Все, что познается, имеет число,
ибо невозможно ни понять ничего,
ни познать без него.
Пифагор

Математичні методи, моделі та інформаційні технології в економіці

УДК 004.738.5:338.24 *JEL Classification: C44; D70; H30*

CORPORATE DECISION-MAKING MULTIAGENT MODELS

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Any goal-oriented activity is related to decision-making, that is why intuitive understanding of the content and structure of decision-making problems is fairly obvious. Nevertheless, until now, there has not been developed a sufficiently general theory of decision-making. This is primarily caused by the diversity of the tasks of decision-making without explicit intersections in their formal structure and substantive content. Therefore, this research is limited to the class of problems where decisions are made by a variety of decision-makers between whom the information necessary for decision-making is distributed, and who operate in parallel interacting with each other in the decision-making process.

Designing a structure of a decision-maker group interaction, and interactions between them for real time effective management of a complex, large-scale system has been discussed. The authors have attempted to combine, on the methodological level, the classic concept of decision-making, approaches to economic system distributed management and multiagent modelling.

Thus, designing a structure in which problems of distributed control can be successfully presented has been described.

The proposed approach is based on the assumption that none of the decision-makers have a complete and accessible to them system model. The proposed structure can be used for a corporate organization design in which a person is one of the resources for decision-making.

Keywords: *multiagent modelling, Markov decision model, system structure, organizational design, interaction of agents.*

МУЛЬТИАГЕНТНІ МОДЕЛІ ПРИЙНЯТТЯ КОРПОРАТИВНИХ РІШЕНЬ

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Будь-яка цілеорієнтована діяльність пов'язана із прийняттям рішень, тому інтуїтивні уявлення про зміст і структуру проблеми прийняття рішень досить очевидні. Проте до сьогодні не існує деякої досить загальної теорії прийняття рішень. Причини цього слід шукати, перш за все, у різноманітності завдань прийняття рішень, які не мають явних перетинів у їхній формальній структурі та змістовному наповненні. Тому справжню роботу обмежено класом тих завдань, у яких рішення приймає безліч осіб, між якими розподілено необхідну для прийняття рішення інформацію, і які функціонують паралельно, взаємодіють між собою у процесі прийняття рішення.

Розглянуто проблему проектування структури взаємодії групи осіб, які приймають рішення, і взаємодій між ними для ефективного управління складною, великомасштабною системою в режимі реального часу. Авторами зроблено спробу на методологічному рівні об'єднати класичні концепції прийняття рішень і підходи до розподіленого управління економічними системами та мультиагентне моделювання.

Таким чином, у роботі відображено процес проектування структури, у межах якої може бути успішно подано проблеми розподіленого управління.

Запропонований підхід засновано на припущенні про те, що жодна з осіб, які приймають рішення, не має повної й доступної їй моделі системи. Запропоновану структуру може бути використано для проектування організації, у якій людина як один із ресурсів прийняття рішення.

Ключові слова: *мультиагентне моделювання, марківська модель прийняття рішення, структура системи, організаційне проектування, взаємодія агентів.*

МУЛЬТИАГЕНТНЫЕ МОДЕЛИ ПРИНЯТИЯ КОРПОРАТИВНЫХ РЕШЕНИЙ

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Любая целеориентированная деятельность связана с принятием решений, поэтому интуитивные представления о содержании и структуре проблемы принятия решений достаточно очевидны. Тем не менее, до настоящего времени не существует некоторой достаточно общей теории принятия решений. Причины этого следует искать, прежде всего, в разнообразии задач принятия решений, не имеющих явных пересечений в их формальной структуре и в содержательном наполнении. Поэтому настоящая работа ограничивается классом тех задач, в которых решения принимаются множеством экономических агентов, между которыми распределена необходимая для принятия решения информация, и которые функционируют параллельно, взаимодействуя между собой в процессе принятия решения.

Рассмотрена проблема проектирования структуры взаимодействия группы агентов, принимающих решения, и взаимодействий между ними для эффективного управления сложной, крупномасштабной системой в режиме реального времени. Авторами предпринята попытка на методологическом уровне объединить классические концепции принятия решений, подходы к распределенному управлению экономическими системами и мультиагентное моделирование.

Таким образом, в работе отражен процесс проектирования структуры, в рамках которой могут быть успешно представлены проблемы распределенного управления.

Предлагаемый подход основан на предположении о том, что никакой из агентов, принимающих решение, не имеет полной и доступной ему модели системы. Предлагаемая структура может использоваться для проектирования организационной структуры корпорации, в которой человек выступает в качестве одного из ресурсов принятия решения.

Ключевые слова: *мультиагентное моделирование, марковская модель принятия решения, структура системы, организационное проектирование, взаимодействие агентов.*

Management decision-making in corporate structures can be considered as decentralized management carried out by a group of economic agents having a common global goal. Such a situation is characterized by the fact that no agent during their work has the possibility of monitoring the processes and the state of the whole system. The behavior of each of the agents can be characterized by independent observations and local target functions. Such a decision-making system can be described quite well by the models of Markov decision processes (MDPs).

Recently, the indicated models have been adequately studied as a mathematical framework for consistent decision-making in stochastic domains. In particular, the decision search planning problem for an individual agent in stochastic domains was modelled as partially observable Markov decision processes (POMDPs) or fully observed MDPs [1 – 3]. For the considered planning problems the optimal scheduling plans can be found using the methods of operations research in relation to the corresponding Markov decision processes. Significant results in the decisions of individual MDPs were obtained using a domain structure [4; 5]. In [6] an approximation of MDPs is described, which suggests that the compensation function can be decomposed into local compensation functions, each of which is dependent on a small number of variables.

Furthermore the authors are interested in a separate Markov decision process, which is jointly run by a set of decision-making agents. They cooperate in the sense that they only seek to maximize a global goal (or to minimize the cost of achieving it). However, each of the agents has no opportunity to monitor the entire system as a whole in the decision-making process. Similar processes are characteristic of many application areas, from individual production (enterprises) to multinational corporations.

These processes are examples of decentralized partially observable Markov decision processes (DEC-POMDPs) or decentralized Markov decision processes (DEC-MDPs). Complexity of decision search for these processes has been investigated in [7; 8]. In [9] an algorithm of a joint research strategy (JESP) is presented, which finds an optimal joint decision. In [10] the researchers made an attempt to explore the method of decentralized decisions based on the gradient descent approach for network learning when the system model is unknown to the agents. The author of [11] suggests that every decision-making agent has an appointed task of local optimization. The following analysis shows how to create a global objective function for optimization of a problem when agents are free to exchange information about the values of their local extremes.

A common feature of these papers is a rejection of the assumption that each agent has their known local compensation function. Questions that they are trying to answer are how to configure or manage the local functions of remuneration to approximate the actual remuneration function of the entire system.

The algorithm for finding an optimal decision in a decentralized corporate management structure is presented in [12]. The presented algorithm is implemented on the assumption of a certain remuneration function structure. The generalization of dynamic programming methods to find optimal structures of decentralized management decisions is described in [13]. Special class models DEC-POMDPs were reviewed and presented in [14]. In [15] a method of searching effective decisions for this class of models was proposed. It is interesting to study the case of decentralized management, in which the agents share information about each other's actions during the off-line planning stage. A decision including a joint strategy of an only one possible action for each agent is presented in [16]. It makes sense to compare the obtained decisions with the decisions found for centralized multiagent systems, modelled as MDPs structures [17], where the planning stage (off-line), and the control stage (on-line) are carried out in a centralized system, where full observability is realized for all agents.

Any goal-oriented activity is related to decision-making, so intuitive understanding of the content and structure of decision-making problems is fairly obvious. Nevertheless, until the present time, no sufficiently general theory of decision-making has been developed. The roots of this should be primarily linked to the diversity of the decision-making tasks that have no explicit intersections in their formal structure and substantive content. A fairly complete review of these problems is contained, for example, in [18; 19]. It seems clear that it is hardly possible to build a universal theory, applicable to any problem of decision-making [20 – 22].

Therefore the authors have restricted themselves to the class of problems in which decisions are taken by economic agents, among whom the information necessary to make decisions is distributed, and who operate in parallel, interacting with each other in the decision-making process.

The research deals with the problem of the interaction framework design for decision agents and interactions between them to effectively manage a complex corporate system in real time. An attempt has been made to combine the classic concept of decision-making approaches in the field of distributed control in economic systems and multiagent simulation on the methodological level.

The proposed approach is characterized by the following features:

1) multidisciplinarity and conceptuality of the approach;

2) the level of detailing that determines the applicability to solving any practical problem;

3) transparency, which means that the proposed approach is one of many approaches that could be used to manage this problem.

Thus, the structure design process has been described, in which the processes of distributed control can be successfully implemented for a group of economic agents.

The proposed approach is based on the assumption that none of the agents who make decisions, have an adequate model of the entire managed system. More specifically, each agent knows about the actions of only a single subsystem, for which he is an "expert", and meanwhile he does not know anything about the structure of the system beyond his domain. Assessing the impact of his decisions on the rest of the system and the influence of external to him decisions on the managed subsystem can only be obtained in the process of interaction with other agents like him. Thus, the process of management decision-making is distributed among the agents, and the coordination of planned activities to a large extent depends on the available resources of interaction. The proposed structure can be used for the design of an organization in which an economic agent acts as a resource for decision-making.

Further consideration of multiagent modelling of processes of management decision-making in corporate structures will be based on the combined use of four main concepts [23 – 25]:

1) the Markov concept of a condition;

2) the law of Bayes in the probability theory;

3) the use of a global performance scalar index;

4) dynamic programming.

When these concepts are used for systems containing multiple decision agents, the following problems arise.

Each agent can assess the conditional probability of the state of its own process, but dynamic programming requires the knowledge of conditional probabilities of the process state effects of other agents, coming in the form of input signals from other agents. That, in its turn, leads to a necessity for any agent to obtain models of other agents (which have a memory, at least in the form of conditional probability, and hence the state space), and for those and other agents to have knowledge about the models of the first agent (and models of their patterns), etc. With this approach, the problem of the optimal strategy formation for multiagent decentralized management usually becomes difficult in this structure.

One of the ways to overcome these limitations is to provide each model agent with only a part of the state space and the related dynamics. In this case models used by all the agents should represent the system as a whole, and each agent should know that all other parts of the system do exist and provide influence on the relevant part of the system. This logic of reasoning leads to the following formulation of the principle of corporate level management decision-making multiagent modelling: every decision-making agent has a limited model of the controlled system.

Next, let us consider two agents interacting with each other so that the action of one agent ("A") directly affects the dynamics of the other one ("B"). There is a need for communication between them. Agent "B" must notify agent "A" of the action taken by him, so that it could be possible to explain the actions arising from these consequences. Agent "A" must inform "B" about his goals, so that agent "B" could plan his own actions that could help agent "A" to achieve the goal set by him. Thus it is necessary to prevent strategies, where the channel with endless bandwidth is used for transmitting all messages to a single node that implements centralized conventional strategy. Therefore, there must be formulated some limitations for relations of a particular type.

If two agents have models that are almost opposite in their variables, the set of attributes, which they could exchange, of course, is limited. A common feature of the two agents, "A" and "B", is the set of interaction variables, produced by the agent, which affects the other. It is only common context that they have as a basis for communication. This reasoning leads to the formulation of the second principle of multiagent decision-making system modelling: "communication between agents is realized only with the use of variables directly related to the main interaction variables".

The traditional approach to the distribution of the computing load between decision-making agents is to use iterative exchanges between them. This approach, while often effective, generally requires a significant bandwidth of the feedback means, since in each step several iterations must be performed to determine the current set of control inputs. For this reason, developed coordination and decision-making strategies of management decisions must take into account the following principle: "iterative methods, which suggest a connection between the agents at each step, must be avoided".

Finally, the definition of the modelled structure itself ensures that the decision-making agents will be often missing information on many processes that can influence them. Thus a decision must be taken under conditions of uncertainty.

The traditional approach in the case of decision-making under uncertainty is the assumption of the worst case (and the relevant criteria). It gives an attractive advantage to provide the autonomy to local decision-making agents: communication serves as a means for reaching agreements between two agents, limiting the actions of each of them. Each agent can be free to choose one of several alternatives within the agreed limits, knowing that another agent would consider his choice as a possible worst case for himself. Thus, the latter formulated principle is as follows: "uncertainty about the future actions of a decision-making agent can be removed or by either messaging or a worst-case assumption".

A distributed multiagent decision-making economic system can be defined as a tuple

$$MAS = < A, E, R, ORG, ACT, COM, EV >,$$

according to which it is understood as a set of *agents* A, which can operate in some *environments* E, which are in certain *relations* R and *interacting* with each other, forming a certain *organization* ORG, having a set of individual and joint *actions* ACT (strategies of behavior and actions), including possible *communication actions* COM, and characterized (as, indeed, individual agents) by capabilities for *evolution* EV.

The decision-making system topology can be expressed in graph G, which consists of a finite set of N-nodes and a set of L-arcs

$$G = (N, L). \quad (1)$$

For convenience, we assume that the nodes are numbered 1, 2, ..., $|N| = N$ in some unique way. Arcs connect one node with another in one direction

$$L \subseteq N \times N, \quad (2)$$

where $(i, j) \subseteq L$ indicates the bond connecting node i to node j. G will reflect the basic dynamic effect of the i-agent subsystem on the j-agent subsystem. (Note that the agent i always affects the agent j, which is implicitly the owner of its own i-model).

Each arc will represent not only a dynamic interaction, but also an appropriate interface in the decision-making structure. Since the graph is not necessarily bidirectional, no assumption about the symmetry of G is needed.

The arcs represent relationships of subsystems to each other, modelled in each node, but we also need to consider their relation to the inputs, outputs and goals of the system.

Inputs: each entry must be defined by one and only one agent (the one that models its direct impact).

Outputs: each system output can similarly be only associated with a single agent, which models the formation of this output, based on the variables in the model of this agent.

Goals: some agents bind specific goals with their own models. Other agents may have no individual goals – their function is to organize (coordinate) operations of other agents so that their goals could be achieved.

This preserves a distinction between the decision agent in the node i, A_i, and the submodel which he has M_i. The model can include formal representation on how to interact with other agents, the strategy of behavior and actions of the agent as well as the possibility of the agent evolution. We introduce the concept of an agency decision-making system module DM_i as a combination of the decision-making agent and the model of the subsystem he represents

$$DM_i = (M_i, A_i). \quad (3)$$

This refers to an agent that makes decisions independently of other agents, and which has a model of some subsystem in which he is an "expert", and which has to communicate with other agents in order to achieve a desired level of the whole system functioning quality.

Now we can say that the problem of distributed decision-making is presented in the form of a multiagent module structure if the local models M_i and interaction relationships G are identified. Thus, the modular multiagent model is an extension of the classical model concept for the explicit forming of a distributed multiagent structure.

Each local model M_i is complete in the sense that it has the Markov properties: there is a set of states X_i, but the local condition change function depends on the interaction variables that reflect the impact of parts of the system whose models are presented in other modules. Interaction variables are selected from the sets Z_{ij}, which reflect the impact of the subsystem, modelled in DM_i, on the subsystem modelled in DM_j. They are defined as the interaction function values on a set of states DM_i as follows

$$g_{ij}: X_i \rightarrow Z_{ij}. \quad (4)$$

The values that reflect the interaction z_{ij} for each state x_i, g_{ij} functions are generally irreversible, i.e. there will be some pair x_i^1 and x_i^2, such as

$$g_{ij}(x_i^1) = g_{ij}(x_i^2) \text{ for } x_i^1 \neq x_i^2 \quad (5)$$

for any i and j. In other words, it may be an expression in which it is impossible to uniquely reconstruct the condition.

The management and monitoring spaces are defined as follows:

U_i is the set of controls, from which one can select the module DM_i;

Y_i is the set of measurements that can be obtained by the module DM_i.

Now the model Mi, which is owned by the DM_i module can be determined. Here is the tuple consisting of the following eight components:

X_i is a set of the local states;
$\{Z_{ij}\}$ is the sets of an aggregated states;
U_i is the set of inputs;
Y_i is the set of outputs; (6)
f_i is the function for definition of the next state;
h_i is the function for definition of the next output;
$\{g_{ij}\}$ is aggregation functions;
c_i is the local cost function,

where

$$f_i: X_i \times Z_{1i} \times \ldots Z_{Ni} \times U_i \rightarrow X_i; \quad (7)$$

$$g_{ij}: X_i \to Z_{ij}; \quad (8)$$
$$h_i: X_i \times Z_{1i} \times ... \times Z_{Ni} \to Y_i; \quad (9)$$
$$c_i: X_i \times X_i \times Z_{1i} \times ... \times Z_{Ni} \times U_i \to R. \quad (10)$$

Equation (7) expresses the constraint that reflects the fact that the transitions depend only on the local state and direct interaction with neighboring agents, as well as control variables; equation (9) does the same for the outputs. Equation (10) defines a local agent target function: $c_i(x_i, x_i^+, z_{1i}, z_{2i}, ..., z_{Ni}, u_i)$ is the cost of transition from the state x_i at the time t to the state x_i^+ at the time $t+1$, where interaction variables $z_{1i}, z_{2i}, ..., z_{Ni}$ are present, and u_i applies. (To simplify the notation, the vector $\vec{z}_i = (z_{1i}, z_{2i}, ..., z_{Ni})$ can be entered as a complete set of interaction variables, affecting the subsystem DM_i).

An important feature of the introduced formulation is that the concept of a centralized state was replaced by the notion of a set of local states. To determine the future local response A_i to the local inputs it is not enough to know only the local state x_i; the knowledge of the other agents' future interactions is also necessary. Optimal strategies for decision search usually require a maximum possible amount of knowledge about the results of the possible decisions, it should be expected that the adoption of local decision will be based on the collected maximum of available information on the local state and future interactions.

For further consideration, to simplify the process, we assume that the functions of surveillance h_i implement the relationship "one to one": each agent at any time t knows the state and interaction variables with full certainty. This helps avoid complications introduced by the problem of evaluation, and allows focusing on the coordination problem. Let us make no assumptions about the relation of local goals and objectives of the organization as a whole, because it involves the consideration of a broad class of organizational structures. The only important structure to be considered is a corporation, where all economic agents, decision-makers seek to minimize the sum of the local decision-making function values.

It is necessary to mention two properties of the previously made statement. It is obvious, that the distributed model is a dynamic equivalent for a centralized model. However, the usual way to transfer deterministic approaches to the modelling of stochastic processes, which is based on the distribution of (conditional) probabilities as the realization of states and transitions from state to state, has a serious limitation in the presented context.

Building a centralized model, which is equivalent to a modular multiagent system is traditional, the original formulation is correct for the modelling and there is no fundamental incompatibility of these two types of models. However, in general, for a distributed multiagent model powers of various sets are much higher than the powers of the sets, used to determine the local models. The equivalent centralized model has sets of states, controls and outputs, which are the Cartesian product of the sets representing the individual states, controls and outputs. The function of state transitions in the centralized model is the direct product of local functions f_i and g_{ij} aggregation functions. Thus,

$$\begin{aligned} x(t) &= (x_1(t), x_2(t), \cdots, x_N(t)) \\ &= (f_1(x_1(t-1), \vec{z}_1(t-1), u(t-1)), \cdots, f_N(x_N(t-1), \vec{z}_N(t-1), u_N(t-1))) \\ &= (f_1(x_1(t-1), g_{11}(x_1(t-1)), \cdots, g_{N1}(x_N(t-1), u(t-1)), \cdots, \\ &\quad f_N(x_N(t-1), g_{1N}(x_1(t-1)), \cdots, g_{NN}(x_N(t-1)), u_N(t-1))) \\ &= f(x_1(t-1), \cdots, x_N(t-1), u_N(t-1), \cdots, u_N(t-1)) \\ &= f(x(t-1), u(t-1), \end{aligned} \quad (11)$$

where x and u are state and control of a centralized model. Similarly,

$$\begin{aligned} y(t) &= (y_1(t), \cdots, y_N(t)) = \\ &= (h_1(x_1(t), \vec{z}_1(t)), \cdots, h_N(x_1(t), \vec{z}_N(t))) = h(z(t)) \end{aligned} \quad (12)$$

for each $z_{ij}(t) = g_{ij}(x_i(t))$.

It can be proved that there is a corresponding centralized model with identical behavior, given by (11) and (12) for each modular multiagent model.

It would be highly desirable to include in the modular multiagent models probabilistic effects, reflecting the stochastic processes. Many stochastic control problems can be reduced to a deterministic equivalents by selecting the appropriate state spaces (such as a probability functions lying in the state-space base). This statement is limited to the case of certain information about the states (and interactions), and stochastic processes can be reflected only in the functions of the state transition, but not in the measurements. Stochastic matrices (graphs) of state transition replace the expression:

$$x(t) = f_i(x_i(t-1), \vec{z}_i(t-1), u_i(t-1)) \quad (13)$$

by the conditional probability densities:

$$p_i(x_i(t) \mid x_i(t-1), \vec{z}_i(t-1), u_i(t-1)) \cdot \quad (14)$$

This, in particular, allows presenting a forecast of future interactions in the following form

$$p(z_{ij}(t+1)) = \sum p(x_i(t+1) \mid x_i(t), \vec{z}_i(t), u_i(t)) \cdot p(x_i(t)), \quad (15)$$

where the summation is performed over all $x_i(t + 1)$, so that

$$z_{ij}(t+1) = g_{ij}(z_i(t+1)) \cdot \quad (16)$$

Thus, any unit of the multiagent model, given by its input interactions, and the state at the time t, can calculate the probability distribution of its output states and interactions at the moment of time $t + 1$, using (14) and (15). In this case it would be desirable to repeat this process: considering a probability distribution of input interactions at the time $t + 1$, computed by other agents, the module can determine the output interactions in a next time $t + 2$, etc.

The model presented above may be defined as a deterministic multiagent system with a variety of local states $P(X_i)$, a variety of control U_i and the set of interactions $P(Z_{ij})$. In this case, on the given $p(x_i(0))$, $u(\tau)$ and $p(z_{ji}(\tau))$ for all j, $i = 1, ..., N$ and $0 < \tau < t$ it is impossible to determine unequivocally $p(x_i(t))$ and $p(z_{ij}(t))$.

The difficulty arises from the fact that the interactions determined by the value of $p(z_{ji}(\tau))$, after some time, are correlated, which is ensured by the dynamics of DM_j.

In the construction of stochastic modular coordination algorithms the result is important, that DM_i requires interaction sequences probability (i.e., density on Z_{ji}^t), instead of the proposed sequence of interaction probabilities (i.e., the density of t on Z_{ji}), to predict the probability of a transition to local conditions and, therefore, the behavior of the entire multiagent system. Besides that, stochastic modules are equally suitable for the models as deterministic ones.

The following conclusions can be drawn from the research.

The key concept of the proposed approach is an individual system component, a module, whose agent is an expert in the unique subsystem with respect to which he and only he has the most comprehensive knowledge, and for which he is responsible.

For modular multiagent systems some methods that support decision-making can be developed. A common approach to developing mechanisms for coordination is to select a sequence of interactions between the subsystems first, and then to solve local, relatively independent optimization problems.

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