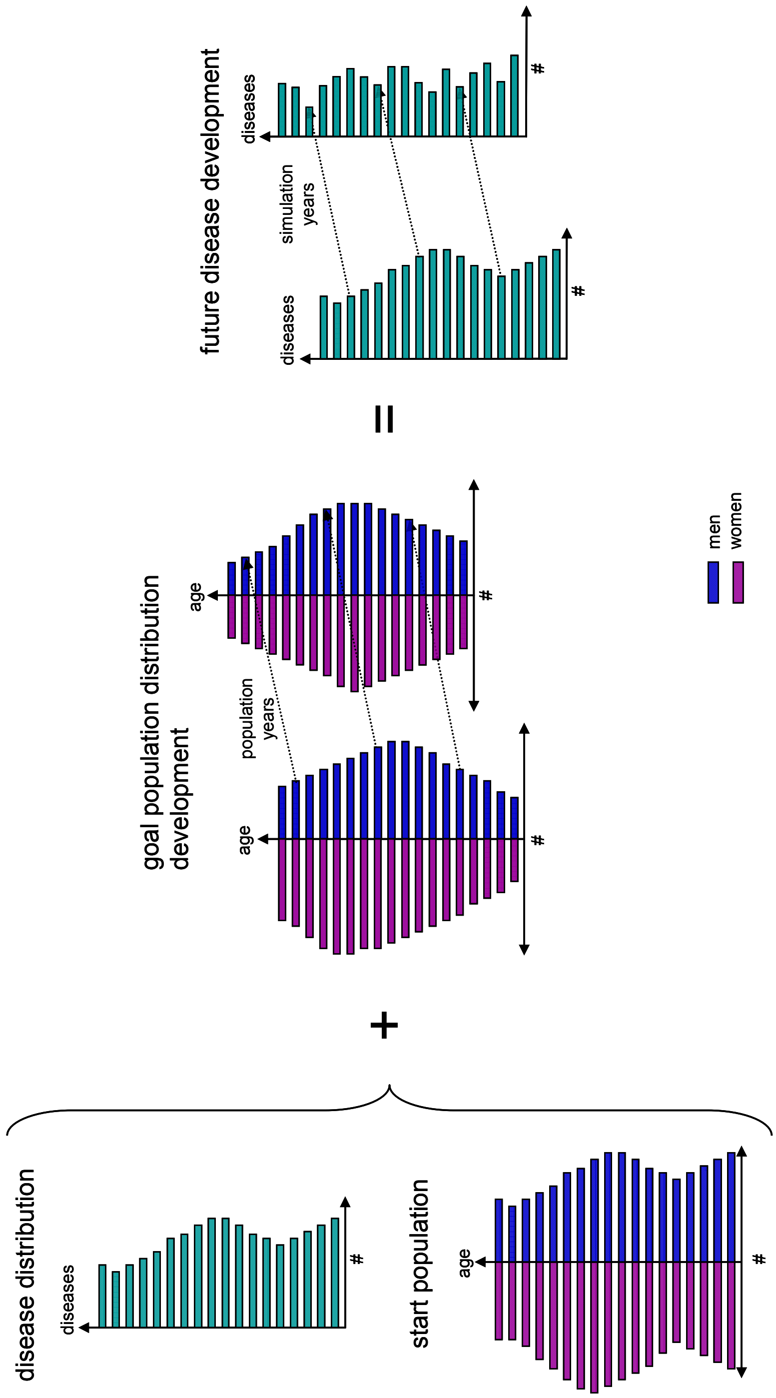


Figure 45: Macro disease simulation – Scaling a disease distribution to a population distribution and apply it onto a population trend

Equation 3: Disease scaling calculation for each population age group

$$S(agegroup) = x_i + x_i * (100 / goal_i * goal_{i+1} - 100) / 100$$

goal … goal population distribution
x … ratio between disease and population for each age group

The selectable disease distribution can either be:

1. Statistical data (data gathered by a local statistical or healthcare department).
2. Simulations file (prior generated disease distribution).

The selectable start population distribution can either be:

1. Statistical data (data gathered by a local statistical department).
2. Simulations file (prior generated population distribution).

The selectable goal population distribution can either be:

1. Statistical data (data gathered by a local statistical department).
2. Simulations file (prior generated population distribution).

4.3.2.3 Trend

In this type of simulation extrapolations of diseases are calculated by using a trend from a selected disease distribution and apply it onto a goal population distribution. The calculation uses the selected trend function (weighted differences, moving average, or linear regression) as shown in Equation 4 to Equation 6 to calculate the weighted trend out of the selected disease development years and start population distribution years and applies this trend onto a selected goal population distribution as shown in Figure 46. This kind of trend extrapolation as published in Martischnig et al. 2008 has recently been applied in two papers (Dill et al. 2008, Grover et al. 2008). The underlying assumption for this simulation is that the trend of all diagnoses and procedures, that are just influenced by the amount of people in the respective age group, will prolong for the future taking in consideration that there will be no change in any diagnose or procedure for the simulation years.

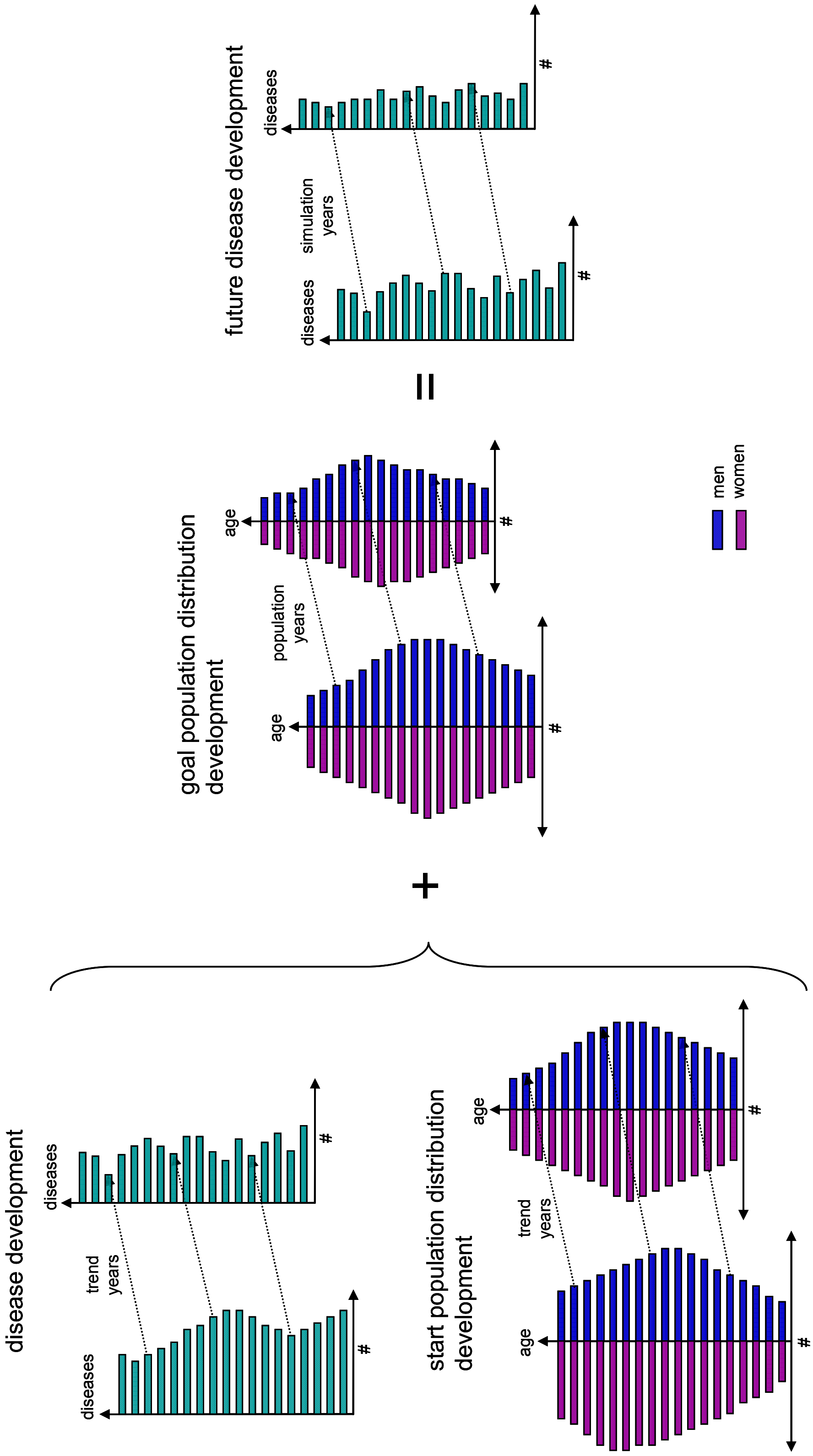


Figure 46: Macro disease simulation – Applying the trend out of a disease distribution and a population distribution onto a future population distribution

The selectable disease distribution can either be:

1. Statistical data (data gathered by a local statistical or healthcare department).
2. Simulations file (prior generated disease distribution).

The selectable start population distribution can either be:

1. Statistical data (data gathered by a local statistical department).
2. Simulations file (prior generated population distribution).

The selectable goal population distribution can either be:

1. Statistical data (data gathered by a local statistical department).
2. Simulations file (prior generated population distribution).

The selectable trend types are:

1. *Weighted Differences (WD)*

Equation 4: Weighted Differences calculation for each age group

$$WD(agegroup) = (\sum_{i=1}^{n-1} (x_{i+1} - x_i) * i * (1 / \sum_{j=1}^{n-1} j)) / n$$

x … ratio between disease and population for the given age group
n … amount of available data rows (years)

Weighted Differences calculates the differences of the data points in a time series by giving the latter more weight than earlier ones.

2. Linear Regression (LR)

Equation 5: Linear regression calculation for each age group

$$LR(agegroup) = gradient(\beta_0) + axisintercept(\beta_1)x$$

$$gradient(\beta_0) = (\frac{1}{n}\sum y_i) - (\frac{1}{n}\sum x_i)\beta_1$$

$$axisintercept(\beta_1) = \frac{\sum x_i y_i - \frac{1}{n}\sum x_i \sum y_i}{\sum x_i^2 - \frac{1}{n}(\sum x_i)^2}$$

x … actual year
y … ratio between disease and population for the given age group
n … amount of available data rows (years)

Linear regression attempts to model the relationship between two variables by fitting a linear equation to observed data.

3. Moving Average (MA)

Equation 6: Moving average calculation for each age group

$$MA(agegroup) = \frac{\sum_{i=1}^{n} x_{(y-i)+1}}{n} \qquad n \le y$$

x … ratio between population and disease for the given age group
n … amount of available data rows (years)
y … selectable data point

A moving average is a set of numbers, each of which is the average of the corresponding subset of a larger set of data points and may also use unequal weights for each data value in the subset to emphasize particular values.

For each selected trend type and age group the standard deviation and the 95% confidence interval is calculated and added to the respective output file as shown in Equation 7 and Equation 8.

Equation 7: Standard deviation calculation

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2}$$

σ … standard deviation for each age group
n … amount of available data rows (years)
$\overline{x}$… average value

Equation 8: 95% confidence interval calculation

$$\overline{x} - 1,96\frac{\sigma}{\sqrt{n}} \leq \mu \leq \overline{x} + 1,96\frac{\sigma}{\sqrt{n}}$$

σ … standard deviation for each age group
n … amount of available data rows (years)
μ … expected value
$\overline{x}$ … average value

To demonstrate the macro disease module a trend calculation for Styria's births for the next thirty years will now be given by taking the trend from 2000 – 2006 with the weighted differences calculation as summarized in Table 7.

Table 7: Macro disease trend simulation parameters

Parameter	Value
disease distribution	Styria's ordinary births 2000 -2006
start population distribution	Styria 2000 - 2006
goal population distribution	Styria 2007 - 2030
trend type	weighted differences
simulation start year	2007
simulation end year	2030

The first step is to calculate the trend within Styria's ordinary births from 2000-2006 as illustrated in Figure 47 and the Styria's population as illustrated in Figure 48.

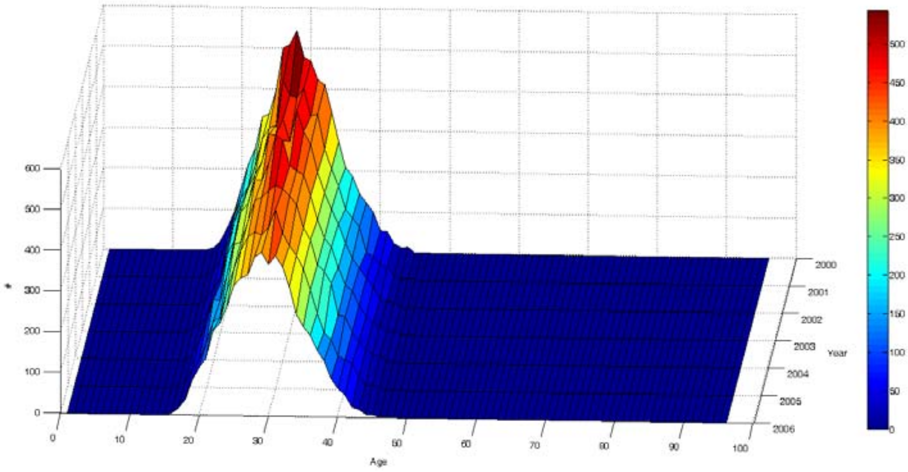


Figure 47: 3D view of real Styria's ordinary births from 2000-2006

The ordinary births indicate a shift to an older age but overall quite lesser births for future.

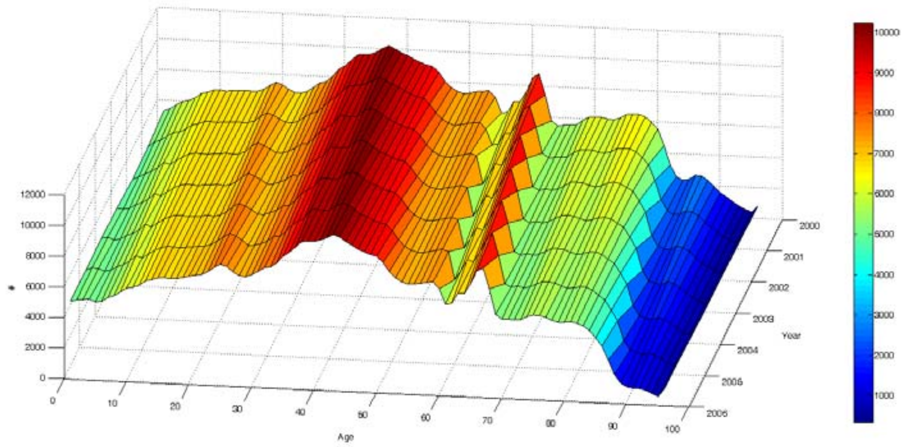


Figure 48: 3D view of Styria's population from 2000-2006

The population indicates a shift to more people in an older age and lesser younger ones. When combining these two distributions for each age group the generated time series includes both distribution trends. These trends for each age group are then extrapolated using weighted differences (Equation 4) including the respective standard deviation to generate the future births progression.

The next step is to apply this generated trend series onto a corresponding population distribution. The generated output for Styria's ordinary births for the year 2007-2030 is illustrated in a 3D diagram in Figure 49 and gender and age separated in Figure 50.

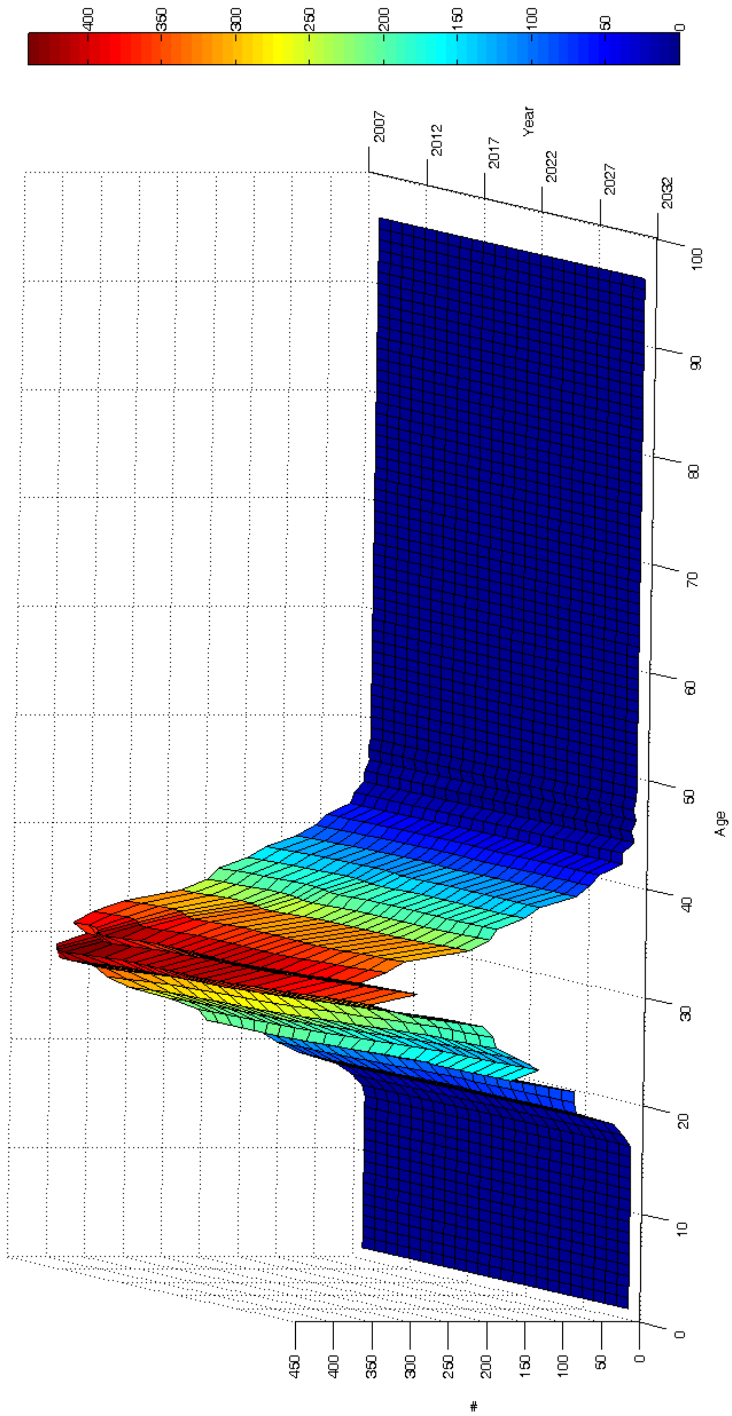


Figure 49: 3D view of extrapolated Styria's ordinary births from 2007-2030

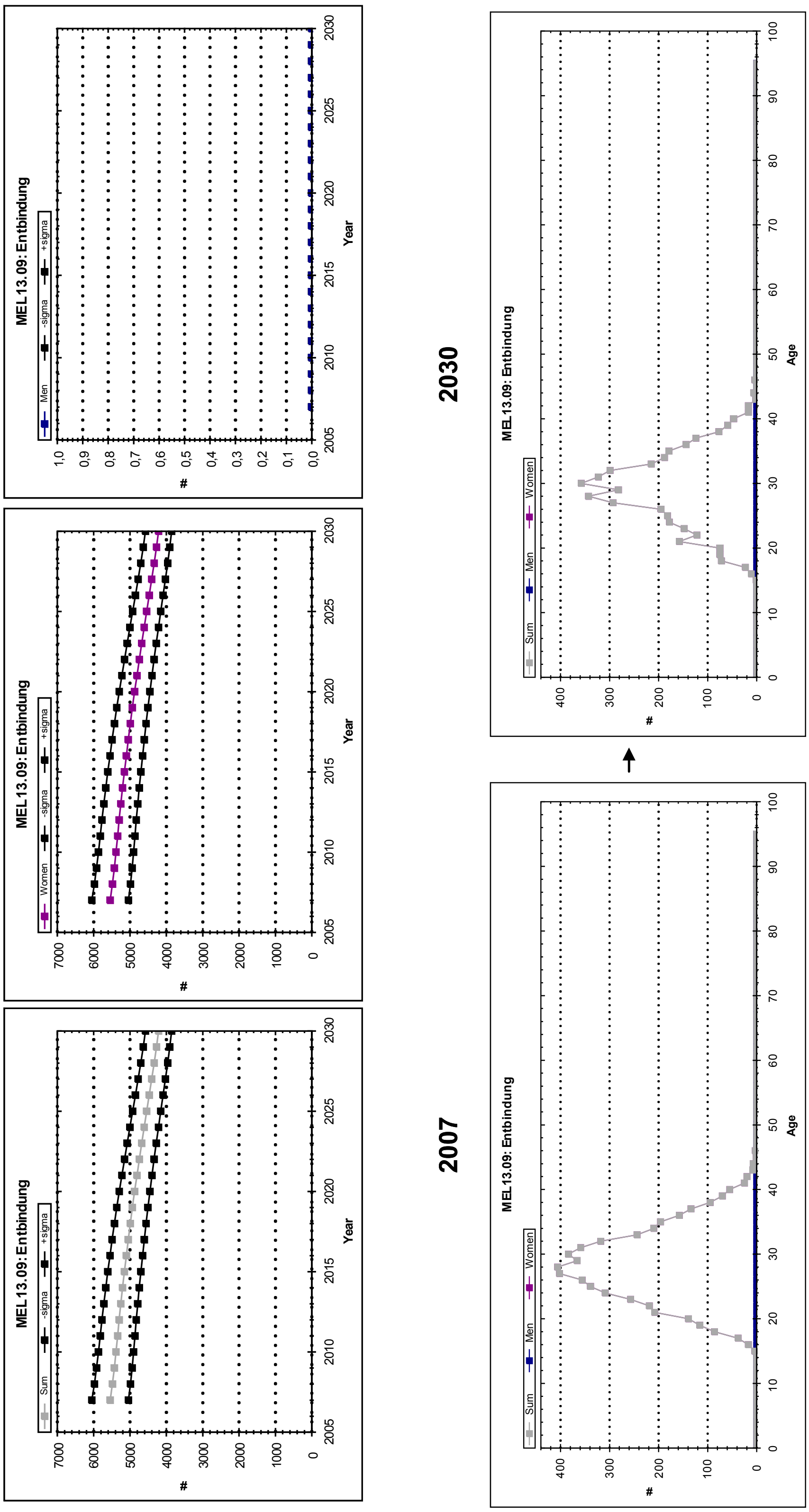


Figure 50: Extrapolated Styria's ordinary births from 2007-2030 with standard deviation and age distribution

The generated extrapolation for future Styria's ordinary births, including both births and population trends, indicates a big shift towards an older maximum and average age of bearing a child and a tremendous decreasing amount of births. In the year 2006 the average age for an ordinary child bearing was about 28 years and will shift to about 30 in 2030 and the absolute amount of new births will decrease from 5600 in 2006 to 4200 in 2030.

4.3.3 Limitations of the macro modules

Scaling disease simulations only take a snapshot from available procedures and diagnoses and calculate an extrapolation by applying them onto a selected population distribution.

Trend disease simulations calculate trends out of the available procedures and diagnoses data points. The more available data points the more accurate the calculation and the lesser the forecasting error. Because procedures and diagnoses are revised and reclassified all two to three years it is necessary that the recalculation is consistent for all data points. This also means that this kind of simulation can only recognize short term trends approximately within the last ten years. Shifts to new procedures or diagnoses normally occurring every ten to fifteen years can not be recognized and if contained within not recalculated datasets would lead to massive forecasting errors.

4.4 Micro models

Micro models act as their name indicates on the micro level of simulations thus using individuals and their behavior to simulate complex systems. This section will first describe the population model that can be assigned to the Micro Simulation approach, then the more complex disease model situated between the Micro Simulation and the Agent Based approach and at last the integrated workforce and education model also situated between the Micro Simulation and the Agent Based approach.

4.4.1 Population module

The individual based population simulation represents an alternative variant to estimate the annual population development over a specific period of time within an acceptable level of accuracy. The fundamental challenge as stated by O'Neill et al. (2001) lies in the determination of the characteristics of the initial population and in the projection of future trends. National and regional population censuses are the primary sources for demographic data. Detailed population-related data along with reliable periodic census counts is usually provided by statistical organizations. The initial population size and age structure as well as the rates of fertility, immigration, emigration and mortality are critical to computing accurate population projections. The assumed future trends of fertility, migration and mortality are based on expert opinions supported by current conditions, past trends and theories about the possible changes and developments regarding the population in the examined country or region. A typical population projection starts with the initial population structured by age and gender at a given time where the individual is the crucial component. The projection is done for each year of the covered period. The age of each individual is increased annually. Each age-group is decreased by the number of deaths and adjusted by the balance of migration. At the same time, the population is increased by the number of births. Population projections are based on hypothesis and therefore underlie uncertainties. The results are dependent on the actual population size and age structure and on the assumptions concerning the development of fertility, migration and mortality. The primary aim of a population projection is not to predict exact results but rather to indicate the future population and its structure under certain premises.

In individual simulations agents can either be simple or complex as described in section 3.4.3.2. Within this thesis the agent framework is specified to be as simple as possible to keep the simulation controllable because simple micro level behavior can also lead to complex macro level behavior. The relevant properties of an agent are age, gender, fertility, mortality and migration, but this can be adopted very easily because of the used object-oriented programming paradigm. There is no need of interacting agents because of the intended purpose just to simulate populations. Thus this population module can be assigned to the Micro Simulation approach. The relevant five agent properties are described below and shown in Figure 51:

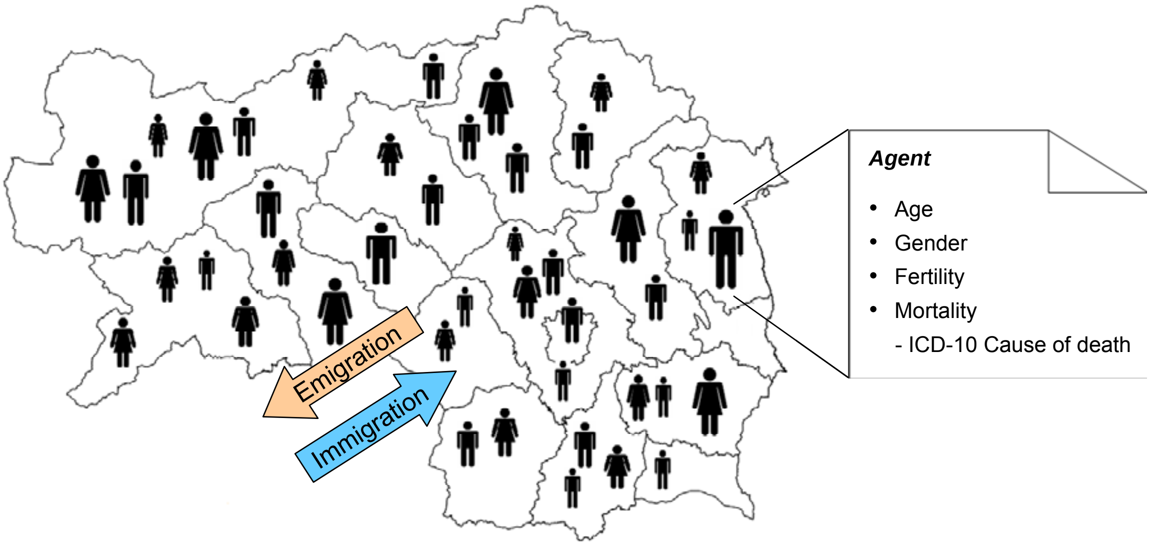


Figure 51: Population micro simulation without special disease

4.4.1.1 Agent Attributes

(1) Age:

Each agent has a specific age starting with cero which is increased annually and remains in the system until he dies. The age interval is set between 0 and 95 years and therefore contains 96 age groups. Agents above the age of 95 are also tracked with an extra parameter.

(2) Gender:

An agent's gender can either be male or female and the initial gender is predetermined by the start population distribution. Newborns are assigned randomly a gender depending on the male-female ratio of the start year's population distribution. Immigrated agent's gender is uniformly distributed.

(3) Fertility:

Of course only female individuals are given an annual birth probability. This value indicates the probability to bear a child in the course of the actual year. The birth probability depends on the age of the agent and on the used probability distribution. There are several distributions available calibrated on statistical data.

(4) Mortality:

The mortality value contains the probability of death for each agent's age. Mortality is divided into the main parts of the ICD-10 (International Classification of Diseases endorsed by the WHO in 1990) code.

(5) Migration:

Migration contains immigration and emigration rates. The annual decision of an agent for migration is based on the used migration distribution. There are several distributions available calibrated on statistical data.

4.4.1.2 Simulation Process

The size and growth of the population is the result of the interplay by these five properties through each simulation cycle which can be performed sequentially or multithreaded as shown in Figure 52 and described below. The behavior of each individual is determined by annual decisions and events. The different decisions (e.g. child bearing, migration) performed by the individuals results in a decreasing or declining population in the respective age group.

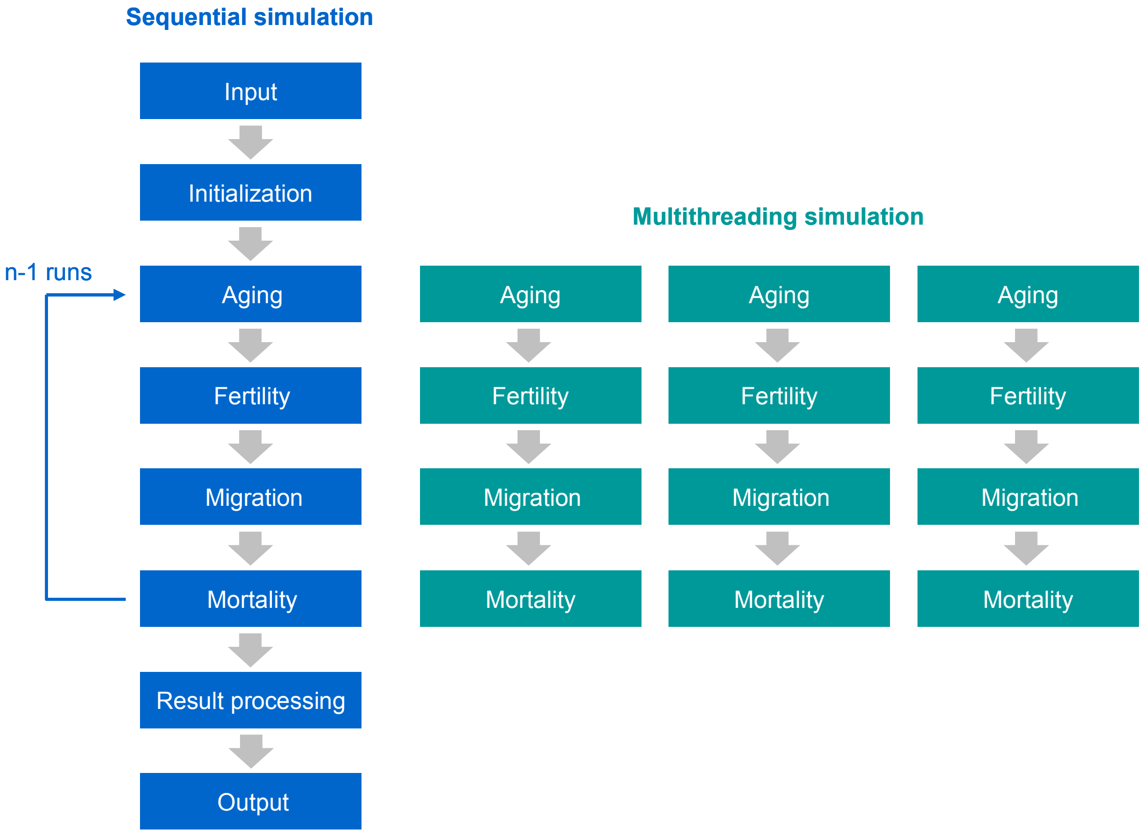


Figure 52: Population module sequence

(1) Sequential simulation:

The sequential simulation option calculates one run after the other. This option is recommended when the simulation is performed on a single-core CPU.

(2) Multithreading simulation:

The multithreading simulation option supports the use of multi-core CPUs. A certain number of runs are calculated in parallel which obviously leads to savings of time.

Due to the modular implementation of the module it is not necessarily required to include all three agent modules (fertility, migration, mortality) in a simulation process. For example when deselecting the mortality module no agent will die within the simulation run.

Initialization:

The first step is to acquire all relevant data from the population distribution as well as setting the various simulation parameters that are provided by the graphical user interface (GUI) simulation. Individual agents are created according to the population in the respective age groups and the global parameters of the ABM panel of the program are initialized like fertility, mortality and so on.

Aging simulation:

The age of an agent is annually increased by one year and between the overall age interval from 0 and 95 years. There is also a system age parameter that is incremented when an agent is aged 96 and above.

Fertility simulation:

The main part of this module is to calculate the annual number of newborn agents. Every female agent has a specific birth probability which is adapted each year. This property indicates the probability to bear a child in the course of the actual year. The individual birth probability is calculated by using the global total birth probability parameter and a probability distribution fitting Statistics Austria data for the age interval. Furthermore, the total birth probability parameter is adapted annually by setting a certain adaptation percentage. The probability to bear a child in the course of the actual year is age specific and considered between 15 and 45 years and is calculated by the binomial probability distribution.

Migration simulation:

The main part of this module is to calculate the number of emigrations and immigrations per age group for each year. Every agent in the system has a specific emigration probability. The global parameters are the total number of emigrations, the annual adaptation of the total number of emigrations and an emigration distribution. There are three types of distributions available for describing the probability of emigration and immigration within the defined age group interval: binomial, rectangle or triangle distribution.

Mortality simulation:

The main part oft his module is to calculate the annual number of deaths. Each agent has a parameter that describes the probability of death based on the International Classification of Diseases (ICD)[3]. The individual death probability is an accumulation of six classified parameters which describe the gender specific causes of death:

- – Neoplasm diseases
- – Circulatory system diseases
- – Respiratory system diseases
- – Digestive system diseases
- – Miscellaneous diseases
- – External causes

This concept allows the adaptation of the probability of death within the scope of certain diseases. The probability of death is also age specific. The death probability distribution and the annual adaptation factor describe the probability of death for each male and female age group.

Result processing:

The results of each simulation run are saved in an appropriate data list. Within this implementation, the arithmetic mean of the population in each gender specific age group is computed as shown in Equation 9.

Equation 9: Calculation of arithmetic mean for the population distribution

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i = \frac{1}{n}(x_1 + \ldots + x_n)$$

n … amount of available data rows (years)

A population file and the associated information file is generated and saved to the local file system.

[3] WHO - ICD website: http://www.who.int/classifications/icd/en/

4.4.1.3 Input and Output

Due to the modularity of the model the simulation output- and input files have the same structure. The first step in the population simulation is to acquire an initial population distribution. This can either be done by selecting a prior simulation or statistical data. There is at least one annual population distribution required to perform a simulation run. The population data is always loaded from plain text files on the local file system. A proper population distribution consists of two files:

Population file:

The population file contains at least one annual population distribution. The population data is denoted for males and females in one-year age-groups for the corresponding year. There is a total number of 96 age-groups (from 0 until 95 years of age). Furthermore, the data is divided into three blocks namely the male distribution, the female distribution and the sum of both distributions.

Information file:

The information file is associated with the respective population file. It is generated automatically in the course of the simulation process. The file contains the properties of the respective population distribution by means of descriptive entries. The basic information includes *username, date, simulation start year, simulation end year* and *type of simulation*. Furthermore, a number of parameters for the used simulation type are added.

4.4.2 Disease module

The simulation of diseases is an additional functionality of the population module. The architecture is extended with additional disease related modules that affect the attributes and behavior of an individual. Before implementing an individual special disease module into the population module a model of the disease has to be generated with all the disease specific characteristics. This model has to be validated by experts to fit the real model and satisfy the simulation purpose. The next step when integrating the model into the simulation is to define the ICD-10 category the modeled individual disease belongs to and then add the needed attributes to an agent. These diseases related attributes are connected to the individual agent as shown in Figure 53.

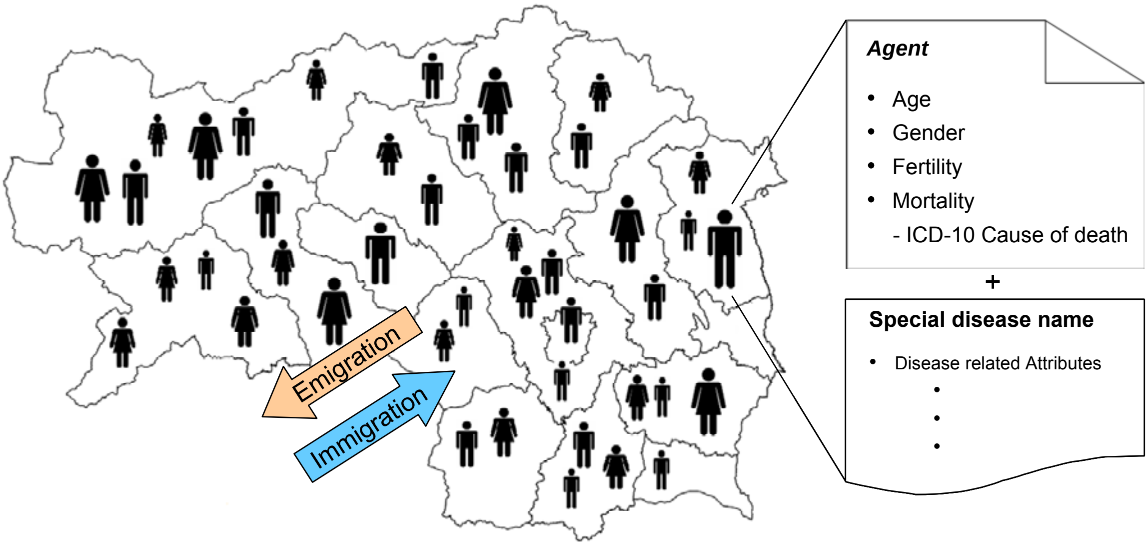


Figure 53: Population micro simulation with attached special disease

4.4.2.1 Agent Attributes

The relevant properties of an agent described above: age, gender, fertility, mortality and migration stay the same in this simulation. Additional to this attributes each special disease module needs its own attributes that correlate to the disease. In the example described below for the preventive cancer checkup process these attributes are the number of performed interventions, the waiting period till next check is performed, the new death probability, and so forth. Due to the modular implementation the special disease module attributes are connected to each agent in the simulation.

4.4.2.2 Simulation Process

The size and growth of the population is the result of the interplay of the basic five properties plus the individual ones from each modeled special disease through each simulation cycle, which can be performed sequentially or multithreaded as shown in the new sequence in Figure 54 and described below. The behavior of each individual is determined by annual decisions and events concerning the basic attributes and the new ones from each individual disease module.

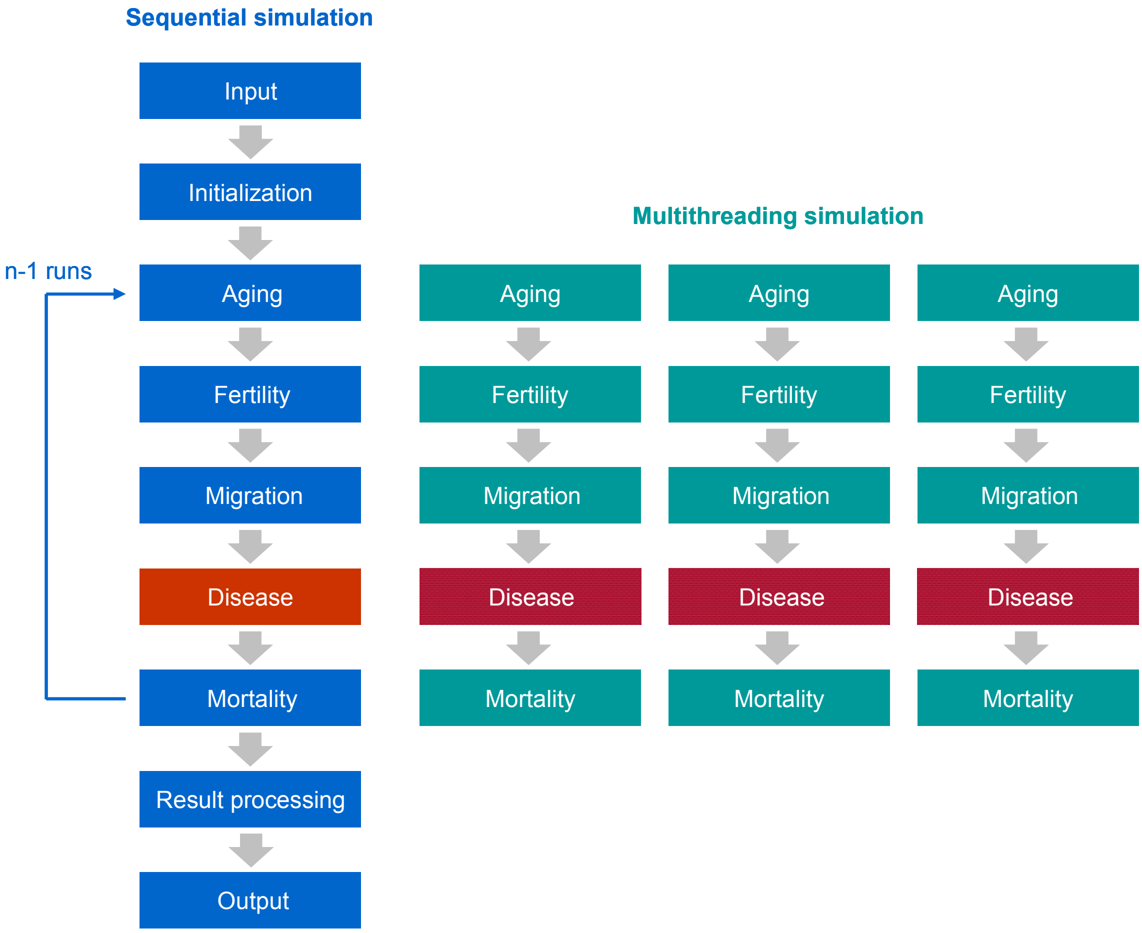


Figure 54: Population module sequence with an integrated special disease model

(1) Sequential simulation:

The sequential simulation option calculates one run after the other. This option is recommended when the simulation is performed on a single-core CPU.

(2) Multithreading simulation:

The multithreading simulation option supports the use of multi-core CPUs. A certain number of runs are calculated in parallel which obviously leads to savings of time.

All relevant modules shown in Figure 54 are described in section 4.4.1.2 except from the additional disease module described below.

Disease simulation:

Each modeled special disease has its own attributes that affect individual's behavior. Due to the modular implementation the special diseases can be selected or deselected before the simulation run. Therefore it is possible to simulate dependencies and interconnections between different modeled special diseases. The results of the disease computation are saved in a disease file for individual diseases and an associated information file to the local file system. The disease file for an individual disease contains at least one annual disease data record. The measure of the spread of each computed value about the mean is given by the respective value of the standard deviation as shown in Equation 7. The reliability of the simulation results is indicated by the desired confidence interval as shown in Equation 8 which is stated at the 95% level. The confidence interval μ quantifies the precision of the mean.

To demonstrate the population model with an integrated special disease module a model of a preventive cancer checkup process will now be described.

Modern preventive cancer checkups can diagnose cancer risks at a very early stage making necessary treatment easier, more effective, and more efficient. Most of the common malignant diseases, if detected in an early stage, can successfully be cured, due to tremendous progress in treatment possibilities. That's why regular checkups can prolong a healthy life.

The basic preventive cancer checkup process (PCCP), developed and verified with medical experts, that is shown in Figure 55 can be applied to all of the malignant diseases for example (colon cancer, prostate cancer, gynecological tumors, skin tumors, etc.). There is always a risk group in a population, normally being addressed by age and gender. This group can then be divided into two parts (percentage R1 and R2): the ones that will never go to a preventive medical checkup and the other ones that go to a preventive medical checkup at least once in their lifetime after entering the specific risk group. Once entering the prevention path there will be a medical checkup. If an indication for the specific cancer is found during the checkup an intervention will be performed and the patient will be send back to regular preventive medical checkup after some years (indicated by X2). If no indication is detected the patient will also be sent back to regular preventive medical checkup after some years (indicated by X1). Once being in the prevention cycle the normal mortality for the specific cancer will decreases with a given percentage (indicated by PI).

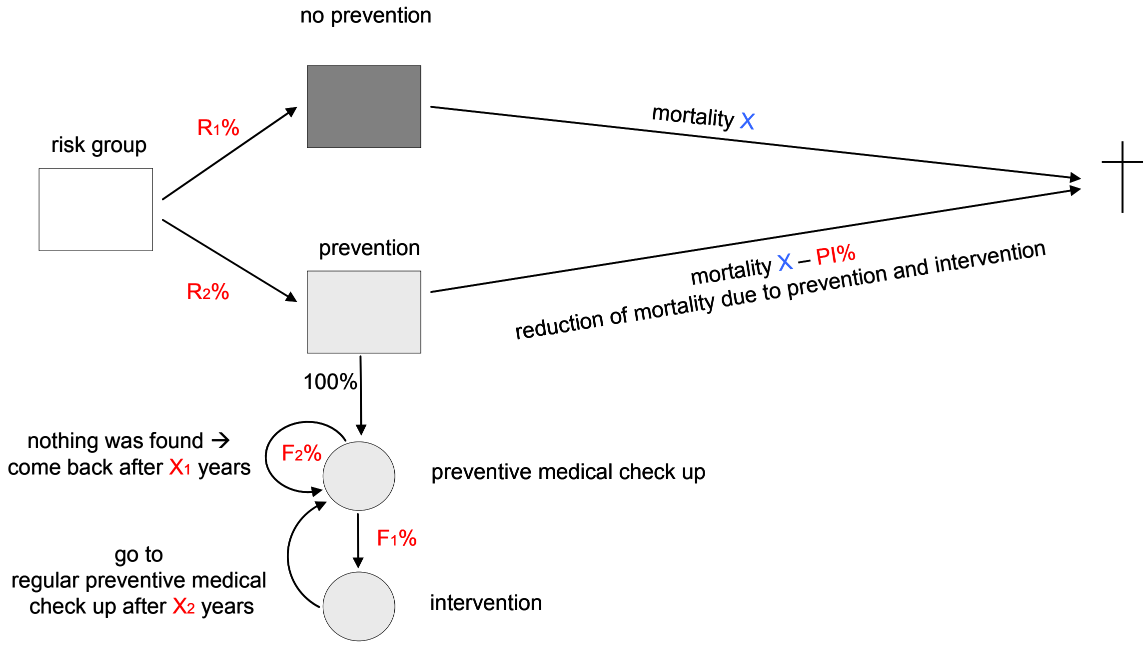


Figure 55: Basic principle of a preventive cancer checkup process

Before demonstrating the PCCP by applying it onto the colon carcinoma, one of the most common cancer types of men and women, some facts and recommendations of this special disease will be described.

Some colon carcinoma epidemiology facts:

- It is the second most common tumor of men and women and the second leading cause of cancer-related death in the Western world.
- The Incidence is about 50 cases per 100.000 inhabitants per year in the Western world.
- The USA is facing a decrease of incidence of circa 3%, whereas in Europe the incidence rate is constant since the eighties.
- There is a global continuous decreasing mortality since the eighties.

Some recommendations for the colon carcinoma taken from literature: (U.S. Preventive Services Task Force 2007), (Cappell 2008), (Weitz et al. 2005), (American Cancer Society 2006).

- Persons at average risk should:
  - Undertake a yearly digital rectal exam (DRE) and fecal occult blood test (FOBT) starting with the age of 40. If the FOBT is positive a colonoscopy should be performed.
  - Undertake a colonoscopy every 5-7 years starting with the age of 50.
- Persons after an intervention (polypectomy) of an adenoma:
  - High colonoscopy rate in the context of the prevention strategy every 5-7 years after excision of one or two tubular adenomas smaller than 10 mm.
  - High colonoscopy rate in the context of the prevention strategy every 3 years after excision of three or more adenomas.
  - High colonoscopy rate in the context of the prevention strategy every 3 years with detected adenomas larger than 10mm or with villous shares, or with severe dysplasia.
  - High colonoscopy rate in the context of the prevention strategy every 3 years after an age of 60.

With these facts and recommendations and the standard values, shown in Table 8, taken from literature (Citarda et al. 2000) (Barclay et al. 1993) (Barclay et al. 2006) the PCCP for the colon carcinoma is shown in Figure 56.

Table 8: System parameters for simulating a preventive cancer checkup process (PCCP)

R1	**R2**	**F1**	**F2**	**X1**	**X2**	**PI**	**X**
60%	40%	10%	90%	7	3	80%	$0{,}45 * 10^{-3}$

With this given values the average year a patient comes to the preventive medical checkup is 6.6 according to Equation 10.

Equation 10: Calculation of the average year a patient comes to the preventive medical checkup

$$\text{average year} = X1 * F2 + X2 * F1$$

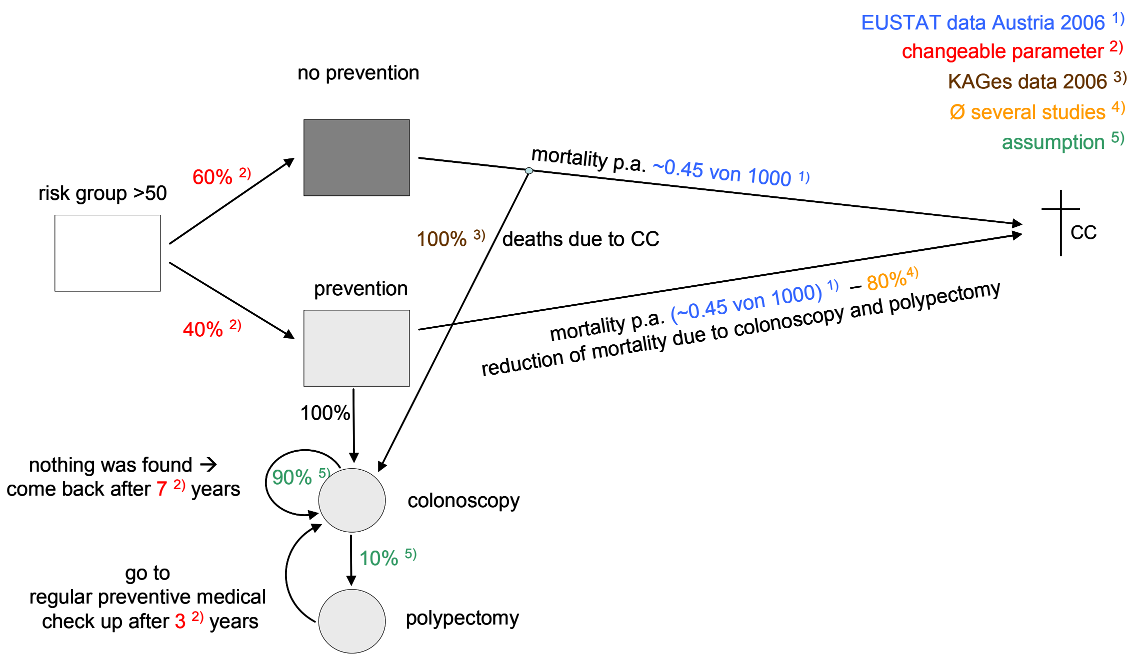


Figure 56: Preventive cancer checkup process applied onto colon carcinoma

Before implementing an individual disease into the population module the output and thus the attributes of the individuals need to be calibrated to build up a population that is quite similar to the real or suggested one. The next step is to define the ICD-10 category the modeled individual disease belongs to and then add the needed attributes to an agent. In this case this new "disease data sheet" that is connected to an individual contains the number of performed interventions, the waiting period till next check is performed, the new death probability, and so forth as shown in Figure 57. Depending on the input data that is linked to the individuals they act on probabilities each simulation period. Due to this definition of the individuals this disease module can be assigned right in the middle of the Micro Simulation and Agent Based approach.

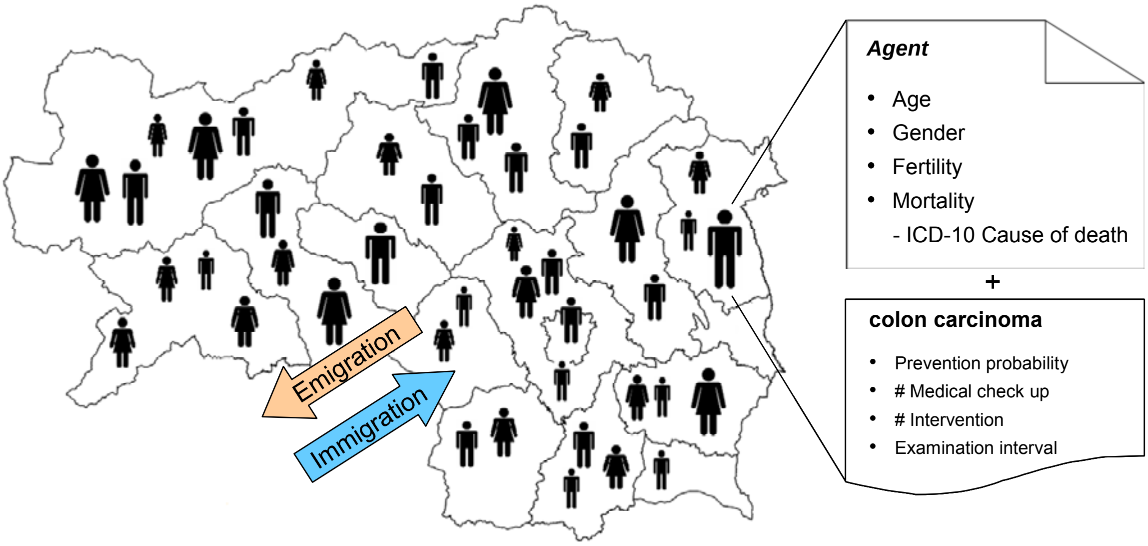


Figure 57: Population micro simulation with special disease – colon carcinoma

The output of the PCCP for colon carcinoma of Styria's population with the given values and additional facts that a treatment last approximately 40 minutes and the division between surgeon and internist is 25% to 75% was really astonishing and is shown in the Figure 58. Although more people are entering than leaving the risk group the demand for preventive checkup will not grow when we assume that the same percentage of people as today will go to checkup in the future. This is because most of the demand is already generated by the people in this two stage cycle. The demand will not grow until the prevention percentage is set up to more than 60% and this is in fact a relatively unrealistic scenario for the future.

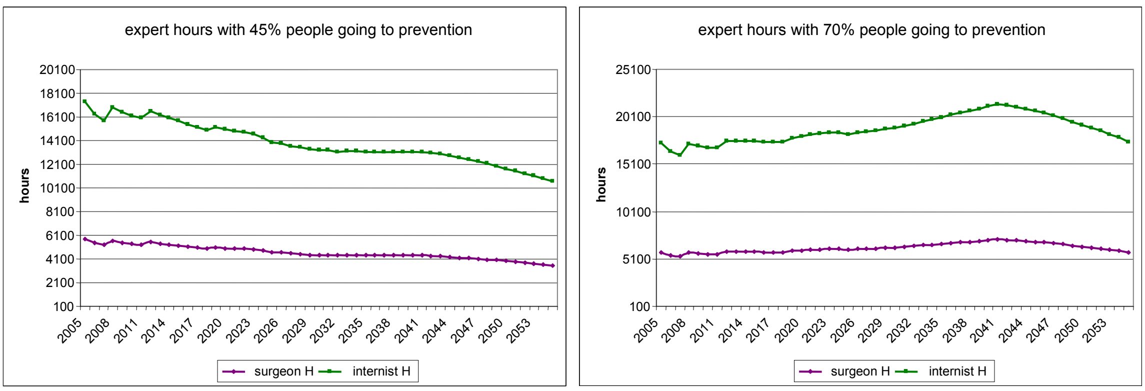


Figure 58: PCCP medical checkups as a consequence of different policies

In Figure 59 we see the absolute difference of people dieing from colon cancer per year. The absolute amount of people that could be saved due to more preventive checkups will not dramatically fall just by doing 55% more of these checkups. This output is because of the changing age distribution of people older than 50 and is really crucial when thinking about investing more money in these preventive checkups or advertisement to increase the amount of people going to cancer prevention.

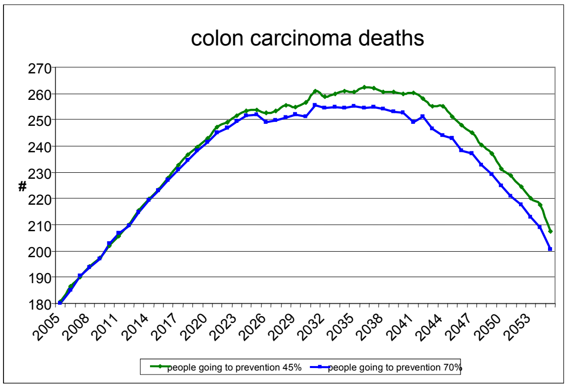


Figure 59: PCCP death rates as a consequence of different policies

4.4.2.3 Input and Output

Due to the modularity of the model the simulation output- and input files have the same structure. The first step in the disease simulation is to acquire an initial disease and population distribution. This can either be done by selecting a prior simulation or statistical data. There is at least one annual population and disease distribution required to perform a simulation run. The population and disease data is always loaded from plain text files on the local file system. A proper disease distribution consists of two files:

Disease file:

The disease file contains at least one annual disease data record. The cases of the disease are denoted for each gender in one-year age-groups for the corresponding year. There is a total number of 96 age-groups (from 0 until 95 years of age). The measure of the spread of a case of a disease about the mean is given by the respective standard deviation value.

Information file:

The information file is associated with the respective disease file. It is generated automatically in the course of the simulation process. The file contains the properties of the respective disease record by means of descriptive entries. The basic information includes *username, date, simulation start year, simulation end year* and *disease record filename*. Furthermore, a number of parameters of the used simulation type are added.

4.4.3 Specialists-service Supply Module

The Specialists-service Supply Module (SSM) simulates the available employees for the future and represents the supply side of the healthcare framework. This module consist of an individual based simulation core, the same one used for the population module, and additionally contains all necessary attributes for modeling the education and jobs system of physicians as shown section 4.4.3.1 and in the sequence in Figure 62. Therefore this simulation is not only able to adjust the employees in their job and their age but also let them die due to diseases or bear a child and so forth.

The obsolescence of the population is also affecting the age of employees in healthcare organizations as shown in Figure 60 and is a crucial fact for the future performance and existence of all institutions. From this figure the average age of employees in Styria's healthcare organizations can be derived as:

- specialists: circa 49 years.
- ward physicians: circa 42 years
- junior house officer: circa 34 years
- specialist trainees: circa 39 years

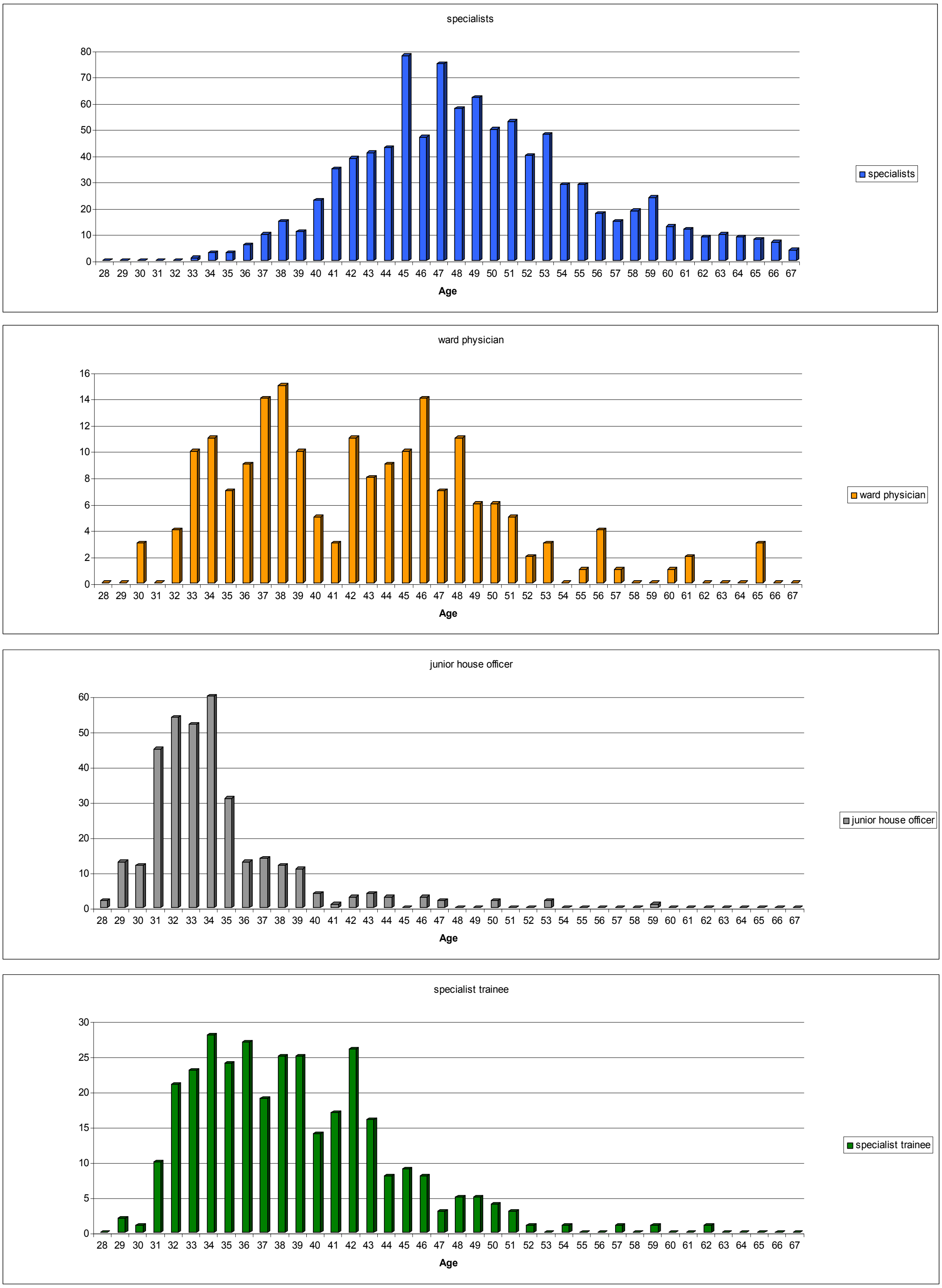


Figure 60: Age distributions of Healthcare employees (specialists, ward physicians, junior house officers, specialist trainees)

Figure 61 illustrates a scenario for a medical department with possible future problems, arising from following realistic assumptions occurring in many healthcare departments:

- No specialists can be assigned or bought from market, thus the department can just regenerate out of its own trained employees.
- Employees can leave the department due to retirement or migration.
- The duration of specialist training lasts six years.
- After education, trainees can occupy the assigned position as a specialist.
- There must be at least one specialist more than trainees.

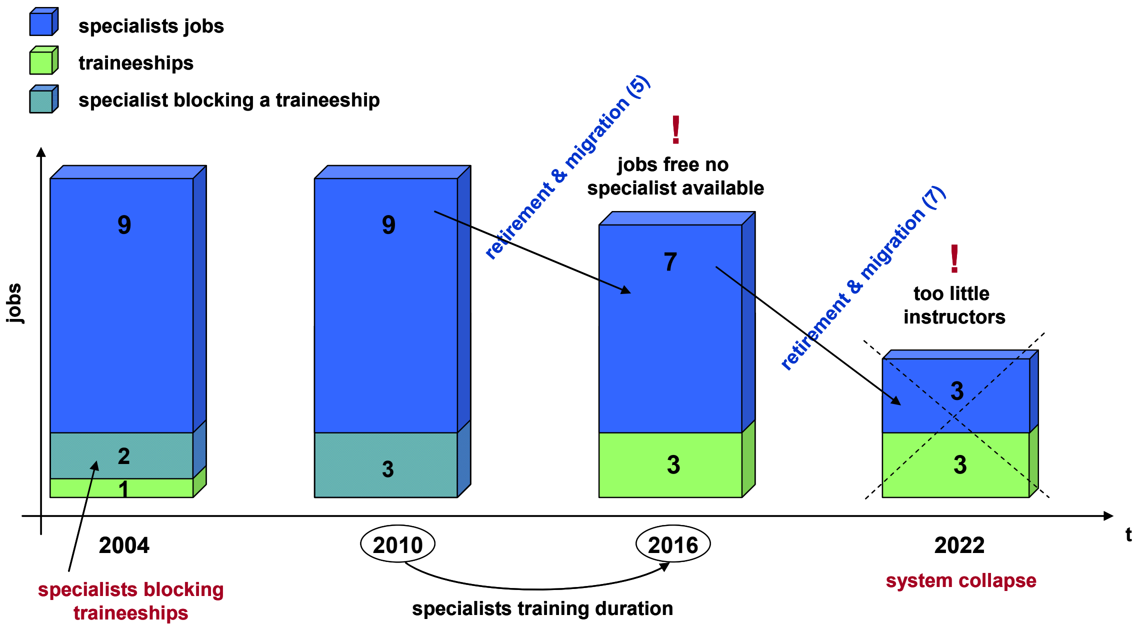


Figure 61: Job occupation scenario for specialists and trainees

In the year 2004 there are nine specialist's jobs and three traineeships but two of them are already occupied with specialists. In the next step, in the year 2010, the department employs only specialists. Because no specialists jobs are available the specialist trainee from step one occupies his traineeship as a specialist after finishing his education. From now on the department is highly efficient and will perform more procedure and diagnosis due to not educating specialists. Until the next step the first retirements and migrations decrease the amount of employees to ten, but the department is still operating, because three new trainees started their education in the department. With the next retirements and migrations until the next step the department isn't able to operate any more. Figure 60 illustrates the usual age distribution of a Styria healthcare institute and underpins the scenario mentioned above where most of the specialists retire or leave the department within eighteen years. This is certainly a worst case scenario but identifying those scenarios is only possible when using computer simulation and gives persons in charge the ability for steering actions far in advance.

The scenario mentioned above is only one variant in the SSM which includes various types of scenarios from different education systems, and job occupation variants to pregnancies, retirements and migrations as described in section 4.4.3.3.

4.4.3.1 Agent Attributes

(1) Age:

Each agent has a specific age starting with cero which is increased annually and remains in the system until he dies. The age interval is set between 0 and 95 years and therefore contains 96 age groups. Agents above the age of 95 are tracked with an extra parameter.

(2) Gender:

An agent's gender can either be male or female and the initial gender is predetermined by the start population distribution. Newborns are assigned randomly a gender depending on the male-female ratio of the start year's population distribution. Immigrated agent's gender is uniformly distributed.

(3) Fertility:

Of course only female individuals are given an annual birth probability. This value indicates the probability to bear a child in the course of the actual year. The birth probability depends on the age of the agent and on the used probability distribution. There are several distributions available calibrated on statistical data.

(4) Mortality:

The mortality value contains the probability of death for each agent's age. Mortality is divided into the main parts of the ICD-10 (International Classification of Diseases endorsed by the WHO in 1990) code.

(5) Migration:

Migration contains immigration and emigration rates. The annual decision of an agent for migration is based on the used migration distribution. There are several distributions available calibrated on statistical data.

(6) Type

There are four different types of employees available in the simulation:

1. specialist (medical specialist in a discipline)
2. ward physician (general practitioner)
3. junior house officer (medical alumnus)
4. specialist trainee (apprenticeship as specialist in a discipline)

After finishing university young physicians have many job possibilities. They can take a three year education in becoming a medical alumnus and be a ward physician at a medical department afterwards or take another six year education in becoming a medical specialist. There is also the possibility to just take the six year education in becoming a medical specialist without taking the three years internship. When taking the specialist path one can decide between 42 disciplines like anesthetist, internist, plastic surgeon, orthopedist and so on.

(7) Subject

The subject determines the specialist discipline. There are four different kinds of subjects available like major, minor, training and additive subject. A major subject always defines the discipline a specialist is working in. The minor subject is one or more additional subjects a specialist has learned in his education period. These two subjects can be swapped when needed. The training subject is the subject a trainee is educated to become a specialist. The additive subject is a further specialization of a specialist in his primary subject.

(8) Working place

Defines the actual job a physician is working at. The working place is divided into house and division.

4.4.3.2 Simulation Process

The amount of the workforce at each working place is the result of the interplay of the basic nine properties through each simulation cycle as shown in the sequence in Figure 62 and described below. The behavior of each individual is determined by annual decisions and events concerning the basic attributes.

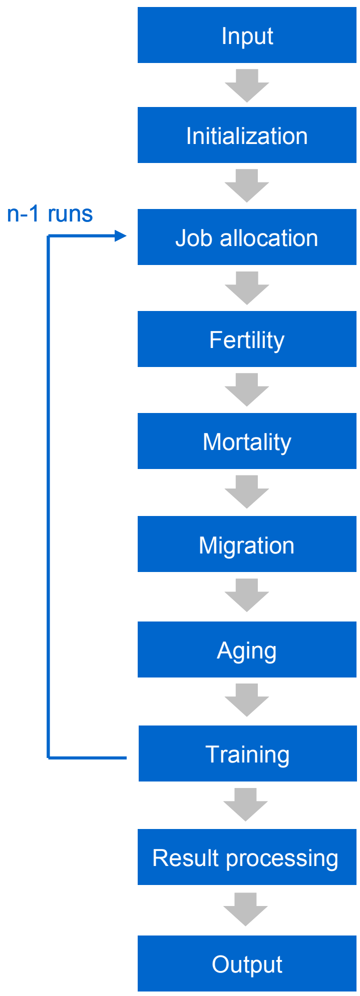


Figure 62: Employee module sequence

Initialization:

The first step is to acquire all relevant data from the employee and job distribution to create individual agents and their respective attributes and jobs according to the available departments.

Job allocation simulation:

The main part of this simulation is to identify job vacancies and allocate new employees to these jobs according to the individual job description. The algorithm searches through the different available queues and assigns the best possible employee for each vacant job. For example only specialists can be allocated to specialist jobs according to their individual discipline and level of education. Job vacancies can occur due to mortalities, migrations or by disbanding a single job or a whole department.

Fertility simulation:

The main part of this module is to calculate the annual number maternity leaves. Every female agent has a specific birth probability which is adapted each year. This property indicates the probability to bear a child in the course of the actual year. The individual birth probability is calculated by using a global total birth probability parameter and a probability distribution both fitting Statistics Austria data for the age interval. The probability to bear a child in the course of the actual year is age specific and considered between 15 and 45 years and is calculated by the binomial probability distribution.

Mortality simulation:

The main part oft his module is to calculate the annual number of deaths. Each agent has a parameter that describes the probability of death based on the International Classification of Diseases (ICD)[4]. The individual death probability is an accumulation of six classified parameters which describe the gender specific causes of death:

– Neoplasm diseases

– Circulatory system diseases

– Respiratory system diseases

[4] WHO - ICD website: http://www.who.int/classifications/icd/en/

– Digestive system diseases

– Miscellaneous diseases

– External causes

This concept allows the adaptation of the probability of death within the scope of certain diseases. The probability of death is also age specific. The death probability distribution and the annual adaptation factor describe the probability of death for each male and female age group.

Migration simulation:

The main part of this module is to calculate the number of emigrations per age group for each year. The global parameter set at the beginning of the simulation allows calibrating the percentage of annual leavings and their respective age group. Furthermore a retirement parameter can be selected for each gender.

Aging simulation:

The age of an agent is annually increased by one year and between the overall age interval from 0 and 95 years. There is also a system age parameter that is incremented when an agent is aged 96 and above.

Training simulation:

The main part of this simulation is to loop through all specialist trainees and increase their level of education. After finishing the education to become a specialist the employee is either given a new specialist job in the department or blocking his apprenticeship training position or transferred to a queue where other departments can access available employees. This depends on the selected simulation parameter. Blocked apprenticeship training positions can only be assigned with new specialist trainees when a specialist at the department dies or emigrates.

Result processing:

The results of each simulation run are saved in an appropriate data list. An employee file with the associated information file and a job file with the associated information file is generated and saved to the local file system.

Possible Simulation scenarios:

There are six possible combinations of the following available simulation types.

A1: apprenticeship training position → apprenticeship training position (ATP → ATP)

1. Static simulation:

   An apprenticeship training position will be free for the next specialist trainee after completion of education. The trained specialist will be sent to an internal queue.

2. Dynamic simulation:

   An apprenticeship training position will be free for the next specialist trainee after completion of education. An additional senior physician position in this division will be generated for the trained specialist.

A2: apprenticeship training position → senior physician position (ATP → SPP)

An apprenticeship training position will be rededicated into a senior physician position after completion of education. This apprenticeship training position can only be assigned with new specialist trainees when another senior physician position in this division is not occupied any more.

B1: Self regenerating

A division can only regenerate out of its own trained workforce. Thus vacant jobs can only be assigned with people working in this division.

B2: Automatically fill jobs

Vacant jobs are automatically filled up with systemic generated physicians. This type of simulation simulates external buying's.

All selectable scenarios can be simulated with or without fertility, mortality and annual leavings.

To demonstrate the employee model the output for the scenario with ATP → SPP and self regenerating for the department of Judenburg-Knittelfeld and the division for anesthetists from the year 2009 to 2030 as summarized in Table 9 will now be shown:

Table 9: Micro employee simulation parameters

Parameter	Value
employee distribution	Judenburg-Knittelfeld 2009
job distribution	Judenburg-Knittelfeld 2009
simulation type A	ATP → SPP
simulation type B	self regenerating
retirement	men 65, women 60
migration, mortality, fertility	-
average age of university alumni	25 years

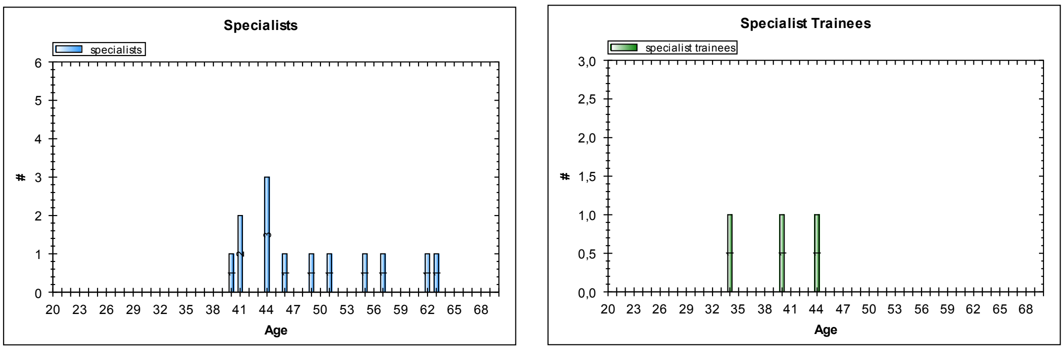


Figure 63: Age distribution for the anesthetists division in the department of Judenburg-Knittelfeld both for specialists and specialist trainees for the year 2009

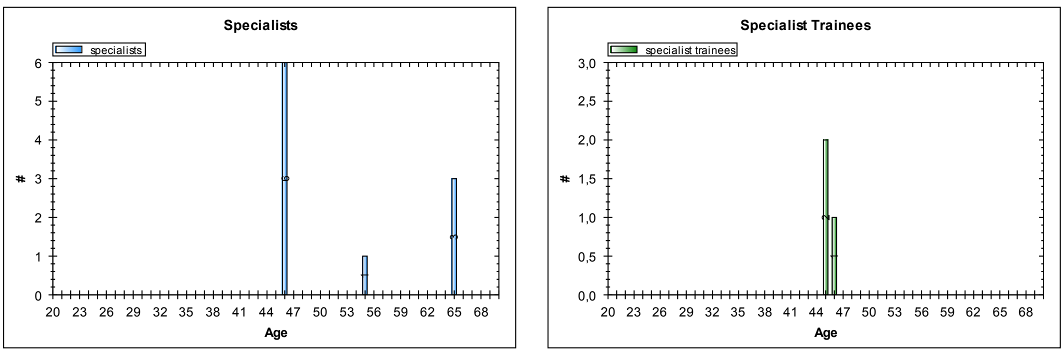


Figure 64: Age distribution for the anesthetists division in the department of Judenburg-Knittelfeld both for specialists and specialist trainees for the year 2030

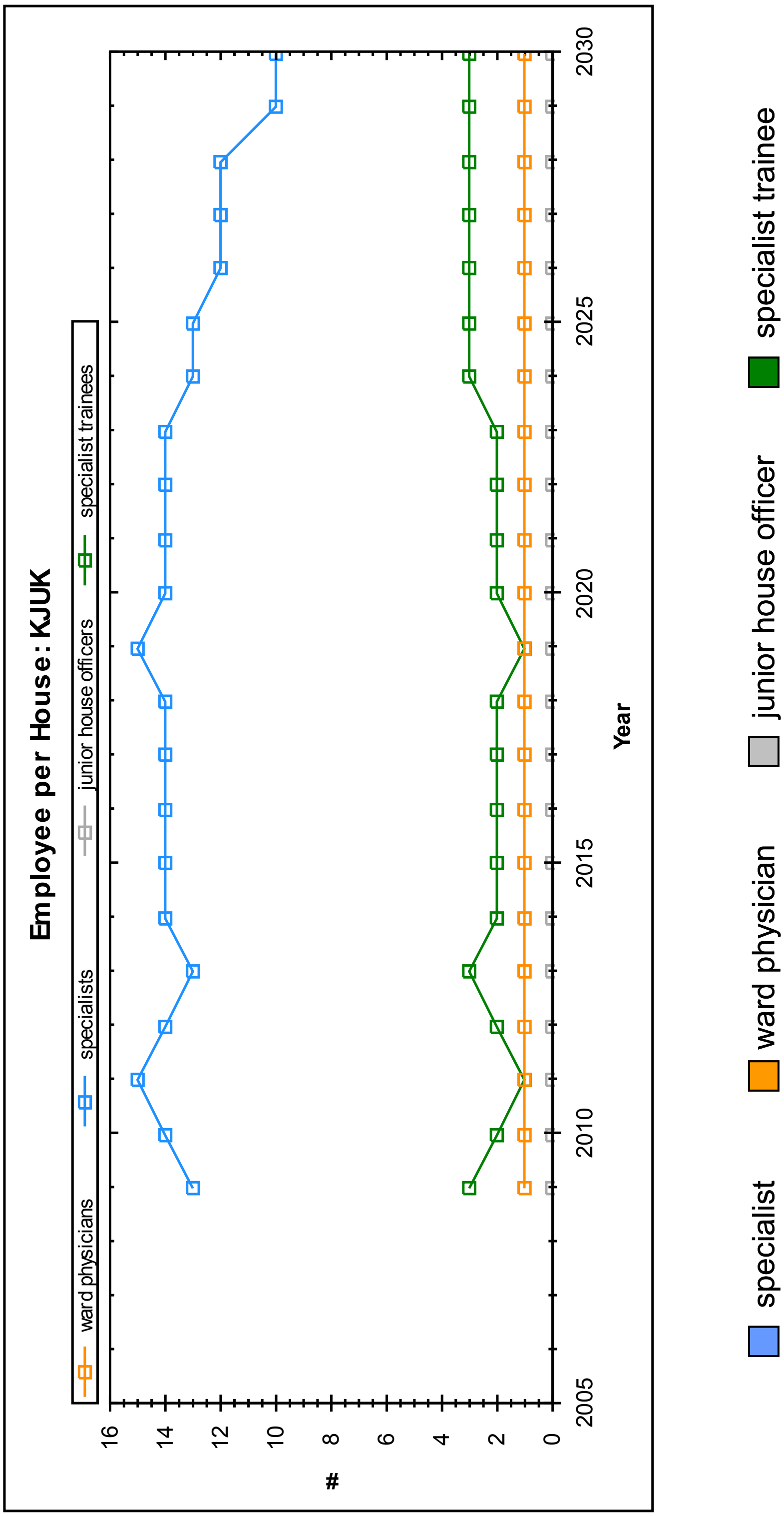


Figure 65: Employee distribution for the anesthetists division in the department of Judenburg-Knittelfeld for all available employee types from the year 2009 to 2030

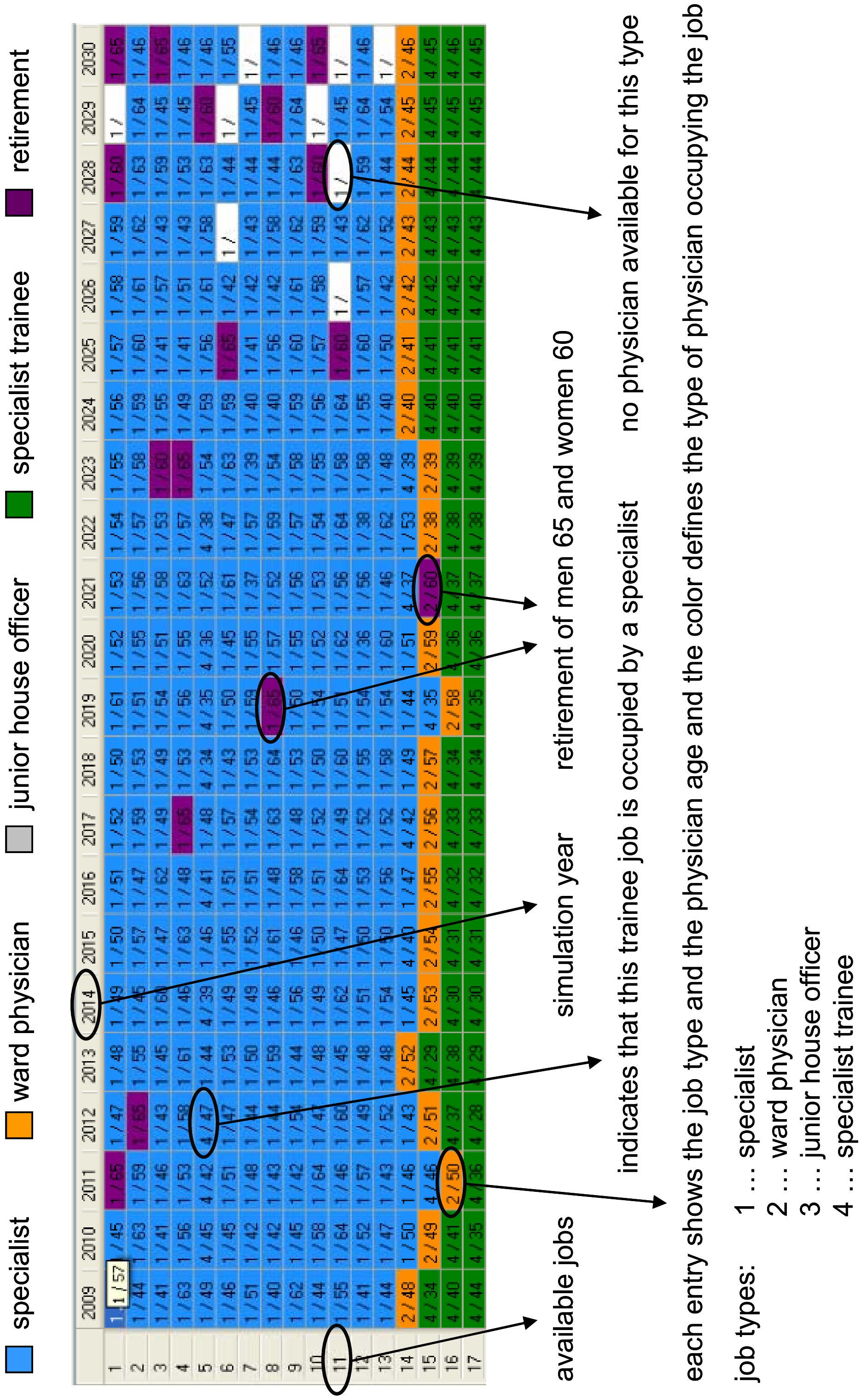


Figure 66: Job distribution for the anesthetists division in the department of Judenburg-Knittelfeld for all available employee types from the year 2009 to 2030

This simulation for the given realistic scenario shows that the anesthetists division in the department of Judenburg-Knittelfeld is not able to regenerate out of itself for the next 21 years. At first the amount of available specialists rises until the first retirements. Till this point the department is highly efficient and able to do more treatment when considering that a specialist can do more work than a specialist trainee. The next crucial thing is that in the year 2030 three more specialists retire and there will be no substitution for them as shown in the age and job distribution in Figure 64 and Figure 66. Because there seems to be much time to intervene with different steering actions one has to remember that there is an almost ten year educational period from finishing university to becoming a specialist. Therefore there are only a few years left for necessary steering actions when considering this realistic scenario.

4.4.3.3 Input and Output

Due to the modularity of the model the simulation output- and input files have the same structure. The first step in the employee simulation is to acquire an initial employee distribution and job distribution. It is not necessary to choose the same data files for employees and jobs because the job allocation algorithm assigns only available jobs to the employees. Therefore it is possible to simulate different scenarios where more, lesser or the same jobs as employees are available. There is at least one annual employee and job distribution required to perform a simulation run. The employee and job data is always loaded from plain text files on the local file system. A proper employee and job distribution consists of two files:

Employee file:

The employee file contains at least one annual employee distribution. Each employee data contains the necessary information for each employee like age, type of physician, working place, subject, earnings, level of education and working hours.

Information file:

The information file is associated with the respective employee file. It is generated automatically in the course of the simulation process. The file contains the properties of the respective employee distribution by means of descriptive entries. The basic information includes *username, date, simulation start year, simulation end year* and *type of simulation*. Furthermore, a number of parameters for the used simulation type are added.

Job file:

The job file contains at least one annual job distribution. Each job data contains the working place, the type of physician associated with the specific job and the subject for that job.

Information file:

The information file is associated with the respective job file. It is generated automatically in the course of the simulation process. The file contains the properties of the respective job distribution by means of descriptive entries. The basic information includes *username, date, simulation start year, simulation end year* and *type of simulation*. Furthermore, a number of parameters for the used simulation type are added.

4.3.4 Limitations of the micro modules

Population simulations use fixed preset distributions for fertility, mortality and migration to simulate population distributions, thus this distributions have to be reallocated when simulating other population than Austria ones. There is no differentiation regarding the amount of child bearings per women within a simulation run. The age distribution is subdivided into 96 groups going from cero to ninety-five.

Disease simulations always use assumptions and simplifications of the modeled treatments. Incidences of those diseases in the past have to be initially determined or if not possible estimations calculated and applied to the selected population distribution. Dependencies between one or more models have to be included in the models and will not be calculated automatically.

Workforce simulations assume that all medical treatments are optimal covered with the selected employees and structure. That means that no suggestions regarding the reasonability of a department or the efficiency of individuals can be derived out of these simulations. Special knowledge regarding a discipline is not being considered within these simulations. Employees are given a job anywhere in the system and there is no differentiation between congested areas and outskirts regarding these job allocations and job shifts. The specialist training system underlies a full rotation principle hence all specialist trainees stay at the same department for their whole trainee duration.

5 Conclusion

5.1 Summary

This thesis stated a generic model for healthcare systems, which is capable of giving adequate quantitative and qualitative statements both on the macro and on the micro level to determine the future demand of performance determining know-how bearers. Starting with an overview of a modeling and simulation process, the most common simulation approaches in social science were discusses and compared to each other within the field of complex systems. The next part described the developed generic framework with all relevant modules and their functionality with possible simulation results for each module.

The developed framework offers a multitude of possibilities for the extension and answers of further questions concerning futures healthcare management and can also be applied to other fields of activity. Possible extensions would be adding further diagnosis and therapy-referred simulation modules for estimations, to for example accurately estimate the capacity of operating theaters or radiate-therapeutic resources et cetera. These estimations could then again aid as a data based decision making for traineeship concepts and in further consequence meaningful decisions regarding new business field developments in the health service.

Research question 1:

What approaches are suited to model complex social systems?

There are several methods in social science that are nowadays used for modeling complex social systems like health care ones as described in chapter 3. The comparison in Table 4 and Table 5 gives a good overview of the available and most accurate approaches and determines the ability of individual based approaches to model complex systems up from the micro level. According to the requirements of the models output and the system that needs to be modeled it is up to the modeler which approach he wants to use. When the models output just needs to be qualitatively accurate then one should use the SD approach. Because of the averaging of individuals over the defined groups this approach lacks in realistic quantitative output and can not produce emergent behavior, where one should use an IB approach. Because of the not explicit and wide definition and of the inexistent global accepted definition of ABM, nowadays almost all models based on the IB theory are argued to be ABM ones.

Research question 2:

Which approaches are suitable to develop a generic model of a Healthcare system to give adequate qualitative and quantitative answers for the prediction of future needs?

All four addressed approaches are capable to model complex social systems as mentioned above.

- SD is useful to model the basic system's behavior. With the causal loop diagram SD provides a powerful tool for modeling, to describe a model and its interactions. A substantial advantage of SD is the big number of available Simulation Software and their intuitive and easy use, when needing quick answers about a systems behavior. SD lacks in generating realistic quantitative output data for such complex systems like healthcare ones as described in the paper in the Appendix.
- CA is useful when dealing with modeling and recognition of patterns and their emergent behavior. Due to the definition and location of the cells on a grid the appropriate use when dealing with healthcare systems is the field of disease models and spatial evolution like the spread of AIDS or Ebola.
- MS is commonly used for analysis of the distributional impact of changes in governmental programs. Across Europe, America and Australia, MS models are used extensively to assess the winners and losers of a population distribution from proposed policy reforms. That's why MS always deals with simulating individuals and cohorts with many attributes but without direct connection between them.
- ABM seems nowadays to becoming a global keyword for all types of simulations regarding individuals as stated in chapter 3. The approach is best used when modeling system from micro to macro level and being confronted with emergent behavior within these systems.

Because of the definition of the available approaches the developed framework can be addressed between the MS and the ABM approach. To give some verified examples of the described MS/ABM framework from Chapter 4 an output of the macro disease model with trend type weighted differences will be given below.

Figure 67 shows the comparison of the forecast from the sum and a representative individual procedure “Athroskopische Eingriffe” for the year 2005 and 2006 calculated from real data from 2000 to 2004 and the real data till 2006. The maximum discrepancy between both series is just 2.4 percent and this is quite accurate when considering that there are only four available data points for the trend calculation. Therefore the output will get exacter with the availability of extra data rows.

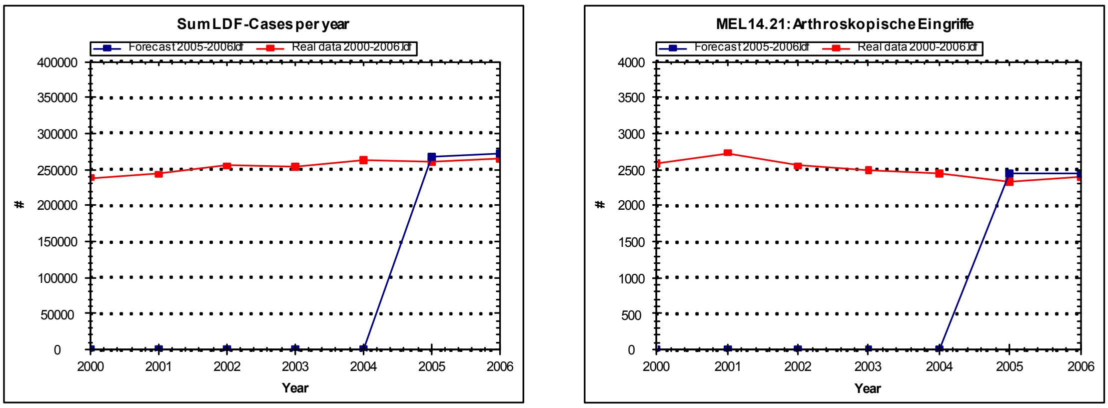


Figure 67: Comparison of real data to models forecast for all procedures and a representative one

Figure 68 shows the calculated forecasted amount of births with the trend type weighted differences of a Styrian healthcare organization until the year 2020 from given births of 2000 – 2006 compared with the confidence interval calculated out of Statistics Austria data of the entire Styrian region.

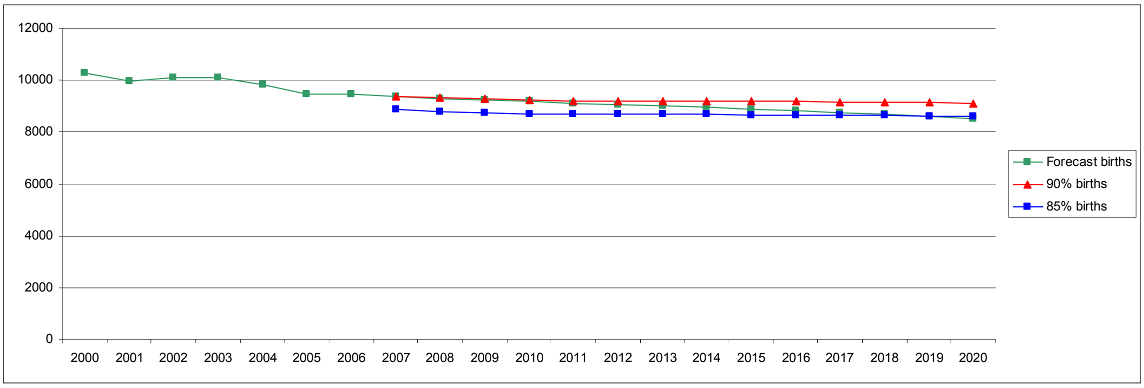


Figure 68: Comparison of births model output to Statistical Austria data

The defined confidence interval from 85%-90% is calculated out of Styria's births performed by the healthcare organization mentioned above and therefore the two series represent the adjusted values from the forecast of Statistic Austria. The generated output of the model fits perfectly between those two bounds generated by Statistic Austria and is an indication of the accuracy of the models output.

These two representative outputs, one comparing the models output to real data and the other comparing forecast data to representative calculations from the statistical department of Austria show the accuracy of the developed model.

Research question 3:

Is this general model suitable to give adequate verified answers on the micro level?

The developed model is capable to address problems both on the macro and micro level as described in the already published module in chapter 4.4.2 that gives validated and verified output for given individual problems on the micro level. The associated publication for a micro disease simulation as described in 4.4.2 is attached in the publications section.

5.2 Future Research

Due to the astonishing but realistic outputs coming from the micro simulations, these modules are now object of further research. On the one hand the population with integrated diseases module gives astonishing answers for the future demand of specialists for the colon carcinoma and on the other hand the workforce module shows vacancies in specialists supply capacity.

Integrating more detailed addressable mortality and fertility tables with trends, to simulate even more accurate scenarios for future population distributions to define representative scenarios like the ones from Statistics Austria, are just a few work packages for the population module. Integrating more cancer prevention models, interactions between the agents like transmissibility of diseases, word of mouth advertising for preventive medical checkup, are interesting scopes of research for the disease module. The simulation of migration concepts, by integrating more attributes to model migrations not only intramural but also extramural, according to attractiveness of jobs, qualification, age and retirements in peripheral practices, are just a few extensions for the workforce module.

These kinds of extensions and integrations would shift the developed micro module to a more realistic ABM module.

Another interesting scope is to extend the developed framework to address questions and problems concerning care.

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Modellierung eines komplexen, vernetzten Systems zur Abschätzung von Angebot und Nachfrage an leistungsbestimmenden Know-how Trägern im Gesundheitswesen

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Modellierung eines komplexen, vernetzten Systems zur Abschätzung von Angebot und Nachfrage an leistungsbestimmenden Know-how Trägern im Gesundheitswesen

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Abstract:

Wir stellen als gemeinsames Forschungsprojekt ein Modell zur Abschätzung von Angebot und Nachfrage im Bereich des Gesundheitswesens vor. Leistungsbedarf und Leistungserbringung sind ein komplexes und stark voneinander abhängiges System in das eine Vielzahl von Faktoren eingehen: von demographischen Bewegungen, soziologischen Faktoren über Ausbildungsthemen von Ärzten bis hin zu medizinisch-technischen Entwicklungen. In diesem Artikel wird ein auf „System Dynamics“ (SD) und „Agent Based Modeling“ (ABM) beruhenden Ansätzen, zur Beschreibung und Vorhersage des Systemverhaltens, erstellte modulares Modell, sowie exemplarisch erste Ergebnisse präsentiert.

Einleitung

Überaus vielschichtige dynamische Einflüsse prägen unser Gesundheitswesen. Die sich ändernde Bevölkerungsalterspyramide und damit verbunden eine Verschiebung der Krankheitsbilder und –häufigkeiten (beispielsweise mehr Gelenkersatztherapien, weniger Geburten), der rasante medizinische Fortschritt, ein höheres Anspruchsverhalten der PatientInnen und auch beschränkte Finanzressourcen sind nur einige der vielen Einflussfaktoren, die sich auf das künftige Gesundheitssystem auswirken. Auch in einschlägigen Medien liest man immer wieder Horrormeldungen von einem zunehmenden Mangel an medizinischem Personal. Wie etwa in der NZZ (02.08), wo laut Expertenschätzungen in den USA im Jahr 2020 bis zu 200.000 Ärzte und 800.000 Krankenschwestern fehlen. Um auf die Frage nach dem künftigen Ärztebedarf eine möglichst treffsichere Antwort zu finden, wurde ein Forschungsprojekt zwischen der TU Graz und der Steiermärkischen Krankenanstaltengesellschaft (KAGes) initiiert. Kooperationsprojekte zwischen Universitäten und Wirtschaft haben in der Praxis oft unterschiedlichen Charakter. Von Projekten die einer "verlängerten Werkbank" ähneln bis zur großzügig geförderten Grundlagenforschung sind alle Varianten üblich. Aufgrund des hohen Anteils an Grundlagenforschung in den Bereichen Simulationsverfahren und Modellierung und der hohen Komplexität und Datenverfügbarkeit, könnte keiner der Projektpartner diese Thematik alleine beherrschen. Der Wirtschaftspartner KAGes brachte seine umfangreiche Erfahrung und Datenbanken im Bereich Public Health / Health Care sowie das notwendige medizinwissenschaftliche Fachwissen ein – der akademische Partner, das Institut für Maschinenbau- und Betriebsinformatik ergänzte dies durch Kompetenz in den Bereichen der Business Modellierung, der quantitativen Methoden und Simulation. Die dadurch entstandenen Synergien sind maßgeblich für den Projekterfolg verantwortlich: Als Ergebnis entstanden innovative Modellierungsansätze sowohl aus systemwissenschaftlicher Sicht als auch wertvolle Ergebnisse für praxisrelevante Fragestellungen im Bereich der Gesundheitsvorsorge und Vorsorgeplanung. Das Ergebnis ist ein eindrucksvoller Beweis von Innovation durch Kooperation zwischen Universitäten und Wirtschaftspartnern.

Zu modellierendes System

Das Gesundheitswesen ist ein hochgradig komplexes System mit unterschiedlichsten Einflussfaktoren, das grundsätzlich in zwei Systeme unterteilt werden kann, einerseits den medizinischen Bedarf und andererseits das medizinische Leistungsangebot. Nicht nur die Komplexität der Einzelsysteme, sondern auch deren Vernetzung machte es schwierig einen geeigneten Abstraktionslevel zu finden, der nicht zu detailliert ist aber trotzdem noch genügend quantitative Aussagen zulässt. Aus diesem Grund wurde das System in vier Module gegliedert, deren Schnittstellen eindeutig definiert sind und dadurch je nach Anforderung ausgetauscht werden können.

Modellierung

Gesamtsystem

Das derzeitige Framework, wie in Abbildung 1 dargestellt, besteht aus folgenden Modulen: Medizinische Bedarfsmodule, Ärzteleistung-Bedarfsmodul, Vergleichsmodul und Ärzteleistung-Angebotsmodul. Als Input für das Medizinische Bedarfsmodul dienen z.B.: Bevölkerungs-, Sterbe- und Fertilitätsdaten bzw. Leistungstypen, woraus eine Summe an Leistungen pro Typ pro Jahr generiert wird, die als Input für das Ärzteleistung-Bedarfsmodul dienen. Aus diesen Daten wird dann in einer Verknüpfung aus vorherrschender Behandlungsmethodendauer, Fortschritt in der jeweiligen Behandlungsmethode und einer zum Beispiel Produktivitätssteigerung im Verfahren eine Anzahl an benötigtem medizinischem Fachpersonal ermittelt. Auf der anderen Seite wird im Ärzteleistungs-Angebotsmodul das vorhandene Fachpersonal vom Studenten bis zum fertigen Facharzt ermittelt. Als Einflussfaktoren dienen z.B.: Arbeitszeitgesetze, Ausbildungsplätze und Ausbildungsdauer. Die generierten Szenarien können anschließend im Vergleichsmodul gegenübergestellt und Handlungsempfehlungen hinsichtlich eines Ist / Soll Abgleichs abgeleitet werden.

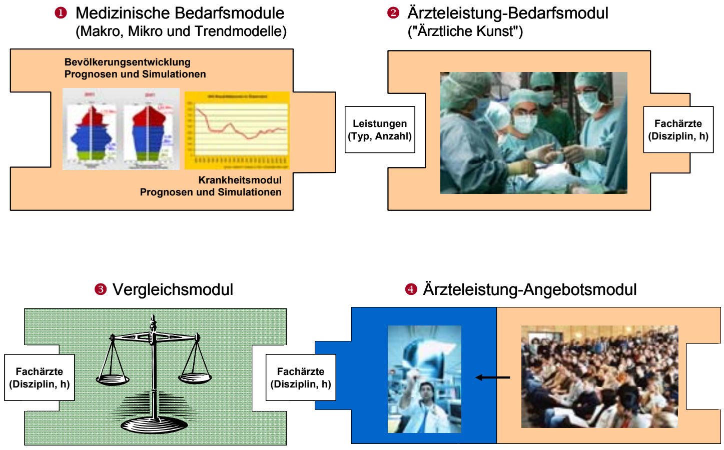

Abb. 1: Module Gesamtsystem – Übersicht

Teilsysteme

Medizinische Bedarfsmodule

Grundsätzlich lassen sich die vorhandenen Module in drei Gruppen unterteilen: Makro-, Mikro- und Trendmodelle. Der Output aller Module ist klar durch die Schnittstelle zum Ärzteleistung-Bedarfsmodul definiert und enthält immer die Anzahl an definierten Leistungen pro Simulationsjahr. Trendmodelle liefern rasche Aussagen über eine mögliche Entwicklung von Krankheiten oder Bevölkerungsverteilungen, da sie Trends in z.B.: Bevölkerungen oder Krankheitsentwicklungen ermitteln und diese extrapolieren. Man könnte also z.B.: Bevölkerungstrends eines Industrielandes auf die eines Entwicklungslandes anwenden und die dortige Krankheitsentwicklung ermitteln. Mikromodelle sind für gezielte Fragestellungen auf der Einzelleistungsebene gedacht. Sie liefern detaillierte Informationen zur Entwicklung von Einzelkrankheiten, wie wir im Kapitel Beispielanwendung noch genauer sehen werden. Hier kann man gezielte Einflussfaktoren der jeweiligen Krankheit mitmodellieren. Im Gegensatz dazu enthalten Makromodelle eher globale Einflussfaktoren und liefern Ergebnisse über das komplette Spektrum der definierten Leistungen.

Ärzteleistung-Bedarfsmodul

Wie in Abbildung 2 gezeigt wird, jede medizinische Leistung nach Dauer auf die einzelnen Facharztdisziplinen aufgeteilt. Je nach Detaillierungsgrad der ermittelten Matrix kann man nun den zukünftigen Leistungsaufwand pro Facharzt ermitteln. Um Änderungen einer Behandlungsmethode zu erfassen, kann die Matrix für jedes Jahr neu angepasst werden. Ein weiterer Faktor des medizinischen Fortschritts ist mittels jährlicher Produktivitätssteigerung implementiert. So ist es möglich aus den ermittelten Leistungsdaten eine Abschätzung für den dafür benötigten Personalstamm zu generieren.

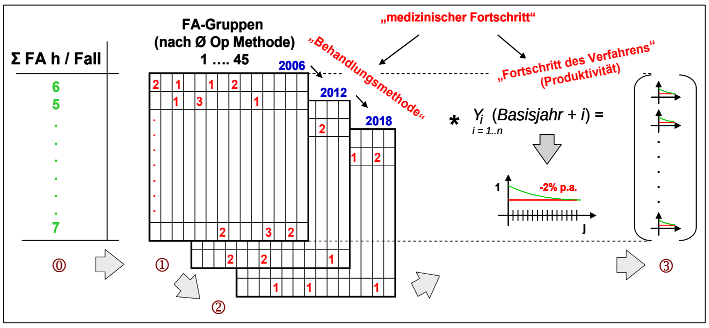

Abb. 2: Schematische Darstellung des implementierten medizinischen Fortschritts

Ärzteleistung-Angebotsmodul

Dieses Modul besteht im Wesentlichen aus einer Personalsimulation und mehreren Ausbildungssimulationen. Die KAGes als Ausbilder und gleichzeitig Arbeitgeber hat hier eine besondere Doppelrolle zu erfüllen, in der man immer genügend Ausbildungsplätze für Studenten, Turnusärzte und Fachärzte zur Verfügung stellen muss, um mögliche Ausfälle so rasch als möglich zu kompensieren. Durch die extrem langen Ausbildungszeiten von ca. 9 Jahren vom fertigen Mediziner zum Facharzt, muss man auf Veränderungen aber schon weit im Voraus reagieren. Dieses Modul ermöglicht es, zukunftsweisende Entscheidungen sofort zu simulieren und kritische Auswirkungen schon jetzt zu erkennen.

Vergleichsmodul

Simulierte Bedarfs- und Angebotsszenarien können in diesem Modul gegenübergestellt werden, um notwendige Handlungsempfehlungen hinsichtlich eines Ist / Soll Abgleichs für die Zukunft abzuleiten.

Simulation

Die Modellierungstechniken die für dieses Projekt gewählt wurden: SD und ABM sind zwei völlig konträre Ansätze, die ein System jeweils aus dem gegenüberliegenden Blickwinkel betrachten. SD ist ein „Top-down" Ansatz, der das System als Ganzes betrachtet und das Systemverhalten mittels geschlossener Wirkungsketten modelliert. ABM ist ein „Bottom-up" Ansatz der Kleinstelemente eines Systems, so genannte Agenten, betrachtet und aus der Emergenz des Verhaltens und der Interaktionen sich das Systemverhalten ergibt. Am einfachsten kann man sich das am Beispiel eines Waldes vorstellen, indem man, grob gesagt, mit SD den Wald als gesamtes und bei ABM jeden einzelnen Baum modelliert. SD ermöglicht es, rasch ein qualitatives Systemverhalten zu generieren. ABM benötigt etwas mehr Zeit bei der Modellierung aber man erhält einen quantitativ genaueren Systemoutput. Je nach Detaillierungsgrad und gefordertem qualitativen und quantitativen Output, kann man also die eine oder die andere Modellierungstechnik wählen.

Beispielanwendung Kolon Karzinom

Das Kolonkarzinom ist der zweithäufigste Tumor von Mann und Frau mit einer Inzidenz von ca. 40 - 60 von 100.000 Einwohnern, trotz einer stetigen Abnahme der Mortalität seit den 80iger Jahren. Moderne Vorsorgeuntersuchungen können heutzutage bösartige Karzinome schon in einem sehr frühen Stadium erkennen und dadurch dringend notwendige Behandlungen einfacher, effektiver und effizienter machen. Dazu ist es aber nötig, dass Personen einer Risikogruppe sich immer wiederkehrenden Vorsorgeuntersuchungen unterziehen. Zur Prävention des Kolonkarzinoms sollte entsprechend geltender Richtlinien sollte man ab dem 50sten Lebensjahr eine Vorsorgekoloskopie durchgeführt werden.

Stehen wir vor einem unbewältigbaren Ansturm an Vorsorgegehern und Wiederkehren und können wir den daraus resultierenden medizinischen Bedarf abdecken, wenn die Bevölkerung, über 60 Jahre, in Österreich bis 2030 um 54% zunimmt? Diese und weitere Fragestellungen wird entsprechend des in Abbildung 3 gezeigten Schemas mittels Modellierung auf Basis der ABM Methode untersucht.

Medizinische Zusammenhänge (Modell)

Grundsätzlich kann man die Bevölkerung in zwei Gruppen teilen und zwar in die Vorsorgegeher und die Vorsorgeverweigerer (diese Leute werden nie in ihrem Leben zu einer Vorsorge gehen). Personen, die zur Vorsorge gehen, werden immer einer Kolonoskopie unterzogen. Wird bei dieser Untersuchung ein Adenom (gutartiger Polyp) entdeckt, wird er mittels einer Polypektomie sofort entfernt, da diese Adenome zur Entartung neigen. Der Patient wird aufgrund des Risikos einer Neubildung nach drei Jahren wieder zur Vorsorgeuntersuchung bestellt. Dies passiert jedoch nur in 10% der untersuchten Fälle. Der Rest ohne Auffälligkeiten wird nach sieben Jahren wiederbestellt. Die Wahrscheinlichkeit an Dickdarmkrebs zu sterben wird durch diese Vorsorgemaßnahmen um rund 80% verringert. Trotz dieser relativ einfachen Zusammenhänge ist es bisher nicht möglich gewesen folgende Fragestellungen zu untersuchen:

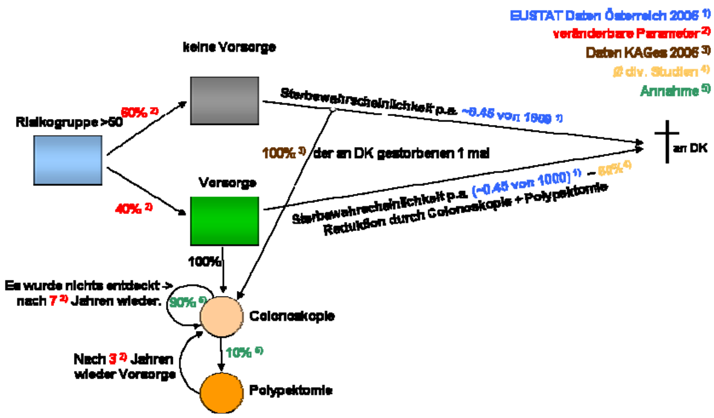

Abb. 3: Vorsorgemodell für das Kolonkarzinom

Untersuchte Fragestellung

Die wichtigsten Fragestellungen bezüglich des Kolonkarzinoms sind:

1. Wie viele Know-how Träger und Trägerstunden (Chirurg, Internist) werden für die zukünftigen Kolonoskopiefrequenzen benötigt, wenn die Aufteilung im Fach 25% bzw. 75% beträgt und eine Kolonoskopie 40 min dauert.
2. Laut Literaturergebnisse sterben jährlich 40 - 60 von 100.000 Menschen am Kolorektalkarzinom. Wie viele Fälle über die nächsten 50 Jahre wird es unter Berücksichtigung der Zunahme der über 50 jährigen geben? Wie hoch ist die Fallreduktion an kolorektalen Karzinomen durch eine entsprechende Vorsorgekolonoskopierate?

Ergebnisse

Abbildung 4 zeigt die erstaunlichen Ergebnisse für die erste Fragestellung. Trotz der Zunahme in der Bevölkerungsschicht der über 50 jährigen, nimmt die Anzahl an Kolonoskopie und dadurch auch die Know-how Trägerstunden, bei 45% Vorsorgegehern, ab. Erst ab ca. 60% Vorsorgegeher nimmt die Anzahl an Untersuchungen leicht zu. Diese Abnahme kann damit erklärt werden, dass sich die meisten Personen schon im Vorsorgezyklus befinden und dadurch die Neuzugänge nicht soviel Bedarf generieren.

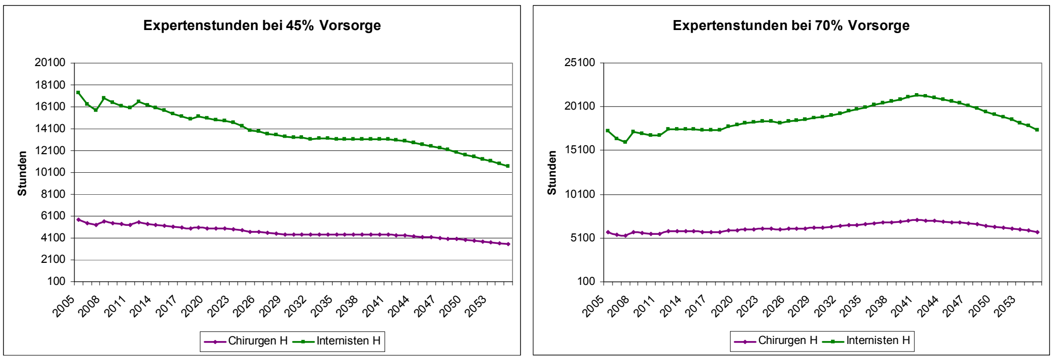

Abb. 4: Benötigte Expertenstunden bei 45% und 70% Vorsorgegehern

Trotz des erhöhten Anteils an Vorsorgegehern von 45% auf 70%, ist die absolute Abnahme an Kolonkarzinomtodesfällen relativ gering, wie in Abbildung 5 dargestellt und ist ebenfalls als Folge der sich ändernden Alterstruktur der über 50 jährigen in den nächsten Jahren zu erklären.

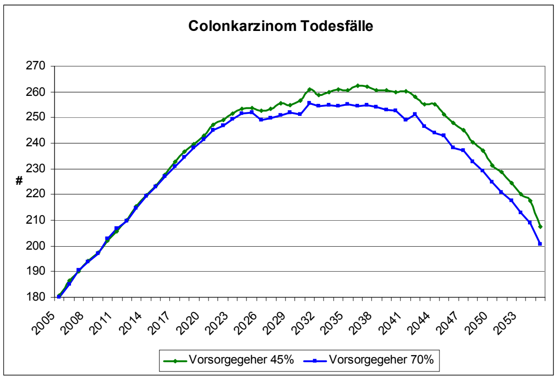

Abb. 5: Kolonkarzinom Todesfälle mit 45% und 70% Vorsorgegehern bis 2055

Zusammenfassung und Ausblick

In diesem Artikel wird durch eine erfolgreiche Kooperation zwischen Universität und einer Krankenhausträgerorganisation (Wirtschaft) am Beispiel der Vorsorgekoloskopie gezeigt, wie sich plötzlich ändernde Ansprüche an den Gesundheitsanbieter (eben durch die flächendeckende Vorsorgekoloskopie) modellieren und damit auch abschätzen lassen. Das entwickelte Framework bietet nun eine Vielzahl an Möglichkeiten zur Erweiterung und Beantwortung weiterer Fragestellungen an und kann auch auf andere Tätigkeitsfelder angewandt werden. Mögliche Erweiterungen wären das Ankoppeln weiterer diagnose- und therapiebezogener Simulationsmodulen und das vorhandene Modell um Abschätzungen über zum Beispiel OP-Kapazitäten, strahlentherapeutische Ressourcen usw. exakt planen zu können. Dies könnte wiederum eine datenbasierte Entscheidungshilfe für Ausbildungskonzepte und in weiterer Folge Ansatz für sinnvolle Entscheidung hinsichtlich neuer Geschäftsfeldentwicklungen im Gesundheitswesen sein.

Modeling two stage preventive medical checkup systems with social science approaches

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Abstract. Modeling preventive medical checkup systems (PMCS) is an important part to predict the future demand for healthcare coverage. In this paper we show how to model a two stage interdependent System as it applies to basic cancer prevention. Starting with a short introduction of the two used social science modeling techniques we show the basic principle of the preventive cancer checkup process (PCCP) and how it was modeled with these opposing approaches. We then extract the key benefits from each technique and also their shortcomings when applying it onto the PCCP. Furthermore we show at what level of detail which method should be used to gain the most valuable insight into those complex checkup systems.

Keywords: agent based modeling, system dynamics, healthcare, preventive medical checkup, preventive cancer checkup.

1 Introduction

In medical science, especially health care, computer simulation is still a relatively young field. In contrast to that social sciences use computer simulation as a well-established domain of research, to gain insight to a system and make predictions for the future. Troitzsch [19] divided prediction into two parts: (1) qualitative prediction, which is prediction of behavior modes, and (2) quantitative prediction, which is to predict a certain system state in timeline. Currently there are two major schools, System Dynamics and Agent Based Modeling, which use computer simulation to gain insight into non-linear social and socio-economic systems [13]. Both approaches have a broad overlap in research topics, but have been quite unnoticed by each other. [15]

There are only a few publications about health care systems concerning prevention frameworks. The health care system itself is complex and large and it is quite hard to understand all the dependencies and influences in this system. Because of the constantly growing demand for preventive cancer checkups, the main purpose of this paper is to show how to model those systems with both approaches.

There are two major facts concerned with futures healthcare coverage. People are constantly getting older and therefore need more and longer treatment. Western industrial countries are facing an over aging of their population. These facts make it necessary to model future health care scenarios to get valid answers to problems arising from these systems because media seems to continuously bombard us with one horror scenario of health care issues after the other. For example the amount of people in Austria above the age of 60 will grow till 2030 by 54% although the whole population will just grow by 8% [16]. Is this significant increase in older people an indication requiring 50% more medical specialists to cope the demand of preventive medical checkup in this age group? This is just one pressing question concerning preventive medical checkups for the future. In this paper we will discuss the main modeling differences of the two approaches based on the preventive cancer checkup process (PCCP) and give a first short answer to the question above.

1.1 The System Dynamics Approach

System Dynamics is an approach that has been developed by Jay W. Forrester, an electrical engineer, in the mid 1950s and was originally called Industrial Dynamics since the initial applications, which he described in the book of the same title, were all in private industry [7]. Later works focused on urban dynamics [8] and on social systems, with the probably most popular publication "Limits to growth" [6]. In 1983 the International System Dynamics Society (SDS) has been established, and within it a special interest group on health issues was organized in 2003 [9]. Although many papers dealing with health care systems have been published, in a variety of journals worldwide, since then very few of them focused on prevention frameworks. [11]
The basic concept behind System Dynamics is that the complex behaviors of organizational and social systems are the result of both reinforcing and balancing feedback mechanisms. The central observation point when modeling a system in SD is to describe its feedback loops, which consist of the real-world processes, called stocks, and the flows between these stocks. These generated computerized models can then be used to test alternative scenarios and policies in a systematic way to answer both "what if" and "why" questions. [3], [17]

1.2 The Agent Based Modeling Approach

Agent Based Modeling (ABM) is a relatively new computational modeling paradigm. Although it had been developed in the late 1940s, it did not become widespread until the 1990s, because compared to SD significantly more computational power is required. The increase of available and powerful computational resources in the last years and the inherent parallel nature of ABM approaches contributed to their popularity. The roots of ABM can be traced back to Cellular Automata (CA) and the field of Complex Adaptive Systems (CAS) with the underlying notation to build a system from the ground-up in contrast to the top-down view of SD. There are three different fields of research for ABM: (1) artificial intelligence, (2) object oriented programming and concurrent object-based systems, and (3) human-computer interface design [10]. The concept of agents can be tracked through many different disciplines, but using agents on designing simulation models is mainly applied in complexity science and game theory [13]. In contrast to SD there is no universally accepted definition of ABM and this makes it much more difficult to identify the basic concept and assumptions underlying this paradigm. An Agent is basically an independent component that has individual rules and is able to interact with its environment or not. The behavior can range from primitive reactive decision rules to complex adaptive intelligence [12]. The global System behavior emerges as a result of the agents following their rules and doesn't need to be known at the beginning of the modeling session.

That's why ABM is often called bottom-up modeling [3]. Agent Based Modeling is used in a wide range in medical health care but mostly to simulate patient scheduling and workflow management [14]. Estimating the medical demand of equipment and specialists for the future is quite a new area for ABM.

1.3 Short Comparison of the Approaches

To characterize both approaches, the major differences are summarized in Table 1 and described below [13], [18].

Table 1: System Dynamics versus Agent Based Modeling.

	System Dynamics	Agent Based Modeling
Basic building Block	Feedback loop	Agents
Level of modeling	Macro	Micro
Mathematical formulation equations	Differential equations	Logic, Differential equations
Perspective	Top-down	Bottom-up
Unit of analysis	Structure	Rules

The core building blocks:

The main behavior of a System Dynamics model is generated by its interacting feedback loops that consist of Stocks and Flows. In Agent Based Models the behavior emerges from the interaction rules of the Agents. These elements can therefore be considered as the basic building blocks of their approaches.

Level of modeling:

In macro simulations, individuals are viewed as a structure that can be characterized by a number of variables, whereas in micro simulations the structure is viewed as emergent from the rules and the interacting individuals. [5]

Mathematical formulation:

The basic principle behind SD is to couple non-linear first-order differential equations. This is done by Levels that accumulate the difference between the Flows (in- and out-flows). In ABM there are many diverse methodologies from logic-based to emergent equations and that's why no universally accepted formalism for the mathematical description of a model exists. [13]

Perspective:

In SD the structure of the basic system phenomenon is modeled and in ABM this evolves in the simulation.

Unit of analysis:

SD models behavior is determined by the structure that is fix and has to be defined before simulation. In ABM the focus lies on the rules an agent obeys to, to interact with other ones

2 The Basic Preventive Cancer Checkup Process (PCCP)

Modern preventive cancer checkups can diagnose cancer risks at a very early stage making necessary treatment easier, more effective, and more efficient. Most of the common malignant diseases, if detected in an early stage, can successfully be cured, due to tremendous progress in treatment possibilities. That's why regular checkups can prolong a healthy life.
The basic preventive cancer checkup process that is shown in Figure 1 can be applied to all of the malignant diseases for example (colon cancer, prostate cancer, gynecological tumors, skin tumors, etc.). There is always a risk group in a population, normally being addressed by age and gender. This group can then be divided into two parts (percentage R1 and R2): the ones that will never go to a preventive medical checkup and the other ones that go to a preventive medical checkup at least once in their lifetime after entering the specific risk group. Once entering the prevention path there will be a medical checkup. If an indication for the specific cancer is found during the checkup an intervention will be performed and the patient will be send back to regular preventive medical checkup after some years (indicated by X2). If no indication is detected the patient will also be sent back to regular preventive medical checkup after some years (indicated by X1). Once being in the prevention cycle the normal mortality for the specific cancer will decreases with a given percentage (indicated by PI). The basic PCCP will now be applied onto the colon carcinoma one of the most common cancer type of men and women.

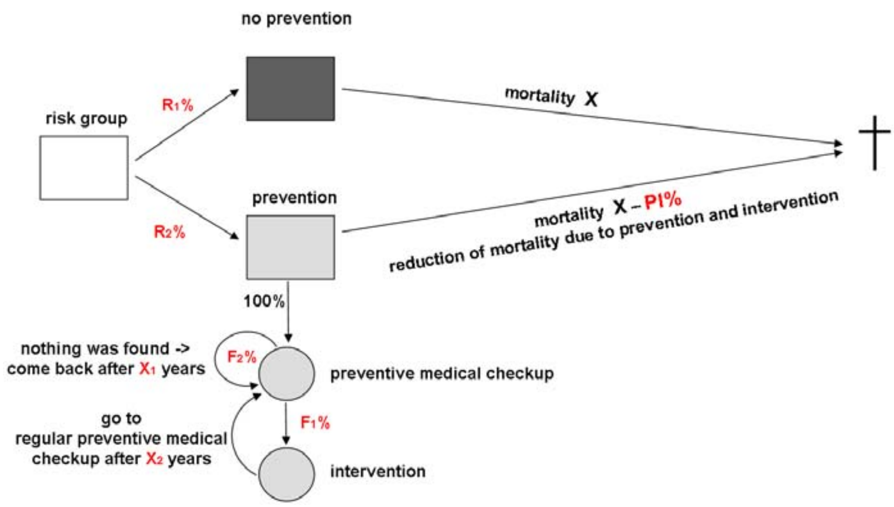

Fig. 1. Basic principle of a preventive cancer checkup process (PCCP).

To demonstrate both principles we assumed the following standard values, taken from literature [1], [2], [4] for the colon carcinoma prevention:

Table 2: System parameters for simulating a preventive cancer checkup process (PCCP).

R1	R2	F1	F2	X1	X2	PI	X
60%	40%	10%	90%	7	3	80%	$0{,}45 * 10^{-3}$

With this given values the average year a patient comes to the preventive medical checkup is 6.6 according to equation (1).

$$\text{Average year} = X1 * F2 + X2 * F1. \quad (1)$$

2.1 Modeling PCCP with System Dynamics

Based on the basic PCCP process we designed a first Causal Loop Diagram (CLD) of the system and simulated it in Powersim Studio 2005. We split up populations age groups into those within the risk group and those outside. Because of the intuitive user Interface of Powersim the model was quickly built but the output did not quite match real systems data because SD averaged all the Stocks representing the age groups. Population distributions in Western industrial countries are more like bulbs or apples than rectangles and because of the two world wars and the baby boom generation Austria's population distribution has two abnormal spikes. And these two spikes are completely filtered in the standard SD model.

So we split up the age groups into one year groups and added both prevention cycles to the simulation to get a more detailed output. A simplified version of the extended basic Causal Loop Diagram (CLD) is shown in Figure 2.

The implemented model now was an "Array Model" with all the different probabilities for each group and the output was qualitatively quite near to real data.

To look at the consequences of another cancer prevention model, for example prostate cancer, we added a second cycle for this disease. This was really a challenging problem because of the arrays and global death rates and at the end we weren't able to complete it because of cyclic references. Both prevention models affect the death rate of the population and are also affected by this rate. When you think in stock and flows you get cyclic references between these rates. Our basic SD model can only capture the qualitative behavior well but lacks realistic quantitative output. The extended model is able to produce a realistic quantitative output but is due to the specialization not able to handle more than one prevention model.

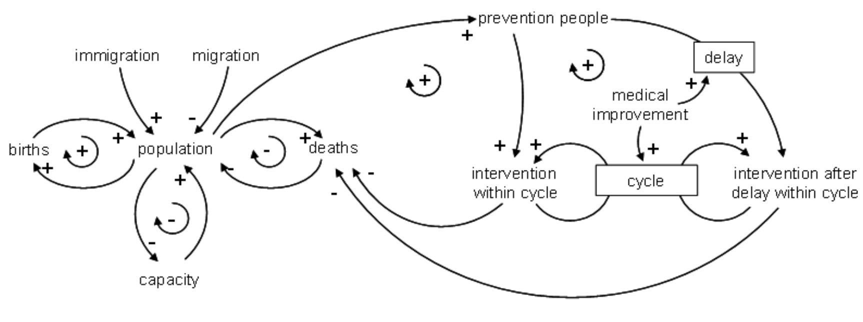

Fig. 2. Basic principle of a preventive cancer checkup process (PCCP).

2.2 Modeling PCCP with Agent Based Modeling

In the ABM solution we first had to decide what defines an agent to produce an output like the real data. So we decided to model an agent with the basic attributes like number, age and gender and some medical attributes we needed for the preventive checkup process as shown in Figure 3. In this first solution we modeled non interacting agents, because it was not necessary for the concerning question.

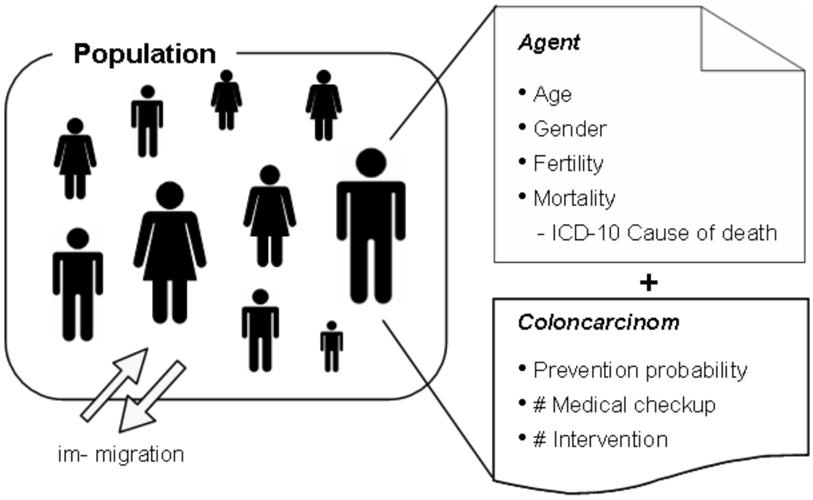

Fig. 3. Population of agents with migration effects.

Before implementing the PCCP into our agent framework we had to calibrate our agents to build up a population that was quite similar to the real one in each age group. That's why we had to add immigration, migration and fertility data to each agent. In this case we took statistical data rates from the past decades and added them to the framework. This data can now be loaded from several input files into the framework. Furthermore this attributes can be changed in time to get a similar characteristic as data from the past. Mortality is divided into the main parts of the ICD-10 (International Classification of Diseases endorsed by the WHO in 1990) code and can also be changed in time. Due to this classification the framework is able to handle all different types of classified diseases. To add a specific prevention model one first has to define the ICD-10 category it belongs to and then add the needed attributes to an agent. In our case this new "disease data sheet" that is connected to an agent contains the number of performed interventions, the waiting period till next check is performed, the new death probability, and so forth. Depending on the input data that is linked to the agents they act on probabilities each simulation period. Because this paper is about how to model a PCCP and not about the whole ABM framework we will not go into deep detail this time.

Since we are looking for population effects the number of agents that make up this population has to be sufficiently high. There is obviously a tradeoff between accuracy and computational effort. Agent Based simulation can be seen as a numerical solver to Dynamic System's system of differential equations. The more agents the smoother is the integration.

In the following we will show the first results from the ABM model to illustrate the great level of detail our framework is able to handle. We used 1.5 million agents and 50 simulation runs to get a robust estimate of mean and standard deviation.
The output for the PCCP with the given values for the colon carcinoma was really astonishing for us and is shown in the Figures 3 and 4. Although more people are entering than leaving the risk group the demand for preventive checkup will not grow when we assume that the same percentage of people as today will go to checkup in the future. This is because most of the demand is already generated by the people in this two stage cycle. The demand will not grow until the prevention percentage is set up to more than 60% and this is in fact a relatively unrealistic scenario for the future. In Figure 4 we see the absolute difference of people dieing from colon cancer per year. The absolute amount of people that could be saved due to more preventive checkups will not dramatically fall just by doing 55% more of these checkups. This output is really crucial when we think about investing more money in these preventive checkups or advertisement to increase the amount of people going to cancer prevention.

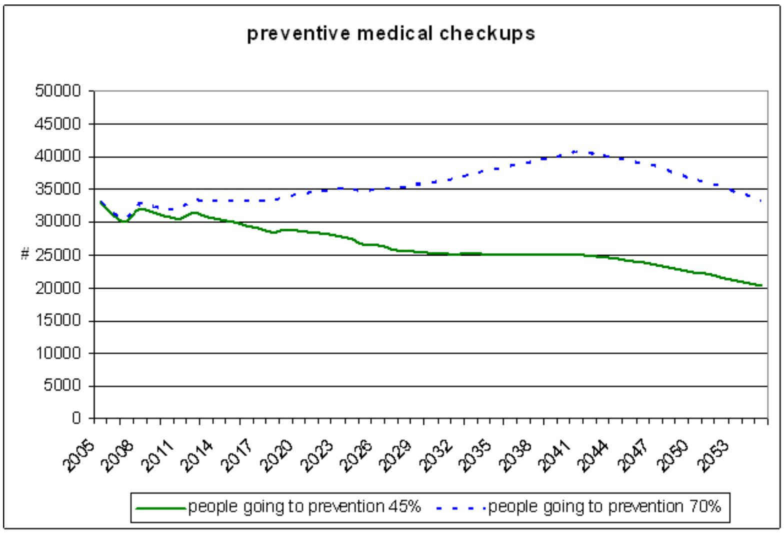

Fig. 4. ABM-Framework output for the PCCP, showing medical checkups as a consequence of different policies.

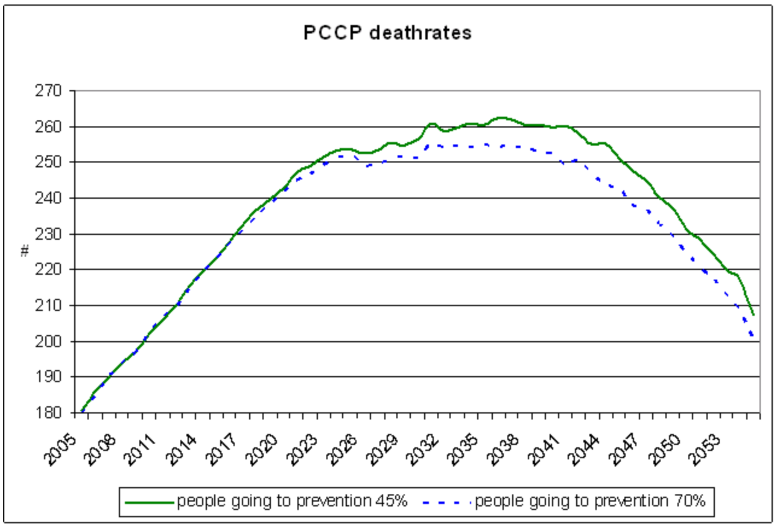

Fig. 5. ABM-Framework output for the PCCP, showing PCCP death rates as a consequence of different policies.

3 Discussion

During our modeling sessions we were able to produce the needed output data with both modeling techniques. Building a SD model with realistic real life behavior was really a hard challenge, because of the averaging effect within stocks. Despite all difficulties we found a solution by transferring the initial model into an "Array Model". Due to the specialization of this model it is not possible to simulate more than one PCCP as mentioned above. That’s why we had to switch the modeling approach to implement the given PCCP with ABM. After defining the attributes and rules of an agent we implemented our own arbitrary extendable framework. Because of the astonishing answers for the future demand in specialists for colon carcinoma the framework will now be object of further research. Integrating more cancer prevention models, interactions between the agents like transmissibility of diseases, word of mouth advertising for preventive medical checkup, are just a few work packages for the future.

In general both techniques can not be differentiated just by modeling size because both are capable to model small and large-scale systems. They can rather be classified by the problem or perspective and the required output information. One fact that should be considered when deciding for one technique is that with today’s modeling tools it is much more complicated to implement a solution in an ABM Framework, when you are not experienced in programming, than implementing a model in one of the intuitive graphic oriented SD tools. Quantifying the parameters of a model is the main difficulty both approaches have in common. In ABM it is tough defining the rules for the agent’s behavior and their attributes and in SD it is sometimes quite hard to quantify or find the correlation function between the connections of variables. In contrast to SD ABM allows increasing the level of detail as long as relevant data is available but will not work when this required data does not exist at that level of detail. The next factors to be concerned with are computational effort, memory management, and simulation time. SD provides the output within a few runs lasting only seconds depending on the method that is used to solve the differential equations. When

trying to solve the same problem with agents one first has to define the width of the confidence interval and then calculate the needed runs to hit that spread. The simulation time with our model in SD is just a few seconds on an ordinary office computer and there is no need to worry about memory management contrary to our ABM solution.
In general picking one or the other modeling approach depends on the system to be simulated. There are lots of applications where it is much easier and efficient to solve given problems with SD but if you want to capture more realistic real-life phenomena you have to choose the ABM approach. A general decision for one of the two techniques always deals with a trade-off between efficiency and significance.

4 Conclusion

As we could see from our simulation System Dynamics is useful to model the basic system's behavior. With the causal loop diagram SD provides a powerful tool for modeling, to describe a model and its interactions. Combined with Vesters sensitivity analysis [20] one can easily extract the different kinds of elements in the system (active, reactive, buffering, critical, and neutral) to make steering actions more efficient. A substantial advantage of SD is the big number of available Simulation Software and their intuitive and easy use, when needing quick answers about a systems behavior. Generating realistic quantitative output data was quite a challenging problem with SD and we could just manage it by transferring the original model into an "Array Model" but due to the specialization of this model it is not able to cope with more details or other preventive checkups and therefore we had to switch the modeling approach to ABM.
The ABM approach took much more time to implement, but now agents, the primary building block, can easily be extended with more and more details. That is why the ABM approach and our framework can get beyond the limits of SD, especially when the system contains active objects. However it is difficult to decide on attributes and rules of agents in order to get a behavior that is sufficiently similar to the real system and it is much more difficult to get all the data at the needed level of detail for the simulation than just modeling the structure of the system which is where SD ends. Memory management restrictions still become a big issue for the future of our framework when simulating with millions of agents as we experienced it in our simulation.
With the existing framework we are now able to answer questions for the future demand of several preventive checkup systems and we will extend the model as mentioned above to address more crucial questions concerning futures healthcare management.

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AWARD: Forschungspreis für Simulation und Modellierung des Landes Steiermark 2009

Modellierung eines komplexen, vernetzten Systems zur Abschätzung von Angebot und Nachfrage an leistungsbestimmenden Know-how Trägern im Gesundheitswesen

Kurzfassung:

In Anbetracht der aktuellen Situation, in der das Europäische Gesundheitssystem zunehmend unter Kosten und Leistungsdruck gerät, steht die bedarfsbezogene Angebots- und Ressourcenplanung im Mittelpunkt eines modernen Gesundheitsmanagements. Die große Anzahl an dynamischen Einflüssen und die sich ständig verändernden wirtschaftlichen Randbedingungen machen es jedoch unmöglich, ohne adäquate wissenschaftliche Modellierung und Simulation qualitative oder gar quantitative Aussagen zu treffen und Handlungsempfehlungen zu geben. Da gerade der Leistungsbedarf und die Leistungserbringung ein komplexes und stark voneinander abhängiges System darstellen, welches von unterschiedlichsten Faktoren wie demographischen Bewegungen, soziologischen Faktoren über Ausbildungsthemen von Ärzten bis hin zu medizinisch-technischen Entwicklungen beeinflusst wird, wurde in einem gemeinsamen Forschungsprojekt zwischen der KAGes und der TUGraz ein generisches Modell zur Abschätzung von Angebot und Nachfrage an Fachkräften im medizinischen Bereich entwickelt. Als Ergebnis dieses gemeinsamen Forschungsprojekts verfügt nun die steirische KAGes über eines der modernsten, zukunftsweisenden Planungsinstrumente für die strategische Ressourcenplanung.

Darstellung des eigenen wissenschaftlichen Umfeldes:

Dieses Forschungsprojekt wurde gemeinschaftlich von der TU Graz und der Steiermärkischen Krankenanstaltengesellschaft (KAGes) in einer mehr als dreijährigen Kooperation durchgeführt. Aufgrund des hohen Anteils an Grundlagenforschung in den Bereichen Simulationsverfahren und Modellierung und der hohen Komplexität und Datenverfügbarkeit, könnte keiner der Projektpartner diese Thematik alleine beherrschen. Der Wirtschaftspartner KAGes brachte seine umfangreiche Erfahrung und Datenbanken im Bereich Public Health / Health Care sowie das notwendige medizinwissenschaftliche Fachwissen ein – der akademische Partner, das Institut für Maschinenbau- und Betriebsinformatik der Technischen Universität Graz, ergänzte dies durch Kompetenz in den Bereichen der Business Modellierung, der quantitativen Methoden und Simulation. Die dadurch entstandenen Synergien sind maßgeblich für den Projekterfolg verantwortlich: Als Ergebnis entstanden sowohl aus systemwissenschaftlicher Sicht innovative Modellierungsansätze als auch wertvolle Ergebnisse für praxisrelevante Fragestellungen im Bereich der Gesundheitsvorsorge und Vorsorgeplanung. Das Ergebnis ist ein eindrucksvoller Beweis von Innovation durch Kooperation zwischen Universitäten und Wirtschaftspartnern. Die Rolle der Kern-Beteiligten ist folgendermaßen definiert:

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