MODELLING HEALTH CARE UTILISATION: A METHOD COMPARISON

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ABSTRACT

Models of health care utilisation help to identify influencing factors and to study the possible impact of different strategies. In addition to static analyses, dynamic models can be used to perform simulation experiments, which yield insights into the dynamical behaviour of the system. Various methods exist to establish a dynamic model. Two widely used, but substantially differing approaches are system dynamics and agent-based modelling. Their benefits and drawbacks for the application in this field are outlined and compared. To demonstrate their differences and analogies under practical application, a simplified model of health care utilisation is established and the implementation as agent-based and as system dynamics model is described. Then, the results of simulation runs are presented and discussed with regards to both the comparison of the two methods and their possible meaning.

Keywords: system dynamics, agent-based modelling, method comparison, health care utilisation

1. INTRODUCTION

Models describing the utilisation of health care services by patients are an important tool to understand and to test the impacts of different strategies concerning for example provider payment or insurance coverage. How to establish such a model and what factors are to be included depends mainly on the problem under investigation.

For the comparison of different reimbursement systems for instance, models based on game-theoretic considerations can be employed (Ma and McGuire 1997). The consequences of price shifts on the other hand can be studied with the help of economical models. Thereby, the system is described in terms of demand and supply of the idealised good "health", influenced by the interests and preferences of patients and providers respectively (Thode et al. 2004). These models are also used to define, explain and analyse the notion of physician induced demand (Kern 2002).

Behavioural models of the social sciences represent another approach to explain the process of health care utilisation. They focus on the factors that influence why, when and how often medical services are used. Various different variants exist. One example is Andersen's Behavioral Model of Health Services Use (Andersen 1995), which has proven its worth as reference model many times (Thode et al. 2004).

All of these models offer a description of the system that can be used for static analyses based on statistical data. Thereby, the impacts of different factors can be studied and new trends can be identified. However, since the utilisation of health care services is a dynamic process, also the investigation of dynamic phenomena present in the system is of interest. For this purpose a dynamic model is needed and an appropriate modelling method has to be chosen.

Agent based modelling (ABM) and system dynamics (SD) are both powerful and widely used methods to model complex dynamic systems. The aim of this study is to examine their advantages and disadvantages for modelling health care utilisation. Therefore, a demonstration model is established and implemented in both methods. After a theoretical comparison of the two techniques, this model is briefly introduced and simulation results are presented.

2. MODELLING METHODS

In agent based modelling the constituent units of a system are identified and modelled as autonomous, decision-making entities called agents (Bonabeau 2002). The global behaviour of the system is not determined a priori, but it results from the (often local) interaction of the agents during simulation, which is why ABM is called a bottom-up approach. In system dynamics on the contrary, the system is described from top down, which means that the global relations and feedback mechanisms between the system components are modelled. Figure 1 shows the concept of a typical agent, cf. Macal and North (2010). Each agent normally has a set of attributes, which can be static, as for example its name, or dynamic, e.g. memory or age. Its behaviour results from methods, which specify how it acts, reacts and interacts. The main structure of an SD model according to J. W. Forrester, who developed this technique, is depicted in Fig. 2. In an SD model, the system is represented as a stock and flow diagram. The different stocks (or levels) correspond to the states of

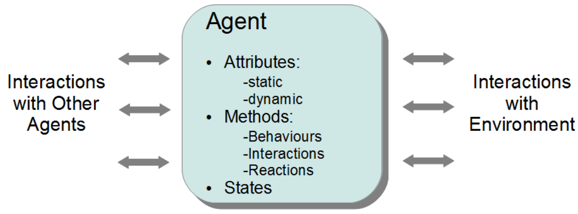

Figure 1: A Typical Agent.

the system. Their change over time is given by the difference of the in- and the outflow, the size of which depends on the information about the other stocks as well as the strategies and decisions considered.

Basically, health care utilisation corresponds to interactions between patients, who decide to use a health care service, and medical providers. Hence the acting entities of the system are individuals, which makes their representation as agents obvious. Thode et al. (2004) identified age, sex, regional aspects, subjective perception of health state and morbidity as the main influences on health care utilisation on the part of the patients. In an AB model, these individual factors can be included in a natural way as attributes of the agents. The regional aspects—or spatial arrangements in general—can be realised by defining an environment in which the agents live. For that reason, ABM is also suitable for analyses regarding the regional provision of medical services (Romstorfer et al. 2011).

SD models are based on the idea that all dynamics occur due to the accumulation of flows in stocks (Radzicki and Taylor 1997). Each stock thereby consists of homogeneous elements, thus distinctions within the elements, i.e. heterogeneities of any kind, have to be modelled by adding new stocks, representing the wanted characteristics. First of all this highly increases the complexity of the model and second this also affects the global model structure. Thus, SD does not provide the appropriate means to depict individual differences, such as varying patient preferences or variable levels of disease risk depending, for instance, on a patient's life style or his genetic disposition. Also, refinements are difficult to incorporate into an existing model subsequently, since they alter its structure. In an AB model on the contrary, extending the properties or methods of one type of agent or even adding a new type causes only local changes, i.e. the current model structure is preserved.

Moreover, dynamics caused by network effects are hard to capture by the means of system dynamics. These are deviations from the predicted aggregate behaviour caused by heterogeneous interaction patterns. Network effects may occur, whenever interactions between the modelled objects have an impact on the state of the system. This is for instance the case with infectious diseases. In SD the change of a stock over time is represented by an average, aggregated flow. As the elements within the stock are indistinguishable, this flow is based on the assumption that interactions between them as well as the distribution of information

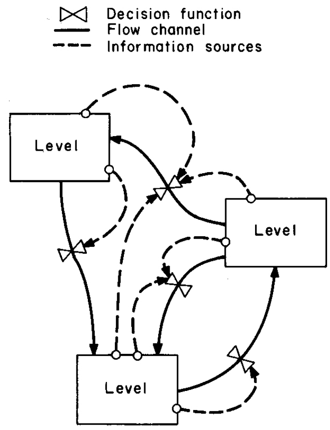

Figure 2: The Main Structure of an SD Model (taken from Forrester, 1961).

among them is homogeneous. Thus, effects due to a heterogeneous mixing are ignored. In the agent-based approach, relations between the agents, representing for example a social environment or a spatial proximity, can be easily established to specify the mode of interaction (Boneabeau 2002).

This clearly shows that ABM is advantageous over SD in modelling dynamics due to heterogeneities both in the population itself and in the way interactions take place.

One of the benefits of SD compared to ABM is that it offers a more standardised practice of modelling. An SD model can be developed from a few standard elements and the resulting stock and flow diagram automatically provides a graphical representation of the system. Furthermore, the implementation of such a model requires no, or at most little, programming knowledge, as different software tools are available that offer graphical modelling environments for this purpose.

Similar toolkits, which provide pre-implemented structures to simplify the implementation, are available for ABM as well. However, there are neither specific guidelines nor a fixed set of standard elements for establishing an AB model. For this reason no software tool is able to cover the broad range of possibilities regarding the actual realisation. Hence the implementation still requires programming knowledge. The lack of standardised ways of proceeding makes it moreover difficult for the modeller to decide on his own strategy, especially, since effects at a system-level can usually not be determined prior to simulation. SD, in contrast, approaches a system by first identifying the cause and effect relationships between the system variables and the thereby occurring feedback loops. Hence the process of modelling itself can already yield insights into the qualitative properties.

The computational power needed for simulation as well as the data requirements represent another difference between the two methods. In general, SD simulation needs less computation time, as an SD model mathematically corresponds to a system of differential equations, which can be solved numerically in an efficient way. Simulating an AB model means simulating each agent, its interactions, reactions and actions at each discrete time step and/or event, which is computationally intensive. Especially if sensitivity analyses and/or variations of a number of parameters are needed, this constitutes a disadvantage in terms of the time required.

Regarding the data needed for parametrisation, the requirements of SD are possibly easier to meet. It is based on aggregated data and overall tendencies. These can often be obtained from national institutes. The type of data needed for the parametrisation of an AB model depends on first, what the agents represent and second, the wanted level of detail regarding their attributes and individualities. For instance, when modelling a disease, it can either be assumed that its course is the same for each individual or that variations concerning its duration or severity occur, as is usually the case in reality. Both options can be realised easily in an AB model. However, whereas averaged data can be used for the first one, the implementation of the second one requires disaggregated, individual data, which is often not available and, especially in the health sector, privacy protection can be an issue. Thus, since the capacity to take heterogeneities into account is one of the biggest advantages of ABM, data can be a limiting factor in using it to its full potential.

Even though the two methods show substantial differences, not least because in SD a system is modelled continuously whereas an AB model is in general discrete (although continuous elements may be included as well), their field of application overlaps and in some cases, the same system behaviour can be obtained with both methods. Borshchev and Filippov (2004) described a way to translate an existing SD model into a corresponding agent-based one. Figure 2 depicts the main idea of their strategy. First, the elements within a stock are taken as agents and the different stocks as their possible states, which are represented in a state chart. Thus, the current size of a stock corresponds to the number of agents in the same state (see Fig. 2 b) Then, the transitions between the states are specified, using the same conditions that determine the size of the flows. For a simple example of bass diffusion, Borshchev and Filippov demonstrated that the thereby obtained results indeed coincide.

3. DEMONSTRATION MODEL

Our model aims to describe the dynamics of health care utilisation in a simplified system, which consists of patients, who use, and providers, who offer medical services. All providers are assumed to have the same specialisation and only one type of disease with two different severity levels is considered. The patients consult a provider for regular check-ups as well as in case of disease. A comparable equivalent in real life would be for example the utilisation of dental services, where a check-up every 6 months is recommended. For

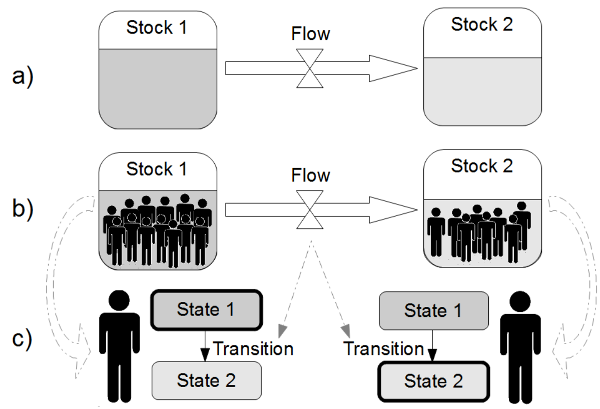

Figure 2: Translation of a Stock and Flow Diagram Into a Corresponding Agent-Based Representation.

female patients, a similar situation occurs with regards to gynaecological examinations.

Both, medical providers and patients, are supposed to have different goals, which they try to attain. The goal of the patients is to maintain a high quality of life, i.e. they are aiming for a fast recovery. For the goal of the providers, a mix between profit and patient's benefit was chosen.

A provider can offer two different levels of services, whereby one (treatment B) is considered to be an extension of the other one (treatment A) and therefore works on both severity levels, but takes longer and also costs more. Moreover he is able to diagnose the patient's severity level with a certain error rate. Providers are assumed to care about profit, which depends on the reimbursement system, and the patient's benefit from treatment, which is normalised to 1 if it was effective and 0 otherwise. In order to maximize their performance, they periodically adjust a diagnosis related threshold above which they prescribe the extended treatment to a patient.

To make the two models comparable, the same parameters and variables are used whenever possible and diagnosis, treatment decision as well as the optimisation process are realised by the same means. Both models are implemented in the multi-method simulation modelling tool AnyLogic (6.5.1) by XJ Technologies.

3.1. Implementation as AB Model

Patients and providers are modelled by different classes of agents, connected by a dynamic network, which establishes a link between each patient and his chosen provider. In addition, a static social network between the patients is set up, which enables them to exchange information about their providers.

The health state of a patient as well as his satisfaction with the provider are represented by state charts. Furthermore each patient has a quality of life, which decreases from the moment he falls ill until he recovers and thereby affects his satisfaction. Additionally, the patient's satisfaction level is reduced when the waiting time for an appointment exceeds a

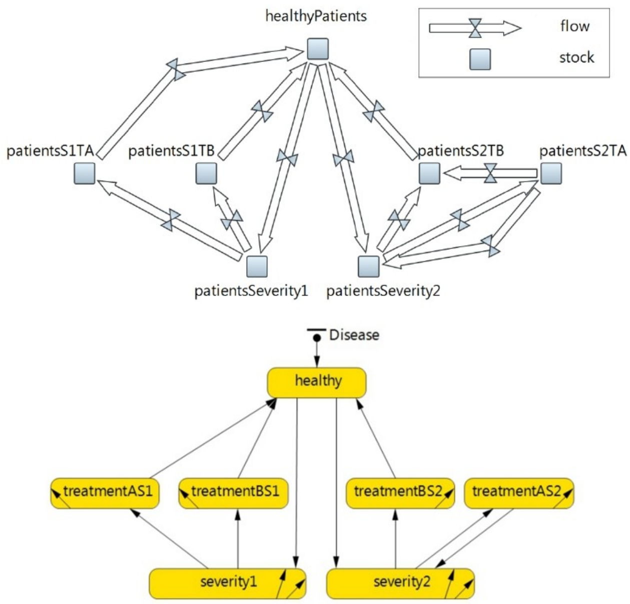

Figure 4: Correspondence Between the Stock and Flow Diagram Used in the SD Model (top) and the State Chart Used in the AB Model (bottom)

certain time span. Thus, this level reflects how a patient perceives the actions of his provider and if, in his point of view, these impede or support his attempts to keep a high quality of life. In case he becomes dissatisfied, he may change provider. To assure that this change improves his current situation, it is based on the recommendations of other agents in his social network. Only if all suggested choices, starting from the first one received, reject the patient due to full capacity utilisation, the new provider is chosen randomly. If the patient is fully satisfied for a longer period, he in turn makes a recommendation.

Each medical provider has the same number of working units per day to see patients, who come either for a regular check-up or because of illness. In the latter case, the provider has to decide which treatment to prescribe. For that purpose, he first diagnoses the patient's condition, i.e. he determines a number between 0 and 1, which is triangularly distributed with the mode depending on the patient's severity level. If the value is greater than 0.5, this indicates a higher probability for the more severe case of the disease, whereas for values less than 0.5, the opposite applies. Comparing this value to an individual threshold, above which the extended treatment is prescribed, then yields the treatment decision. Each medical provider aims at maximising his performance with respect to the patient's benefit on the one hand and his profit on the other hand by adjusting this threshold. The objective function is realised as the weighted sum of normalised income and benefit, times the utilisation ratio of the provider. A similar approach is used by Ellis (1998).

There are twofold interactions between medical providers and patients. First, the treatment chosen by the provider influences the health state of the patient and consequently his quality of life. Second, the choice of provider by the patient influences the performance of the provider. In the first place, the patient randomly chooses a medical provider. Later on, as soon as information based on past experience becomes available, this choice is influenced by recommendations of the social network, waiting times for appointments in the past and satisfaction with the treatment.

3.2. Implementation as SD Model

In the SD model, the stocks describe the current amount of healthy and ill patients. The flows between the stocks are determined on the one hand by natural disease rates and treatment durations and on the other hand by the available supply of medical services and a factor, which represents the averaged (individual) treatment decisions of all providers, who are themselves modelled homogeneously.

The above described analogy (Borshchev and Filippov 2004) is used to assure the comparability of the two models regarding the way patients become ill as well as their recovery, see Fig. 4. Thus first, the transitions between healthy and sick, used in the AB model, should correspond to the rate-dependent flows between the level of healthy patients and the level of sick patients in the SD model. This correspondence is ensured by modelling the change of state from healthy to sick in the AB model by a transition, which is triggered after an exponentially distributed time span. If the parameter of the exponential distribution is set to the same value as the rate determining the size of the flow in the SD model, their behaviour is equivalent. Second, the transitions from the three treatment states to healthy, should correspond to the flows between the three treatment stocks to the stock “healthyPatients”. It is assumed that the time needed for recovery is the same for every patient but dependent on the prescribed treatment. This can be realised by a so called “pipeline material delay” in SD and a time-out triggered transition in the AB model.

In contrast to the AB model where each agent tries to attain his goal individually, the goals of patients and providers are first averaged and then combined in one objective function, which is maximized during simulation. The providers' objective was again implemented as the weighted sum of normalised profit and patient's benefit. The goal of the patients is represented by the minimal level of quality of life, which is on average reached during the course of the disease.

The optimisation is realised by a discrete event, which might be an unusual approach because of the continuous nature of SD. But as mentioned before, this is due to the intended analogy between the models.

4. SIMULATION

The default parametrisation for the simulation uses 5000 patients and 150 medical providers. The disease rates are set to 0.03 and 0.01 for the less and for the more severe form of the disease respectively. These

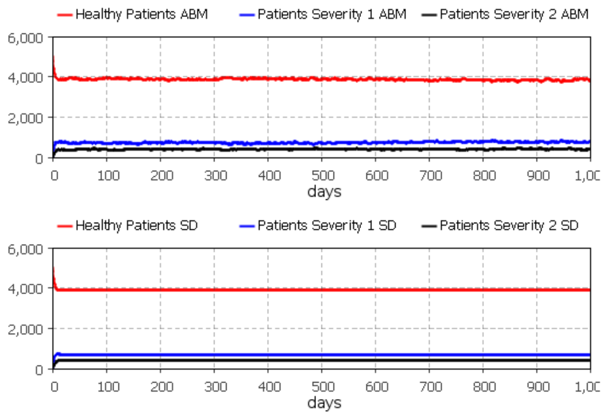

Figure 5: Number of Healthy and Sick Patients in the AB Model (top) and the SD Model (bottom) over a Simulation Period of 1000 Days.

values assume a very high density of medical providers, as they are all assumed to have the same specialisation. Moreover a person becomes ill on average about once a month. This setting may not be entirely realistic. However, the above values were chosen for practical reasons. The simulation of an AB model is computationally intensive and therefore too big samples are not convenient. Then again, if the number of agents is too small, the results show too much noise due to the stochastic elements included in the behavioural rules of the agents. Therefore, less patients, but more providers as well as a higher disease rate were taken as compromise. If one patient is assumed to represent 80 patients with the same behaviour patterns, the provider density is realistic (Habl and Bachner 2010).

The reimbursement of treatment B is supposed to yield 50% more profit than that of treatment A, and the durations of the treatments are set to 3 and 7 days for A and B respectively. How often a patient consults a medical provider is specified as, on average, once every two months for check-ups and two days after the first symptoms have occurred.

Simulation runs with the default parametrisation yield very similar results for both models. The derived average behaviour of the providers in the AB model and the assumed one in the SD model seem to correspond.

Figure 5 shows the number of healthy and sick patients (divided into two groups according to the level of severity) over time for both the AB and the SD model with the default parametrisation. The quantitative values look alike for both methods with the difference that the results obtained from the agent-based approach show fluctuations caused by the individual, stochastic behaviour of the agents. In contrast, with the SD model a steady state is reached after the optimisation process is finished.

The behaviour of the providers is represented by their treatment decision. Thus, it can be studied by looking at the number of prescribed treatments of the two different types. Figure 6 shows the total amount of health care services used per month over a simulation period of 20 years. During the first half of this period, the parameters are kept at their default values. After an

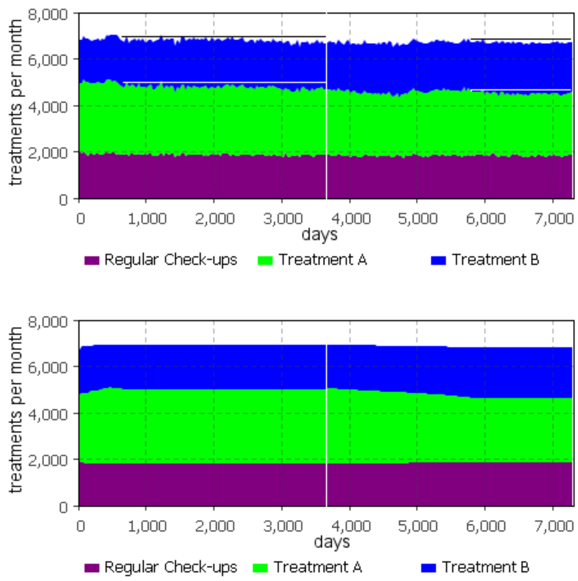

Figure 6: Total Number of Health Care Services Used per Month over a Simulation Period of 20 Years With a Raise of the Reimbursement for Treatment B after 10 Years, Marked by the White Vertical Line (AB Model Top, SD Model Bottom). The Horizontal Lines in the Top Panel Indicate the Corresponding Values of the SD Simulation, when Steady State is Reached.

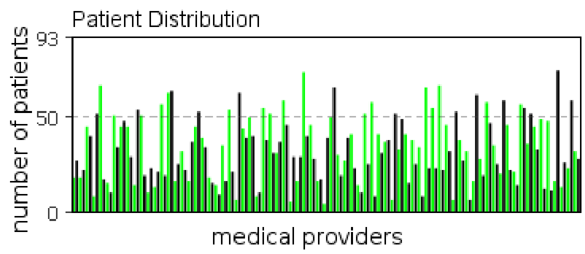

Figure 7: Competition of the Medical Providers in the AB Model

initial adaptation time, the optimal behaviour is found and hence the system stabilises. Like before, a steady state is reached in the SD simulation, whereas the values computed with the AB model show an oscillating behaviour, yet within a certain range.

After ten years, the reimbursement for treatment B is risen such that it brings 4 times the profit of treatment A. The reaction of the system looks alike. In both cases, the increased financial incentive for prescribing treatment B influences the treatment decision. However profit is not the only concern of the medical provider and also quality of life of the patients has an impact on their behaviour. In the SD model the influence of the patients is realised directly, as the objectives of providers and patients are maximised simultaneously. In the AB model, the quality of life of a patients affects his choice of a provider and thus induces a competition between the providers (see Fig. 7), which then again influences their behaviour. Because of these additional influences on the treatment decision, treatment B is indeed prescribed more often, but again the amount stabilises at a certain level, which represents the optimum for both patients and medical providers. Furthermore, as the increase is moderate, the plus in prescriptions of treatment B concerns only cases where the diagnosis is uncertain, i.e. the number obtained by the provider is close to 0.5, which might also happen in reality.

Regarding the quantitative outcome, the obtained results for regular check-ups almost coincide, whereas those for treatment A as well as for the extended treatment show deviations. This could be explained by the differences in the way the patient-provider contact is modelled. In the SD model, the current supply of total health care services is distributed among the different stocks of patients according to their demand. This process is more complex in the AB model, as the time until a patient has an appointment with his provider depends not only on the total available supply but also on the chosen provider. Hence, the average time until a patient sees a provider and consequently the total illness duration is higher. Therefore, even though in both models the same amount of patients is sick, less treatments are prescribed in the AB model.

5. CONCLUSION

SD and ABM both have their benefits and drawbacks for modelling health care utilisation. But if these are compared, it is apparent that the strengths of the methods concern the description of totally different aspects of the system. With the agent-based approach, individual characteristics and behaviour patterns can be considered, which are impossible to include in an SD model. However, if the focus lies on the the global relations in the system, SD certainly is the better choice.

The demonstration model was implemented in a rather intuitive way and the used variables and relations are all interpretable in both methods. The simulation results show that the models describe the same qualitative behaviour. However, deviations in the quantitative outcome exist. Parts of them are caused by the stochastic elements used in the AB model and are thus inherent in the approach. The rest is due to effects emerging from the heterogeneous distribution of patients among the providers, i.e. network effects, in the AB model, which are ignored in the system dynamical implementation. Thus, even though the specified system is kept as simple as possible, the differences between the methods already carry weight.

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