Multiscale Modeling of Social Systems: Scale Bridging via Decision Making

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Abstract. In recent years technological advancement makes it possible to connect heterogeneous systems at hierarchical levels, such as macro level where strategic decisions are made, and micro level where organizations interact with the users. Modeling of these connections alongside with systems is one of the problems, which can be solved by modeling techniques that take hierarchical nature of the systems into consideration. In this paper, we propose a multiscale modeling approach for social systems. We suggest to design a model by adopting certain entities: decision makers, resources, actions and propagation variables. The proposed approach is evaluated on an example of collaboration between two systems: electricity suppliers and manufacturers. Results of the computational experiments demonstrate the effectiveness of the proposed technique.

Keywords: Multiscale modeling · Simulation · Social systems · Scale bridging

1 Introduction

Recently, due to advanced development of technology connecting heterogeneous systems has started to emerge. Usually, stakeholders of heterogeneous systems are more concerned about their own objectives and goals. On top of that, in some cases those objectives are conflicting as well, which makes connection of heterogeneous systems a very complex endeavor.

Connection of multiple systems is also one of core ideas behind the concept of Super Smart Society (or Society 5.0)[1], which was proposed by Japanese government. It was highlighted that social implementation and proper risk management are the necessary points to achieve new society without loses. Making a simulation model can be an useful tool to deal with this kind of problems. However, some processes in this setup are performed on different temporal or spatial scales. Users, systems, and the government are concerned about different objectives, that differ a lot in terms of the scope. For this reason, a novel modeling technique, which can capture multiscale nature of the problem, is necessary.

There exist different modeling techniques, such as Multimethod modeling [2], and Hybrid modeling[3] that try to connect multiple parts of the system in one model. In authors opinion, Multiscale Modeling would be more suitable technique in this case. Mainly, because of its ability to manage submodels with different temporal and spatial scales. This paper contributes to a certain part of multiscale modeling: a scale bridging phase. Authors suggest to connect different scales of the model by using set of entities: decision makers, resources, actions and propagation variables. In the next section more comprehensive explanation of a target model and of the technique is performed.

2 Target model and multiscale modeling

2.1 Target model

In a target model we consider a collaboration between two systems: electricity suppliers and manufacturers. In general, stakeholders of these systems are more concerned about their own business, and do not take into consideration decision variables of other systems. For example, if we consider connection between electricity suppliers and manufacturers, formers are interested in reducing peak demand and making electricity load pattern as flat as possible (to avoid using inefficient power plants). Meanwhile, manufacturers are focused on making profit and reducing costs. In this case, one of the scenarios of collaboration might be shift of manufacturers' work time to the later hours, which would be helping in reducing peak electricity demand. However, due to late working hours, manufacturers have to spend more money on the salary to the workers. Therefore, direct collaboration is not in interest of manufacturer, and in order to achieve a connection which will benefits both sides, more comprehensive scenarios are necessary. There are three parties considered in this example: electricity supplier, manufacturer and residents.

Electricity supplier In reality, electricity supply is a very complex system, which includes a lot of decision makers on different levels. In our example, we consider electricity supplier to be interested in one objective: reducing peak demand(or flattening electricity load pattern). This problem can be tackled by equation of Peak-to-Average Ratio (PAR). Mathematical representation of the average (L_{avg}) and the peak (L_{max}) loads of the grid looks as follows:

$$L_{avg} = \frac{1}{T} \sum_{t \in T} L_t \text{ and } L_{max} = \max_{t \in T} L_t. \quad (1)$$

Consequently, the PAR is calculated as $PAR = \frac{L_{max}}{L_{avg}}$.

Electricity provider interacts with residents at one side, and with the manufacturer at another. Resources of the electricity supplier are power plants. They are utilized to generate the electricity and satisfy demand coming from manufacturers and residents. Electricity supplier makes decisions about which kind of power plants to utilize in order to satisfy demand. This decision is represented as cost minimization problem.

Manufacturer Here we consider simple supply chain which consists of the manufacturer and users(residents). The manufacturer produces one type of product and uses certain amount of electricity. Basic electricity usage of the manufacturer is performed by using electricity load pattern. Manufacturers are mainly concerned about minimizing costs and maximizing their profit. Cost and profit are captured in the model in the straightforward way: $C = FC + VC$ and $Pr = pN - C$, where FC is a fixed cost, VC is a variable cost, Pr is a profit, p is a price, and N is a number of sold products. In this particular case, resources of the manufacturer are its products. The propagation variable is the price of the product. An action which is performed over this resource is selling it.

Residents In this model, residents are considered to use electric appliances, based on their daily activities as shown in Fig. 1, and to demand the electricity from the electricity supplier.

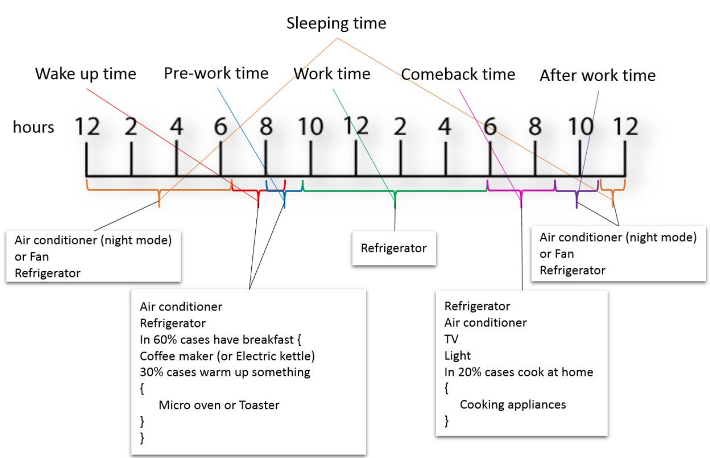

Fig. 1. An example of the usage of home appliances by single working person on hourly basis

Users are mainly concerned about their spendings. They possess money and electric appliances, these resources ensure connection of users to the systems of the higher level. Through money and electric appliances to the electricity supplier, and to the manufacturer through money.

2.2 Multiscale modeling

In general terms, multiscale modeling is a way of designing a system by separating it into several scales, where each scale has its own inner dynamics. Multiscale modeling is mostly used in areas, such as meteorology, mathematics, physics, material science, chemistry, and etc.[4] Majority of available literature are less concentrated on the theoretical part of the approach and put their main focus on the details of the specific case. There are only a few researches concentrating on theoretical or methodological aspects of multiscale modeling [5][6][7]. Lack of standardized theory is the only tip of the iceberg: in case of multiscale modeling for social systems, to the best of our knowledge, there are a limited number of studies which address to this topic. Accordingly adaptation of the existing methods, as well as the creation of novel methods specific for social systems would be helpful to deal with multiscale cases of social systems.

Explanation of the approach will follow two steps of creation of multiscale models mentioned by Hoekstra et all.[5]: Scale separation and Scale bridging.

Scale separation Scale separation is the step where we identify and clarify what our scales are, and what do they do. As it was mentioned, modeling of social systems includes several heterogeneous systems, which we are trying to connect. We made an assumption here that society is located on the lowest scale and accessible to the all systems. Each heterogeneous system can be divided into several scales, and their number might be different from each other. The main idea is to connect particular scales of one system with the appropriate scales of the other. This is going to breakdown connections into sublevels, providing more insights into modeling of connections.

Scale bridging Scale bridging is a way of connecting scales. There already exist a lot of scale bridging techniques such as sampling, projection, up-scaling, homogenization and etc.[7][8][9] However these techniques are used in exact sciences, therefore, due to the differences of them from social systems, an adaptation of scale bridging methods or creation of new ones is necessary. In social systems decision makers and decisions play very important role. Therefore, we propose connecting scales using decision makers. Proposed connection approach is based on four entities: 1) Decision Making Entity(DME) 2) Resource 3) Action and 4) Propagation variable. Definitions are: DME - an entity which owns and has control over particular resource; Resource (R)- an asset that is possessed by a particular DME, including but not limited to information, materials and people; Action over resource (A) - is a process which affects or alters particular resource; Propagation variable - variable that propagates through scales. DME owns resource(s) and has particular set of actions which are performed on a particular resource. Each resource has properties. Propagation variable is a property of the resource which is in interest of DME of other scale.

Scale bridging is tightly related to the timescale. In general, bottom-up propagation of decision is captured as an impact of propagation variable on resource of the higher scale. Propagation variable shifts upwards based on time step of lower scale.

Application of scale separation and scale bridging Based on the dynamics of each actor mentioned in this example, there are two scales. First scale is the residents. They have specific dynamics like using electric appliances on hourly basis, which make them different from dynamics of the next scale. On the second scale we have manufacturer, and electricity supplier. Connection among scales is performed by using the proposed approach. In total there are three DMEs in the model: manufacturers, electricity suppliers and residents.

Bottom-up connection relies on two types of resources that residents possess, which are electric appliances and money. They use electric appliances each hour, and then send their consumption, as its property, to the electricity supplier. Residents are connected to the manufacturer through their money. If a particular resident wants to buy a certain product, amount of money is sent to the manufacturer. Top-down propagation is the price of the electricity and a product respectively for each DME of the second scale. In Figure 2, we can see how bottom-up connections are performed in the target model.

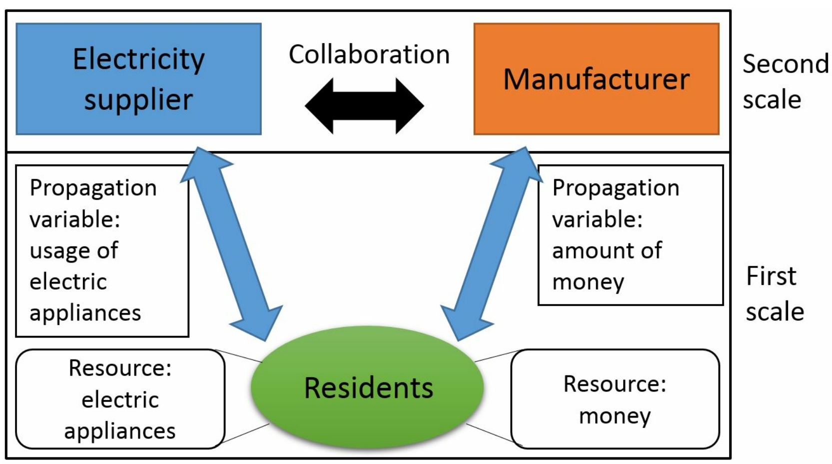

Fig. 2. Scale bridging of the target model: bottom-up connections

In this example, upper level decision makers, such as the government, is omitted, therefore only prices of both electricity and products are sent to the users as its property. In the model where the government is also considered, more different kind of properties like volume of electricity, energy fuels that have been used, amount of sales, and etc. should be taken into consideration.

3 Computational experiment and discussions

In this experiment we consider collaboration between two systems. The main objective of the collaboration is an identification of an optimal scenarios. We consider collaboration in terms of incentives given by electricity supplier. Manufacturer will have a cheaper electricity bill, if it shifts the working hours to the low load hours. However, shifting working hours will lead to raising of cost of the manufacturer, because it has to pay more salary. Therefore, the objective of the simulation is to find an optimal conditions for minimizing the negative impact of the trade-off.

The main experimental setups are done in the following way. Electricity supplier: types of energy fuels - 6(coal, oil, gas, nuclear, hydro, renewable), basic electricity price - 20 (yen/kWh). Manufacturer: electricity usage per product: 2 kWh, number of workers: 20, salary per hour - 100 yen. Users: number of residents - 150. Detailed setups are omitted due to space limitation.

State of the systems before collaboration Experimental results before any type of collaboration, show the existence of the peak at the side of the electricity supplier (Fig. 3). Here, PARs look as follows: PAR of the manufacturer $PAR_m = 1.8017$, PAR of the residents $PAR_r = 1.5891$ and in the combined case $PAR_c = 1.3149$.

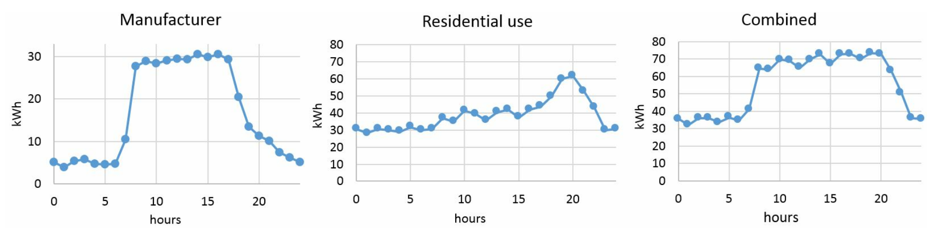

Fig. 3. Demand pattern of electricity supplier before collaboration

Costs necessary to work at normal hours (8:00-18:00) of the manufacturer is 20000 yen(for salaries) +6280.7 yen (for electricity) = 26280.7 yen per day.

Results of the collaboration It is assumed that manufacturer has to pay 1.5 times more salary for working at (22:00-5:00), also electricity price is 15 yen/kWh at night(day price is 20 yen/kWh).

After several simulations obtained results show that if we setup six of the workers would work at night hours (0:00-7:00) and rest of the workers work as usual, we will get a solution which affects cost of manufacturer the least. In this case demand pattern changes as can be seen in Fig. 4. PARs of the changed patterns are $PAR_m = 1.384$ and $PAR_c = 1.3122$. We can notice that as expected PAR_m becomes smaller, but PAR_c of combined case has not changed much. The reason behind this is related to the fact, that the changes had only affected manufacturers.

Costs of the manufacturer: night shift salary-7200 yen, day shift salary - 14000 yen, spendings on night-shift electricity consumption - 1843.964 yen, spendings on day-shift electricity consumption - 4720.7039 yen, and total- 27764.6686 yen. Those values differ from original cost only by 5.6%.

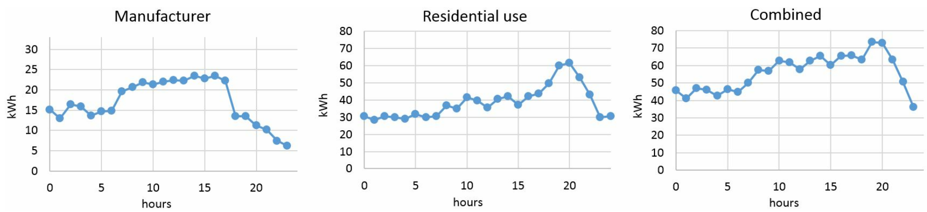

Fig. 4. Demand pattern of electricity supplier after collaboration

Additionally if we consider collaboration of residents and electricity suppliers via home batteries[10], we will get more promising results. In Fig. 5, we can clearly see that combined demand pattern becomes much flatter after implementing collaboration on multiple levels. Calculating peak-to-average ratio gives us: $PAR_r = 1.1069$, $PAR_m = 1.1769$. That is very good results. However, it should be mentioned here, that this is only simulation, and it gives us results of what might happen under certain conditions.

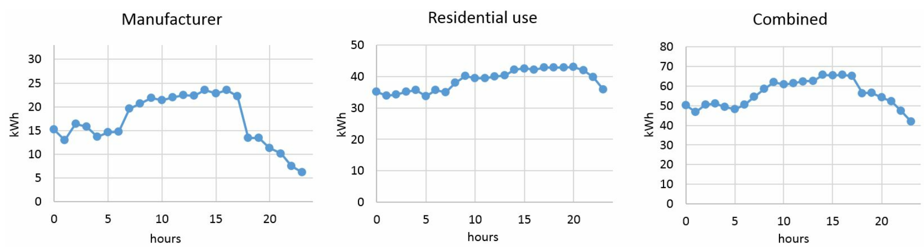

Fig. 5. Demand pattern of electricity supplier in case of collaboration with residents and manufacturers

To sum up, the proposed technique demonstrated its ability to connect several systems in one executable social simulation model. Clarifying resources and their properties that should propagate, helps to understand how connections among several systems work, which is in general not a trivial task to deal with.

4 Conclusions

This paper describes an implementation of multiscale modeling to design social systems. This work contributes to existing knowledge of scale bridging by extending it to the case of social systems. More specifically, authors suggest to perform scale bridging via decision makers. Multiscale model can be designed by adopting four entities: decision makers, resources, actions and propagation variables. This way of modeling helps to clarify which kind of resources ensure connection among multiple systems. Moreover, there was presented example of collaboration between an electricity supplier and a manufacturer. Computational experiments demonstrated necessity of multiscale perspective when considering cases, similar to one mentioned in this paper. In addition, it was figured out that under certain conditions, collaboration among heterogeneous is possible to achieve.

Finally, a number of limitations need to be considered. At first, the presented example does not include certain features such as higher level decision maker, like the government, or the product market. More comprehensive cases might bring some challenges, which can help to improve the proposed technique. Secondly, theoretical part of the proposed technique still lacks concretization, and more standardized approach would be helpful in dealing with complex systems. At last, simulation models have difficult point in terms of the validation of the model, and multiscale modeling is not an exception. These limitations are subject to the future work.

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