COMPLEX AGENT-BASED MODELS: APPLICATION OF A CONSTRUCTIVISM IN THE ECONOMIC RESEARCH

Vladimír Bureš, Petr Tučník

Introduction

Economies constitute complex and dynamic systems, which have been studied from multiple perspectives and with various tools, techniques and methods. They encompass behavioural patterns, interaction among particular subjects, or several functional principles [34]. There are two dominating issues related to modelling of economic systems. Firstly, study of economic systems is traditionally based on analytical and econometric tools, which have been the main arbiters of the veracity or plausibility of assumptions and hypotheses in economics. Theoretical models are usually developed for analytical tractability and offer internal consistency within prescribed conditions and assumptions [28]. This approach is highly suitable for theory development. However, in practice the pace of change and existing uncertainty about the way in which markets will evolve has made it increasingly important for companies to be aware of modelling techniques, which would enable support of decision-making processes. Due to this necessity various modelling tools, methods, or techniques have already been applied in the business realm, ranging from standardised tools and techniques such as Unified Modelling Language (UML) or Petri nets [30], to non-standardised "fun diagrams" helping managers to capture mental models and ideas [5]. Moreover, the pool of applied techniques comprises both models grounded in exact mathematical representation of reality, which can be further simulated (e.g. Markov chains), and more or less vague models helping only to express significant elements and relations in the studied business domain (e.g. flow charts, or causal-loop diagrams). Secondly, majority of these approaches and techniques usually fail when coping with one particular attribute of real economic systems – complexity [6]. These two gaps might be bridged with the help of new modelling paradigms that have been established only recently. Application of agent-based modelling in the realm of economic systems is labelled as Agent-based Computational Economics (ACE). Current ACE research divides into four streams distinguished by objectives [34]:

1) Empirical understanding.
2) Normative understanding.
3) Qualitative insight and theory generation.
4) Methodological advancement.

This paper purpose is to support constructivist approach to economic theory and it aims to apply basic ACE principles in newly developed and original model of a complex economic system. In particular sections it introduces results of experiments run on the created model. As such, it contributes to the second and fourth ACE objectives.

The paper is organised as follows. The literature review focused on ACE and research already done in this realm is provided in the next section. Whereas the third section formulates the research problem, the developed model is depicted in the fourth section. Consequently, experiments conducted for verifying the model validity and usability is described. The sixth section outlines further research directions and possible model extensions. Finally, the discussed issues are concluded in the last section of the paper.

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1. Literature Review

Agent-based modelling is a quite popular modelling approach which is widely used in many disciplines. This approach is characterised by three main tenets [2]:

(i) there is a multitude of objects that interact with each other and with the environment;
(ii) objects are autonomous (hence, they are called agents), no central or "top down" control over their behaviour is admitted; and
(iii) the outcome of their interaction is numerically computed.

Up to date, current scientific papers indexed in recognised scientific databases (ISI Web of Science or Scopus) are classified to tens of research areas. Whereas the majority of research papers belong to the field of computer science or engineering (approximately one third of them); plethora of other application areas such as toxicology, entomology, oceanography, crystallography, management of biological incidents, mobile applications and enterprise, or tourism can be identified [7], [23], [24], [29].

In the economics domain ACE represents relatively new field of study. It is primary based on using of computational power for research and scientific purposes. Thus, the first studies, which were tied with agent-based simulations, were published in the scientific literature in the mid of 1990's [4], [15], [19]. Since then, it has been possible to undertake the first computationally demanding experiments required to model the interactions of a large number of heterogeneous agents with bounded rationality in an economy characterised by non-equilibrium dynamics and information asymmetries [2]. In his study Giaglis [17] concluded that complexity of economic modelling requires application a single, 'holistic' technique that could effectively represent various perspectives in a rigorous and concise fashion, and hence be applicable in all modelling situations. In general, the agent-based modelling enables to develop models with a large number of heterogeneous components, where the emerging dynamics is not known a priori, and outcomes are not trivial and immediately deducible from individual behaviour [8], [37].

In the business and economy realm, the agent-based modelling is applied from the earliest stages of development of this research paradigm. For instance, Janssen and Vries [21] develop a simple dynamic model of the economy-energy-climate system and prove that the adaptive behaviour can be included in global change modelling. Vidal and Durfee [38] use an economic multi-agent system to determine when agent should behave strategically (i.e. learn and use models of other agents), and when it should act as a simple price-taker. Their results show how savvy buyers can avoid being cheated by sellers, how price volatility can be used to quantitatively predict the benefits of deeper models, and how specific types of agent populations influence system behaviour. Trading between buyers and sellers represents a segment of economics which was often selected for application of multi-agent modelling and simulation principles. Systems such as Kasbah [9] or Magma [35] can serve as examples.

Since the first pioneering studies had been published, the application area in the business and economy field was extended. For instance, Babita, Rao and Shukla [1] investigate general possibilities of multi-agent systems in the e-business realm, Guessoum et al. [18] propose a new adaptive multi-agent model that includes the organisational forms into the economic models, or Wilkinson and Young [39] apply agent-based simulation models for identifying and modelling underlying mechanisms and processes in the marketing realm. Damaceanu and Capraru [10] focus their attention on banking market. In their study, they conduct 11 computer experiments and study the evolution of various banking market indicators such as total amount of money, savings, wallets, or bank reserves. Due to its complexity, Sinha et al. [33] studied and created model of petroleum supply chain. Dosi et al. [14] develop an evolutionary model of output and investment dynamics yielding endogenous business cycles. The model describes an economy composed of particular organisations and consumers. Whereas firms belong to two industries, consumers sell their labour and consume their income. Simulation results show that the model is able to deliver self-sustaining patterns of growth characterised by the presence of endogenous business cycles. Desmarchelier et al. [13] (re)assess the relationship between knowledge intensive business services (KIBS) and the economic growth with the help of a multi agent-based system involving industrial firms, consumer-services firms, consumers, KIBS firms and a banking system. This model helps them to conclude that that KIBS can be regarded as an engine for the economic growth and that they operate as a substitute for the material capital accumulation.

In the field of economics, latest research directions aim at simulating and synthesizing emergent phenomena and collective behaviour in order to understand economic and social systems. Particular topics addressed in scientific journals include artificial markets with heterogeneous agents, multi-agents in economics, experimental economics [36], financial markets with heterogeneous agents [26], non-linear economic dynamics [25], interacting particle systems in economics, markets as complex adaptive systems, or theory and simulation of agent-based models. According to Bargigli & Tedeshi [2], these models have been able to:

- Drop the unrealistic assumptions prevailed in general equilibrium theory.
- Obtain the macroeconomic level through the interaction of agents at the micro level, without imposing either unrealistic representative agents or simple aggregation processes, which only provide a rough, inefficient approximation.
- Allow the existence of an intermediate meso-scale, which also plays a role in describing the economic and financial system.
- Offer a realistic environment that is well suited for studying the out-of-equilibrium transitory dynamics of the economy, as caused by changes in the policy parameters.

Considering all these advantages, it is not surprising that Delli Gatti et al. [12] discuss issues and challenges facing modern macroeconomics and state that there is the necessity to replace the reductionist approach at the heart of mainstream a dynamic-stochastic-general-equilibrium (DSGE) model with an approach rooted on the science of complexity and agent-based modelling. For instance, Lengnick and Wohltmann [27] combine a simple agent-based model of financial markets and a New Keynesian macroeconomic model with bounded rationality via two straightforward channels. They bring a macroeconomic model which enables the endogenous development of business cycles and stock price bubbles. They show that market sentiments exert important influence on the macro-economy, i.e. impulse-response functions [20] of macroeconomic variables become more volatile which makes the effect of a given shock hard to predict. Furthermore, Pegoretti et al. [31] analyse how the structure of social networks affects innovation diffusion and competition under different information regimes. Diffusion is modelled as the consequence of idiosyncratic adoption thresholds, local network effects and information diffusion. The experiments reveal that for example a high social cohesion decreases the probability of one innovation cornering the market, while a low social cohesion also increases the probability of falling into traps of under-adoption.

However, the ACE movement has to cope with issues related to this research paradigm. For instance, ACE modelling requires the construction of dynamically complete economic models. It means that a modeller has to start from initial conditions and the model must permit and fully support the playing out of agent interactions over time without further intervention from the modeller. This completeness requires detailed initial specifications for agent data and methods determining structural attributes, institutional arrangements, and behavioural dispositions. Consequently, there is the difficulty with validating ACE model outcomes against empirical data. ACE experiments provide outcome distributions for theoretical economic systems with explicitly articulated micro-foundations. Mostly these outcome distributions have a multi-peaked form suggesting multiple equilibria rather than a central-tendency form permitting simple point predictions [34]. Then, intensive experimentation must often be conducted over a wide array of plausible initial specifications for ACE models if robust prediction is to be achieved [22].

2. Model Description

2.1 General Characterisation

Although slight extension of application domains and development of more complex models is apparent, the literature review reveals that several main areas can be identified in the business and economics modelling. However, these areas are mostly problem-based focusing on particular issues and their solutions. Thus, they are inevitably independent from the research perspective and do not allow simulation and analysis of mutual interrelationship that represents typical feature of the real economic systems. Moreover, even though the systemic nature of conducted research is obvious in some cases, several models are still based on the "ceteris paribus" assumption when model analysis and simulations are run. Therefore, effort needs to be focused on mutual connection of the following economic segments and related issues, which individually represent a challenge from both the modelling and business perspective [36]:

1. Logistics – path finding and application of the graph theory; mechanisms of group transport coordination; dynamical route changes.
2. Consumer behaviour – accordance with existing theories in economics; content of the consumer basket and its determinants such as taxing, education, or social level.
3. Production processes (manufacturing) – production chain management; standardisation; achieving a certain quality level with existing technological limitations.
4. Supplying processes – supply chain management; continuity of processes with minimisation of delays; relationship of volume to number of transportation agents.
5. Managerial decision-making and planning – level of autonomy; pricing; decisions related to organisational development.
6. Labour market – education and qualification issues; accordance with existing theories; structural differentiation in an economy.
7. Services – composition of services; influence of consumer utility function; (dis)similarity to tangible products.
8. Representation of environment – maps utilisation; infrastructure; mobility of agents.

The model described below aims at simulation of economic principles and behaviour of subjects, e.g. effective price and quantity setting under specific demand and capacity constraints [32]. Hence, the focus is on trading products and services, and demanding work on a labour market. Virtual economy simulation is similar to the work of Deguchi et al. [11], however, in that representation the entities considered are more specific, producing more complicated net of relations than necessary. On the other hand, trust issues as discussed for example in [16] and similar concerns are not of primary attention in the presented virtual economy. Due to the simplicity and clarity of relations and transparency of design, several service sectors such as banking or governmental sector are not included in the model. Thus, the model represents structured two-sector model of economy described in the macroeconomics.

2.2 Formal Model Structure

The created model comprises four types of agents: a) consumer agent, b) factory agent, c) mining agent and d) transportation agent. In general an agent is described as a vector of eight observed parameters

$$AGENT = (pos, w, k, s, con, e, pro, mob, a) \tag{1}$$

where

- *pos* represents the agent's position in the 2-D Cartesian coordinates during the simulation;
- *w* means wealth with the assumption $w_{agent} >= 0$, i.e. no debts are allowed;
- *s* represents storage capacity, which is any type of container in which material can be saved;
- *con* gives an agent's consumption, in case of consumer agents it represents combination of production manufactured by factory agents, in case of mining and transportation agents it represents consumption of capital required for production, and in case of factory agent it expresses combination of products on inputs and labour;
- *e* stands for efficiency (i.e. technological level in case of factor, mining and transportation agents, and qualification of consumer agents);
- *pro* represents a production function, which represents combination of inputs used by factory and mining agents;
- *mob* gives mobility, i.e. working efficacy of a transport agent; and
- *a* stands for agent's affiliation to a colony (defined below), whereas agent $\rightarrow$ COL that express that each agent belongs to just one colony in the model;

Thus, particular agents are formally described by the following vectors of parameters:

- consumer agent: $C = (pos, a, w, s, con, e_C)$,
- factory agent: $F = (pos, a, w, s, con, e_F, pro)$,
- mining agent: $M = (pos, w, s, con, e_M, pro)$,
- transportation agent: $T = (pos, a, s, con, e_T, mob)$.

Moreover, a colony is added as the fifth type of agent (meta-agent) and has the following parameters

$$COL_{metaagent} = (pos, s, w, cw, CP) \quad (2)$$

where

- *cw* reports the creditworthiness of a colony; and
- *CP* indicates the colony population, i.e. size of the colony in terms of number of agents.

2.3 Detailed Agent Description

Consumer agent embodies the economic entity that consumes products and services (i.e. goods) and offers work. Consumer agents can buy goods based on the wealth they possess. The wealth of a consumer agent is a product of work and qualification (higher qualification results in faster accumulation of wealth). A consumer agent makes a trade-off between investment into higher qualification (e_c) and consumption. The combination of products consumed and the speed of consumption is given by the consumption function. The combination of products forms a pattern of consumption that can be used to divide consumers into three categories. The three categories are low income, middle income and high income consumers. The pattern determines the ratio of goods that the consumer agent is buying. There three types of goods: necessity, normal, luxurious. For example the proportion of goods bought by a low income class consumer might be 70% of necessity goods such as food and basic household services; 20% of normal goods and 10% of luxury goods. The willingness to buy a certain product depends on the stock. The lower the stock of that particular product the higher price is consumer agent willing to pay). In other words, the scarcity increases acceptable price. This principle is corresponding with standard price and demand relationship. The price p_{max} is the amount a consumer is willing to pay when the stock of that product is empty. Conversely, as the stock is close to 100% of the capacity the price approaches zero i.e. the consumer is willing to buy only if the price is very low.

The second type of agent, a factory agent, corresponds with a company in a real economy. Factory agent is responsible for transforming input to output i.e. material and other products to final product that is bought by consumer agent for consumption or serves as a sub-product that is used by another factory agent in its manufacturing processes. The consumption function determines types of materials and their proportions. The production function determines the portfolio of goods produced. Production requires workforce i.e. employing consumer agents. The production depends on the technological level e_F and qualification of the workforce i.e. employed consumer agents e_C. The production equation is as follows:

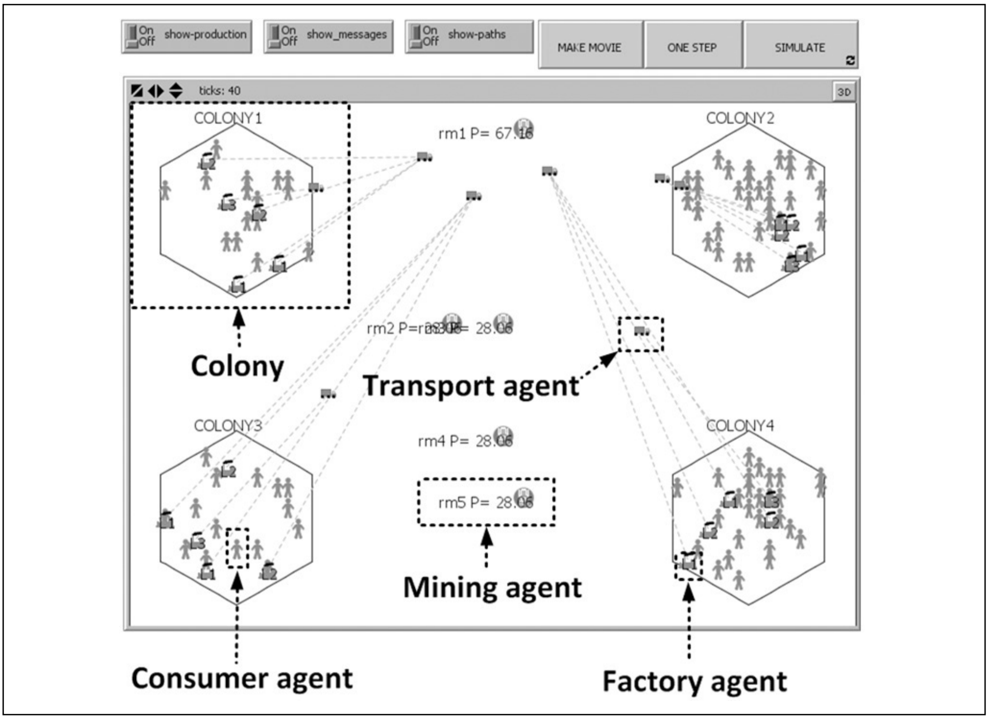
$$\sum_{i=1}^{n} k_i^{con} x_i + WF \xRightarrow{production} e_C e_F \left(\sum_{j=1}^{m} k_j^{pro} y_j\right) \quad (3)$$

Let k_i^{con} be the speed of consumption of a material x_i and WF is the workforce; e_c is qualification level of a consumer agent and e_F technological level factory agent; k_j^{pro} be the speed of production of a product y_j.

Third type of agent in the model is mining agent. This is agent responsible for transforming resources, located in the environment, into raw materials that are used by factory agents in production of goods. The cost of mining is determined by the consumption function in which the energy and technology necessary for mining is reflected. The function is similar to consumption function of a factory agent. Each mining agent supplies only one type of raw material (if several types of raw materials are produced simultaneously, each is represented by a single specialised mining agent). Raw material, as transformed from resources, is stocked in order to be later sold to transport agents and distributed to processing facilities (i.e. factories) by logistic network.

Transport agents serve as intermediary between mining agents and factory agents. The cost of transportation is given by the distance. There might be barriers or obstacles on the way from mining agent to the factory agent; hence, it is the task of the transportation agent to find a route that is the most economical or otherwise efficient. Different strategies may be used for solving path-finding and distribution problems, e.g. transport agents may co-ordinate transportation effort with each other in order to achieve maximum efficiency. The performance of a transportation agent is determined by the speed (or mobility), capacity and technological level. Transport agent is a proxy for a particular factory agent. Thus, transport agent does not have any wealth and is buying material on behalf of a factory agent. The technological advancement of a transportation agent is also the same as for the factory agent. Transportation agent is always buying all available material up to the capacity of transportation. Transported material that is not used directly in production is stored in factory agent`s warehouse.

Fig. 1: Prototype of virtual economy in NetLogo



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The modelled virtual economy contains also representation of a society of agents which is called “colony” in this context in order to avoid possible confusion with sociological semantics. The colony consists of consumer, factory and transportation agents. Mining agents do not belong to any colony, as they are distributed throughout the environment, depending on the location of resources they process (see Fig. 1). The colony is characterised by its position in the environment and size of population. Colonies compete for resources that are supposed to be scarce or at least limited. The environment is important for transportation services provided by transportation agents.

The success of a colony can be measured by several factors. The most common efficiency metric is wealth. This metric can be used as default even in case of scenario when no special task is assigned to the colony. The wealth of a colony is given by the sum of wealth of all agents. Due to different colony populations the comparison among colonies requires computing wealth per agent. The formula is as follows:

$$cw_{COL} = \frac{\sum_{i=1}^{n}(w_{C,i}+w_{F,i})+w_{COL}}{p} \quad (4)$$

where

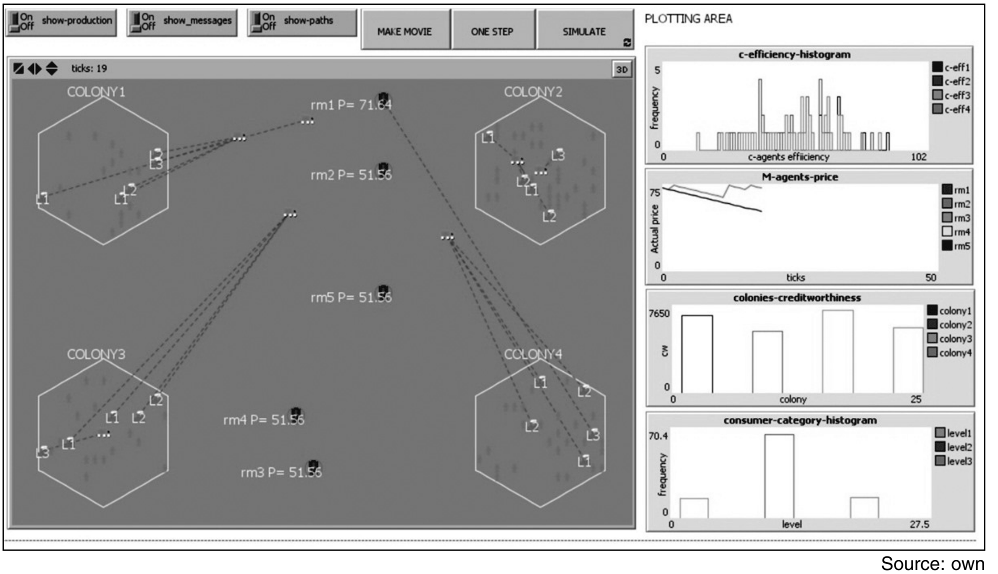
$$p = \sum_{i=1}^{n} c_{COL,i} \quad (5)$$

Scalability and configuration options of the model enable for various configuration and thus for conducting specific experiments. These experiments might be focused on thriving of big colonies with a large population of agents. Other set of experiments might include the competition among colonies in case of a universal resource that cannot be substituted in the production process. Similarly, an interesting experiment might reveal the speed of wealth accumulation in case of one large colony as compared to a number of smaller competing colonies.

2.3 User Interface

The user interface is designed in order to provide maximum transparency of the model. As can be seen at the Fig. 2, the environment representation is situated on the left side of the screen and model output (charts) is on the right side. Control buttons on the top allow switching display of additional information on/off. Individual agent communities are distinguished by colour code. Additional configuration settings for basic model parameters (such as number of colonies, resources, or their location in environment) are also available; however these are not shown at the Fig. 2.

Fig. 2: User interface layout in NetLogo application



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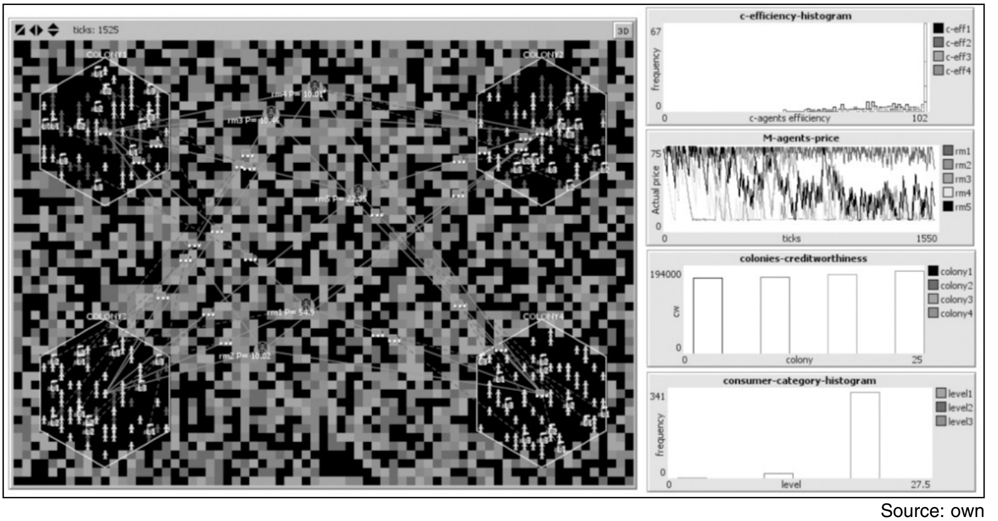
3. Example Scenarios

The presented system is already implemented as a prototype version in NetLogo environment and several experiments have been conducted. However, since this platform has certain limits for large scale experiments, full version is intended to be implemented in a more sophisticated environment. Two resource-oriented scenarios showing model behaviour are provided in this section of the text. In both cases the working hypothesis about system's ability to find a solution were tested.

3.1 Example Scenario #1 – Resource Production

In this scenario, the working hypothesis H_0 states that "the created model is capable to capture dynamics of price development when the demand is continuously saturated". There is an M-agent producing one type of material needed at four colonies of different sizes. Fig. 3 shows user interface used in prototype application with described scenario settings. At the beginning, each colony has certain amount of resources in stockpile in order to survive the initial phase when the production is established. However, when the colony runs out of this stockpile, scarcity of resources will be reflected by increased price of the given commodity. Depending on the type of resource, the scarcity might ultimately result in termination of colony existence (in case of some sort of vital resource, e.g. food) or the production in the colony will be suspended until the supply line is established again.

Fig. 3: Scenario layout



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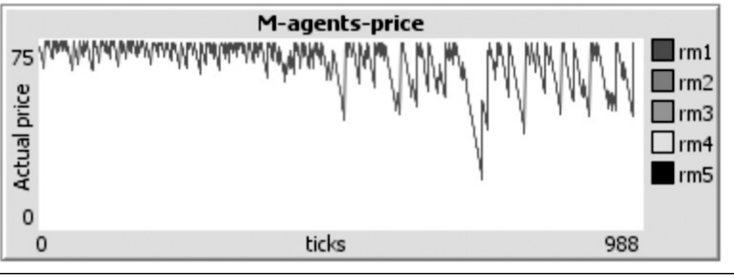
The price chart, shown at the Fig. 4 covers first 1,000 iterations of the model run. During first 500 steps, the agent was unable to produce satisfactory amount of material to satisfy demand of all colonies. The scarcity of this resource is reason why the price holds at high levels during this time. This situation is favourable for the M-agent and it accumulates wealth quickly. This allows it to purchase technological upgrades after approximately 500 steps, allowing it to increase level of production and satisfy more customers. Individual agents are more saturated, and price level drops occasionally (price which customers are willing to pay is derived from the size of their reserve). At this point, M-agent strategy should be adjusted to maximisation of profits, becoming efficiently a price-maker for the given commodity.

Fig. 4: Chart of "rm1" material price in 1000 iterations



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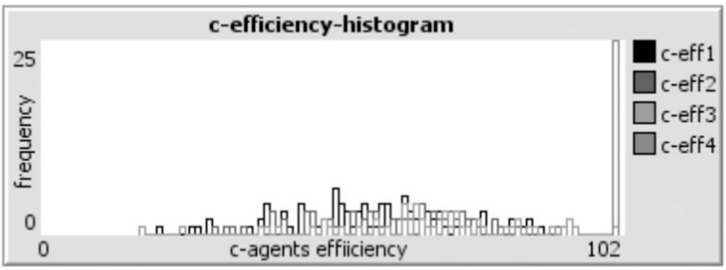
From the colony perspective, the satisfaction level is heavily dependent on its size (i.e. population). In this case, data related to four considered colonies are labelled *c-eff1*, *c-eff2*, *c-eff3*, and *c-eff4* respectively, with size of 100, 75, 50 and 25 agents respectively. Situation is shown at the Fig. 5. Best results are achieved by colony #4, due to its small size (it is easier to satisfy demand of smaller community of agents) where satisfaction has quickly risen to high values. Colony #1 was able to fully satisfy demand of its inhabitants for first 200 steps only (probably also because of some small supply of material in reserve given at the initialisation of the model). This resulted in unsatisfactory saturation of C-agent population (consumers) inside of the colony (which reached even critical levels) in the latter phases of the simulation.

Fig. 5: Satisfaction of inhabitants (C-agents) of four colonies



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It is apparent the hypothesis H_0 is confirmed be the achieved results. There are possible expansions of this scenario which may be considered. There is a question of selection of appropriate strategy for all participants – for example the M-agent may maintain such level of production which maximises its profit for as long as possible. But a new source of material or a competition may be introduced to the model in later phase. New mining facility may be purchased by colonies in order to reduce the price. The idea is to create system able to adapt to changing conditions in the dynamic environment. All this is done autonomously, without intervention of human operator (user).

3.2 Example Scenario #2 – Resource Proximity

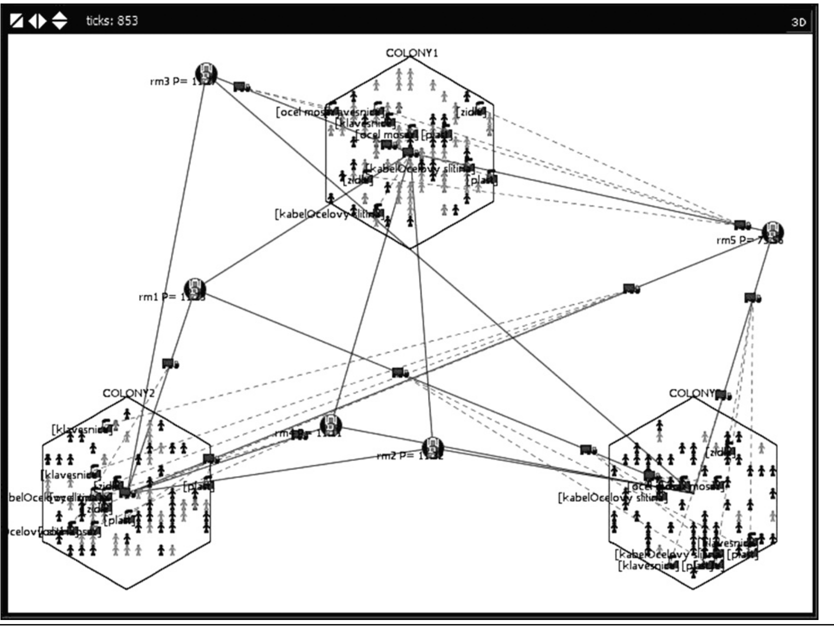
This scenario tests the working hypothesis H_0 that "proximity of a critical source influence efficiency of a colony". The production chain is more complex in this case, consisting of five raw materials and three levels of production with eleven products in total (it will not be presented here in detail but rather described as needed). However, the experiment is focused mostly on raw material number 5 (labelled as "rm5" in charts). There are three colonies used in this scenario. In order to allow comparison of effectiveness, *rm5* is near one of them – "Colony #3", see Fig. 6, where the key raw material *rm5* is situated in the upper right quarter. Alternative configuration is shown at the Fig. 7, where *rm5* is situated in the middle of the screenshot.

After 1,000 iterations of the model run, there can be seen some similarities in results. The most significant is price of the *rm5* commodity. While other resources tend to lower their price over time, as the demand is gradually more satisfied, price of *rm5* stays high all the time. Also, the overall efficiency of colonies is influenced by the proximity of *rm5* resource. Being the most important resource in the environment, effectiveness of the given colony depends heavily on the distance from it. Other resources have clearly some impact too, but in comparison, it is not so intense.

Two configurations shown at Fig. 6 and 7 are just examples of more extensive testing. After thirty simulation runs, behaviour of the price of *rm5* commodity remains always the same. This leads to following conclusions. The proximity of the critical resource is determining economic dominance in the environment. The behaviour of the colony should be adaptable to both environment and competition. As soon as the economic dominance is clearly recognised by tendency to achieve high c-efficiency score shown in histogram over long period of time (iterations), typically in correlation with price chart, the colony should re-specialise its production to other type of product. This statement is supported by Fig. 8, where left side shows result related to environment configuration shown at the Fig. 6, whereas the right side is tied to the Fig. 7. Notice similarity in price development "M-agents-price" for "*rm5*" material. Thus, the hypothesis H_0 is confirmed. Moreover, specialisation should be determined by initial conditions of the model, ideally at the beginning of the simulation but even during its run, and the choice regarding specialisation is influenced by these factors:

- Majority of given raw material is in close proximity of the colony.
- Other sources of this resource are insignificant in quantity or distant for competition.
- Production facilities and workforce required for its processing are available to the colony.

Fig. 6: Model environment layout



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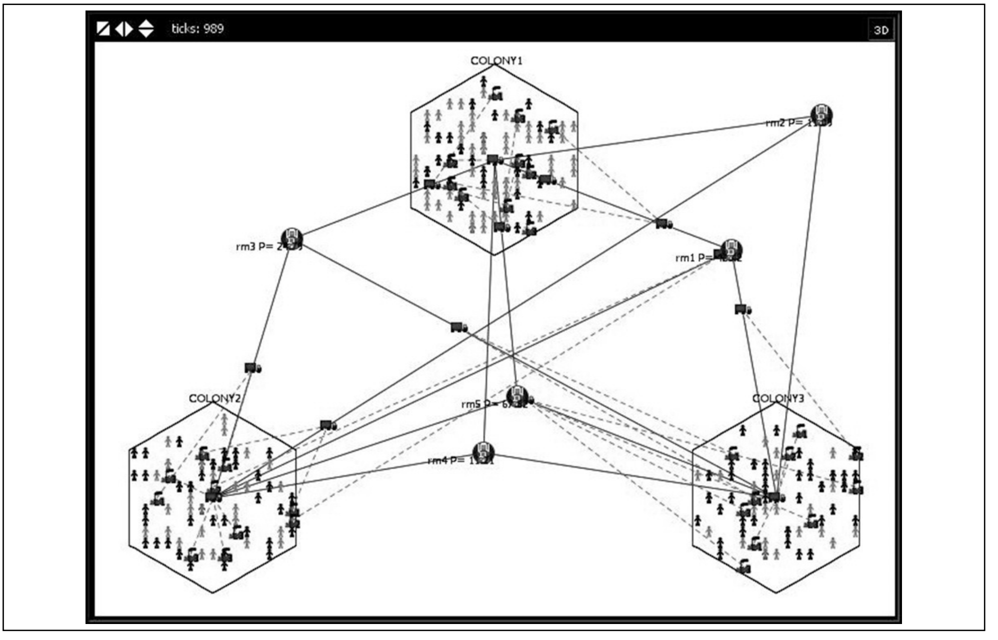
To conclude, colonies should specialise their production according to the initial configuration of the model, capitalizing all the advantage over competition environment may provide. Described factors also allow colonies to autonomously recognise error in judgement even later and eventually re-specialise. In configurations where all colonies use the same production pattern it is a matter of optimisation of workforce allocation. Obtained results will be fully utilised in full version of the model which is being implemented. Nonetheless, they may serve as an example of information which can be used to improve autonomous decision making and effectiveness of agents in the proposed model.

Fig. 7: Another example of model environment layout



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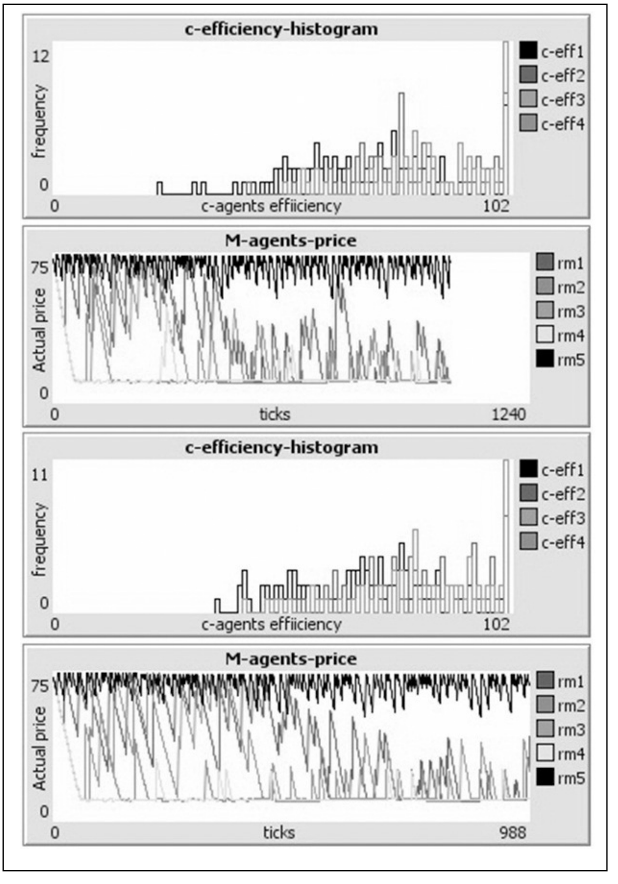
4. Further Development – Collective Perspective

Most of the work done so far was focused on individual agents. On the other hand, group perspective is important as well since a colony is a collection of agents supposed to be working together collaboratively, not just at the same place and in the same time. Behavioural concepts where agent would act simply unselfishly are typically inconsistent with general economic theory since an individual is expected to maximise its own utility. In fact, such concepts would probably have more in common with control mechanisms of insects or other animals, rather than humans [33]. Although the task at hand is not to create a complete real-world simulation but only a simplified model, we would not like to recede too far from reality of human economy.

For this reason individual approach to decision making at the level of a single agent is a requisite. It leads to more autonomous behaviour, which makes models more credible, decentralised and agent-oriented. Moreover, real-world customers are also able to decide on their own course of actions. However, as it was clearly described by Batten [3] in game theory's classical scenario of prisoner's dilemma, it is more efficient to cooperate than to scam each other from the long-term perspective. Since the range of possible actions for individual agents is wide, provided model is designed rationally and is run in several iterations. This leads to conclusion that there should be rules at the community level allowing this collaboration to happen on the scale of the whole group.

In order to narrow possible actions and manipulate agents to work for the benefit of the group as a whole, a set of rules should be established. There might be general ground rules applied in the model such as the following statement: it should be more profitable for the individual agent to follow such rules than to defy them. This actually reflects laws existing in human communities. This does not necessarily means that agents could not break rules at all, but it should only be done rarely. On the other hand, there are also other incentives other than general rules or laws that can be used to

Fig. 8: **Comparison of results**



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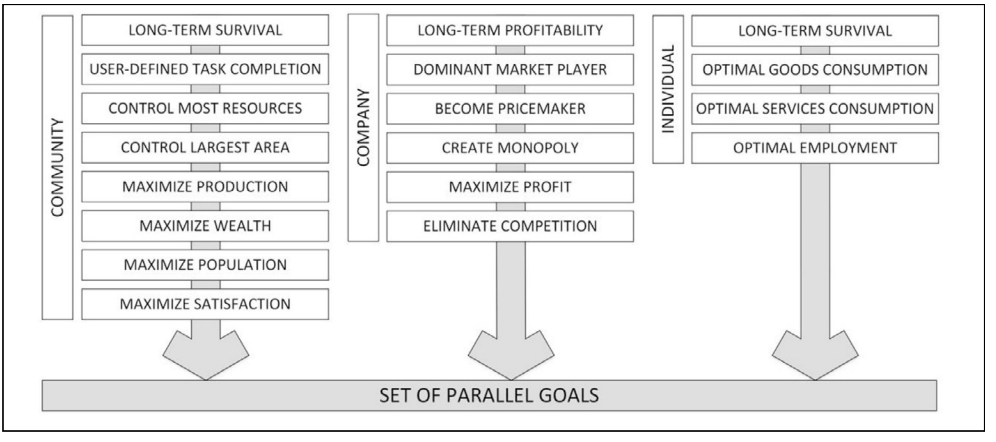
stimulate appropriate behaviour, e.g. financial bonuses, price reduction for services, or more effective community services (such as transportation, infrastructure condition, education, security, etc.). Thus, it is becoming more important to focus more attention on stimuli allowing agent to decide correctly, i.e. according to global (community) goals, corresponding with adopted community policy and priorities. It is natural to expect that under given conditions and with provided information the agent will be doing its own decision rationally, act efficiently and predicatively. But one may ask: what can be considered to be an efficient or rational decision?

The question of "correct" or "proper" decision making is not as complicated as it might seem at the first glance. It only requires approach suitable for machine processing of information. In context of this paper, this requires definition of a global goal in a way which allows mathematical comparison of a new state over previous state(s) of the environment as the simulation develops over time in order to monitor progress in goal pursue. This global goal may be defined by the user, randomly selected from the set of goals or adopted autonomously by the colony when circumstances require it (like switching manufacturing priority to food production when scarcity of food occurs). In all cases, it must be clearly numerically represented in the form of a variable value.

Although very general metrics to measure efficiency of the system like “colony wealth” described in the equation (4) can be used, the goal definition is important for measuring efficiency of the model on a larger scale. As there is more information and attributes being implemented in the model, the wealth metric is gradually becoming insufficient to cover all important factors contributing to “efficiency”. Furthermore, similarly to real-world, there is not only one goal but several goals to be pursued at the same time. As the model becomes more detailed and covers more factors, more goals are to be pursued as well. Examples are depicted in the Fig. 9.

Fig. 9: Examples of parallel goals of agents in the system



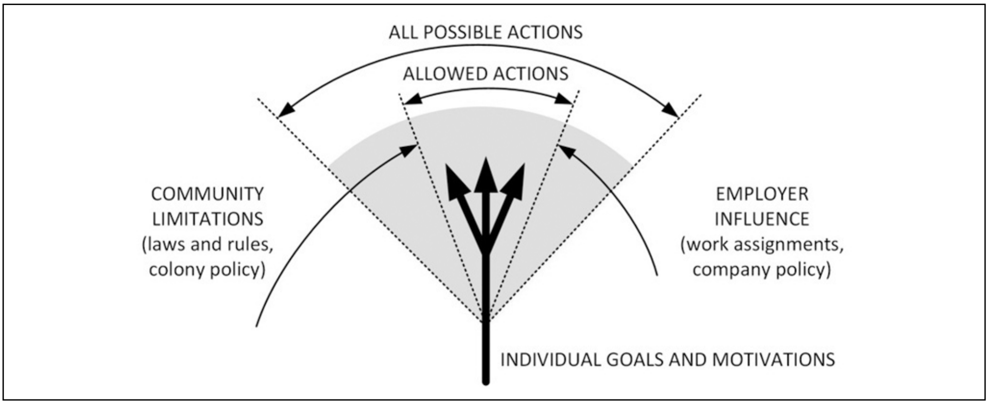
Source: own

As it can be seen from these examples, goals are to be pursued simultaneously at several levels. Priorities may differ for individual goals according to actual policy. Moreover, all goals are mutually interrelated. Thus, setting of their priorities (weights) and structure of relationships needs to be considered as a further research direction. The task at hand is how to motivate all types of agents to work together efficiently. The solution is in establishing set of constraints which would limit agent`s decision making capabilities to the form which manifests above mentioned parameters – predictability, efficiency, rationality – at both individual and community levels. These constraints can be implemented by two major factors, see Fig. 10.

Inevitable parallelism in goals’ pursue leads conclusively to some form of aggregate attribute, representing overall progress and efficiency of any singular agent. In the proposed model, this aggregate attribute is marked as “satisfaction” – which is numerically represented without units of measure. In general, an agent tries to maximise its satisfaction. This concept also allows further expansion of model with new features or in more detail without a need to redesign efficiency measurement system with every new addition.

The most difficult task is proper design and balance of the environment (prices, wages, taxes). For this, we use data provided by Czech Statistical Office, up to the limited (reasonable) extent. This helps us to configure system parameters, but we try to avoid overwhelming complexity which would result from full scale implementation of all data available. Proposed model is to be modular and transparent.

Fig. 10: Constraints for agent`s decision-making



Source: own

Conclusions

Modelling of economic systems is tied with economics as an independent discipline from early stages of its formulation. As investigated phenomena had become more comprehensive, usage of various tools and methods was necessary. One of the most current approaches in the field of business and economics modelling is grounded in agent based approaches, which resulted in establishment of Agent-based Computational Economics. In this regard, this paper provides readers with a novel model of economy with two dominant attributes. Firstly, it is theoretically grounded in the ACE paradigm. Secondly, it is complex in its nature and thus not focused merely on selected standard problems solved in the economic research (searching for equilibrium might serve as an example). Depicted model serves as a platform form wide variety of tests and experiments, which can be used for better understanding or verification of both basic economic principles and practical problems. The model proved its validity and reasonability with the help of several experiments, while two resource--oriented tasks are presented in this paper. Modularity of model implementation and transparency of the system allows further model development and incorporation of new features in future.

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doc. Ing. Vladimír Bureš, Ph.D.
University of Hradec Kralove
Faculty of Informatics and Management
Department of Information Technologies
vladimir.bures@uhk.cz

RNDr. Petr Tučník, Ph.D.
University of Hradec Kralove
Faculty of Informatics and Management
Department of Information Technologies
petr.tucnik@uhk.cz

Abstract

COMPLEX AGENT-BASED MODELS: APPLICATION OF A CONSTRUCTIVISM IN THE ECONOMIC RESEARCH

Vladimír Bureš, Petr Tučník

The current state in research of economic systems is characterised by two prevailing issues. Firstly, study of economic systems is traditionally based on analytical and econometric tools, which have been the main arbiters of the veracity or plausibility of assumptions and hypotheses in economics. This approach has been proved to be highly suitable for theory development. Secondly, practical issues and necessity to support decision-making led to development of various modelling and simulation techniques or tools. However, majority of these approaches usually fail when coping with complexity. Furthermore, several main areas of interest can be identified in the business and economics modelling. Nevertheless, these areas are mostly independent due to their problem-based focusing on particular issues and their solutions. Depicted gaps might be bridged with the help of new modelling paradigms that have been established only recently. Application of agent-based modelling in the realm of economic systems is labelled as Agent-based Computational Economics (ACE). In particular sections of this paper results of experiments run on the novel model are described. The model is based on agents, which are described as a vector of several observed parameters, and four types of agents are used, namely consumer agent, factory agent, mining agent, and transportation agent. In addition, a colony is added as the fifth type of meta-agent. Scalability and configuration options of the model enable for various configuration and thus for conducting specific experiments. The presented system is already implemented as a prototype version in the NetLogo environment. The paper depicts two example scenarios, resource production and resource proximity, and offers interpretation of achieved results. Since most of the work done so far was focused on individual agents, group perspective as an important extension of ACE modelling is suggested as the further research and development direction.

Key Words: *Multi-agent modelling, agent-based computational economics, NetLogo, resource.*

JEL Classification: *C6, D8, M2.*

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