Modeling of Agents in Organizational Context

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Abstract. At present the agent paradigm is often used for computational modeling of human behavior in an organizational setting. However, not many of the existing computational approaches make use of a rich theoretical basis developed in social science. Therefore, often mathematically sound models are invalid in practice. This paper proposes a formal approach for modeling of characteristics and behavior of agents in organizations, diverse aspects of which are represented using an expressive formal framework. The approach is based on the theoretical findings from social science and enables analysis of how different organizational and environmental factors influence the behavior and performance of agents. The approach is illustrated by a simulation case study.

1 Introduction

The agent paradigm has been extensively used for modeling and analysis of both human and artificial organizations. In particular, in the area of Multi-Agent Systems (MAS) artificial agent organizations have been investigated [4, 9, 15]. Representation of MAS as an organization consisting of roles and groups facilitates handling high complexity and poor predictability of dynamics in a system [9]. Some of the MAS frameworks are also aimed at modeling human organizations [6, 8, 16]. Although such models can be computationally effective, most of them lack the expressivity for conceptualizing a wide range of concepts and relations of human organizations. Also, such frameworks only rarely use extensive theoretical findings from social science.

Modeling of individuals in a social setting using the agent paradigm has gained popularity in the area of computational social science [2]. In this area many approaches have been developed for analyzing, predicting and improving the efficiency of task allocation to and execution by agents. In particular, the frameworks TAEMS [5] and VDT [12] provide the elaborated models for task environments and the computational means to analyze the performance of agents and of a whole MAS with respect to the task execution. In [21] it is demonstrated how agents can be allocated to tasks based on the match between the task descriptions and the agent capabilities. The agents in these and other similar frameworks are represented as autonomous entities characterized by skills, competences, experience, and, sometimes, goals. In task-oriented agent-based modeling it is often assumed that agents comply with organizational goals and will perform tasks in such a way that a high level of organizational performance is ensured. However, in some cases such an assumption may not be valid. In particular, for feasible modeling of human organizations various (sometimes conflicting) interests of different organizational actors should be explicitly considered, as they often (significantly) influence the organizational performance. In general, to be productive an organization should arrange work and provide incentives to its employees in such a way that they are constantly motivated to adopt the behavior that ensures the satisfaction of the essential organizational goals. The topic of work motivation received much attention in Organization Theory [14,17]. Also, in the area of MAS different motivation models and the mechanisms for manipulating them have been proposed [3]. However, only a little research has been done on the computational modeling of motivation of agents situated in organizational context. Organizational factors that influence motivation of agents are diverse and often interrelated: e.g., norms and regulations related to the task execution, to communication, a power system, a reward/punishment system etc.

In this paper, a formal agent-based approach for modeling of characteristics and behavior of individuals in organizational context is proposed. The approach makes use of a rich theoretical basis developed in Organization Theory. In particular, the motivation modeling of agents is based on the expectancy theory (the version of Vroom) [23] that has received good empirical support. The formal motivation modeling has an advantage that automated tools can be developed using which managers can make estimations of how different organizational factors influence the motivation and performance of different types of employees (agents). Agents are situated in a formal organization modeled using the general organization modeling and analysis framework proposed in [10]. This framework comprises several interrelated views: the performance-oriented view [19] describes organizational and individual goal and performance indicators structures; the process-oriented view [18] describes task and resource structures and dynamic flows of control; within the organization-oriented view [10] organizational roles, their power and communication relations are defined. Concepts and relations within every view, as well as models of agents are formally described using dedicated languages based on an order sorted predicate logic [13]. Temporal aspects of agent-based organizational models are formalized using the Temporal Trace Language (TTL) [22], which is an extension of a sorted predicate logic that allows reasoning about dynamic properties of systems.

The paper is organized as follows. Section 2 introduces the proposed modeling approach. The application of the approach is illustrated by a simulation case study in Section 3. Section 4 concludes the paper.

2 An Agent-based Modeling Approach

In a formal organizational model goals are structured into a hierarchy using the refinement relations. Goals are satisfied by execution of tasks. Different sets of tasks are associated with roles. Interaction and authority structures are defined on roles with respect to tasks. To enable effective and efficient execution of tasks, agents with appropriate characteristics should be allocated to roles. In this Section, a description of different types of agent characteristics is provided (Section 2.1), followed by the introduction of a motivation model of an agent (Section 2.2).

2.1 Characteristics of agents and allocation to roles

For each role a set of requirements on agent *capabilities* (i.e., knowledge and skills) and *personal traits* is defined. Requirements on knowledge define facts and procedures, confident understanding of which is required from an agent. Skills describe developed abilities of agents to use effectively and readily their knowledge for tasks performance. In literature [7] four types of skills relevant in organizational context are distinguished: technical (related to the task's specific content), interpersonal (e.g., communication, cooperation), problem-solving/decision-making and managerial skills. More specific requirements may be defined on skills reflecting their level of development, experience, the context in which these skills were attained. To enable testing (or estimation) of skills and knowledge, every particular skill and knowledge is associated with a performance indicator(s) (PI) (e.g., the skill 'typing' is associated with the PI "the number of characters per minute"). Moreover, a skill may be associated with a compound PI built as a weighed expression on simple PIs.

In psychology [11] personal traits that may also influence the execution of tasks are divided into five broad categories: openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism. Some agent's traits may mediate the attainment of agent's skills. For example, extroversion and agreeableness play an important role in building interpersonal skills.

Agent capabilities and traits can have different levels of importance. Whereas the required for a role capabilities and traits are compulsory for taking the role, desired capabilities and traits considered as an advantage.

In modern social science behavior of individuals is considered as goal-driven. A goal is as an objective to be satisfied describing a desired state or development of the individual. It is recognized that high level goals of individuals are dependant on their needs. Currently the following division of needs is identified in social science: (1) *extrinsic needs* associated with biological comfort and material rewards; (2) *social interaction* needs that refer to the desire for social approval, affiliation and companionship; (3) *intrinsic needs* that concern the desires for self-development, self-actualization, and challenge. The discussed characteristics of an agent can be formalized using the sorted first-order predicate logic as it will be shown in Section 3.

In general, the efficiency of allocation of an agent to a role is dependant on how well the agent's characteristics fit with the role requirements. However, modern organizations implement very diverse allocation principles (e.g., based on equality, seniority or stimulation of novices) [17]. Such principles can be formalized as allocation policies comprising executable (temporal) rules (see Section 3).

In modern organizations when an individual is allocated to a role, the identification of his/her specific lower level goals is performed in cooperation with a managerial representative of the organization. During this process, the high level goals, based on the agent's needs are refined into more specific goals aligned with organizational goals using AND- and OR- relations as it is shown in [19]. Many authors argue that the lower level goals should as detailed and specific as possible [7, 17]. Often two types of such goals are distinguished: development (or learning) and performance goals. Development goals reflect wishes of agents to gain certain knowledge or some skills that are also useful for the organization. Individuals vary in the abilities and desires to learn; therefore, this type of goals is particularly dependent on the individuals' traits and goals. Performance goals usually concern the effectiveness and efficiency of the execution of the tasks already allocated to the agent. Both development and performance goals may change over time.

Within the performance-oriented view of the modeling framework [19] the formal specification of a goal is based on a mathematical expression over a PI(s). The characteristics of a goal include, among others: *priority*; *horizon* – for which time point/interval should the goal be satisfied; *hardness* – hard (satisfaction can be established) or soft (satisfaction cannot be clearly established, instead degrees of *satisficing* are defined); *negotiability*. For example, the hard performance goal "it is required to maintain the time for the generation of a plan < 24 hours" is based on the PI "the time for the generation of a plan". Another example is the development goal "it is desired to achieve the state in which the framework JADE is mastered". In the latter example the goal is desirable, which points at its low priority.

The satisfaction of goals in the organizational context is associated directly or indirectly with the performance of tasks. In particular, goals associated with intrinsic needs are often satisfied by intrinsic rewards that are a natural consequence of the agent behavior related to the execution of a task. Some agents receive intrinsic rewards irrespectively of the execution results. While intrinsic rewards for other agents are contingent upon the execution outcomes. In the latter case if the actual task result equates to or exceeds the agent's expectation, then the agent receives an intrinsic reward. Furthermore, as follows from [17] the amount of intrinsic reward is dependent on the task complexity. Externally provided rewards (e.g., salary, bonuses, group acceptance) serve to the satisfaction of goals related to extrinsic and social interaction needs. At any time point the (level of) satisfaction of a lower level goal may be established by the evaluation of the PI expression, on which the goal is based. Further, using the rules defined in [19] information about the satisfaction of lower-level goals is propagated to determine the satisfaction of high-level goals.

Many organizations have reward/sanction systems contingent on the satisfaction of goals. Furthermore, besides general organizational policies also particular individual policies (e.g., concerning promotions, bonuses etc.) can be defined. Many studies showed that making explicit rules based on which rewards and sanctions are provided increases the motivation of an agent to perform certain actions (tasks) [7]. The motivation of agents to perform certain tasks is important to ensure the satisfaction of both individual and organizational goals related (directly or indirectly) to these tasks. Therefore, the motivational aspect of the agent behavior should be explicitly represented in the models of organizational agents.

2.2 Modeling the motivation of an agent

The topic of motivation in work organizations has received much attention in social science [7, 14, 17, 23]. In [23] the motivation is defined as a *process governing choice made by persons among alternative forms of voluntary activity*. We adopt the Vroom's version of the expectancy theory [23] that received good empirical support.

According to this theory, when an individual evaluates alternative possibilities to act, s/he explicitly or implicitly makes estimations for the following factors: *expectancy*, *instrumentality*, and *valence* (see Fig.1).

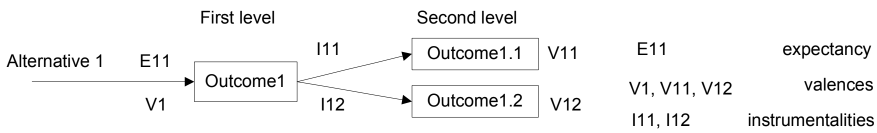

Fig. 1. An example of the motivation model by Vroom [23]

Expectancy refers to the individual's belief about the likelihood that a particular act will be followed by a particular outcome (called a first-level outcome). In organizational context expectancy of an agent related to successful task execution is determined by the characteristics of the task and the agent, and by the organizational and environmental conditions. Tasks can be characterized along multiple dimensions: (a) complexity and predictability; (b) specialization; (c) formalization. Usually agents that possess knowledge and the skills required for some task have a high level of expectancy of the successful task execution. Furthermore, agents with highly developed skills tend to assign a high value to expectancy associated with complex and not completely predictable tasks. On the opposite, inexperienced agents decrease their expectancy when dealing with complex tasks. For such agents the formalization of a task (e.g., by detailed procedure descriptions) will increase their expectancy level. If a task requires from an agent a contribution from or collaboration with other agents, then the agent's belief about reliability of these agents will play an important role in his/her expectancy estimation. Many modern organizations actively interact with the environment, which is often highly dynamic and unpredictable. The less certainty and knowledge about the environment an agent has, the less his/her expectancy level. As expectancy is defined as a subjective perception (or a belief) of an agent, the agent's personal traits also have influence on his/her expectancy.

Instrumentality is a belief concerning the likelihood of a first level outcome resulting into a particular second level outcome; its value varies between -1 and +1. A second level outcome represents a desired (or avoided) by an agent state of affairs that is reflected in an agent's goal(s) (e.g., bonus receipt, imposition of a sanction). Although the notion of instrumentality can be perceived as probability, in contrast to the latter instrumentality may take negative values, in case a second-level outcome does not follow a particular first-level outcome. Note that the agent's experience gained by the execution of tasks influences the values of expectancies and instrumentalities associated with these tasks. For example, if despite high performance the agent did not get the promised/expected (amount of) rewards, then his/her instrumentality between the level of efforts and the previously identified reward will decrease. Similarly, the agent adjusts the expectancy value associated with a task based on his/her actual amount of efforts put into the task execution.

Valence refers to the strength of the individual's desire for an outcome or state of affairs. While second level outcomes are directly related to the agent's goals, the valence values associated with these outcomes refer to priorities of these goals. Thus, similarly to goal priorities, the values of valence change over time (e.g., depending on the satisfaction of goals).

In the Vroom model *the force on an individual to perform an act is a monotonically increasing function of the algebraic sum of the products of the valences of all outcomes and the strength of his expectancies that the act will be followed by the* *attainment of these outcomes* [23]: $F_i = f(\sum_{j=1}^{n} E_{ij} \times V_j), \quad V_j = \sum_{k=1}^{m} V_{jk} \times I_{jk}$ here E_{ij} is the strength of the expectancy that act i will be followed by outcome j; V_j is valence of first-level outcome j; V_{jk} is valence of second-level outcome k that follows first-level outcome j; I_{jk} is perceived instrumentality of outcome j for the attainment of outcome k.

3 A Simulation Case Study

In this Section we shall investigate the behavior of the employees of a small firm that develops web graphics by request from external clients. Such an organization manages all its activities using a cohesive team structure. Teams have a flat power structure. Although the role of a leader (or manager) is identified, all important decisions are made with the assistance of all team members. The manager is responsible mostly for organizing tasks: e.g., searching for clients, distribution of orders, monitoring of the order execution. The firm consists of highly motivated members and has a very informal and open working style. The risky, environment-dependant nature of the firms of such type may cause financial insecurity and deficiency for their members. In the following the model used for the simulation is introduced. Due to the space limitation the model introduction will be mostly informal, providing the formalization only for the most essential parts. Subsequently, the simulation results are presented.

Modeling tasks and the environment
Tasks received by the firm are characterized by: (1) *name*; (2) *type*; (3) *required level(s) of development of skill(s)*; (4) *average / maximum duration*; (5) *extra time delay per unit of each skill development*; (6) *material reward*; (7) *intrinsic reward*; (8) *development level increment per skill*. For this case study the generalized PI “the development level” for each skill is used, which is an aggregated quantity (a real number in the range 0-5) reflecting the skill-related knowledge, experience, task execution context etc. The task average duration is the time that an agent that possesses the skills satisfying the task requirements will spend on the task execution. Agents with insufficient development levels of skills will require additional time for the execution. This is specified by the extra time delay characteristic per deficient unit of each required skill. The maximum task duration specifies the maximal time allowed for the task execution. For the successful performance of tasks agents are granted with material rewards; also the development level(s) of their skill(s) is (are) increased by the experience increment amount(s). Note that for simplicity the intrinsic rewards associated with the tasks in this case study are made independent of the specific characteristics of the agents who execute these tasks. The task types used in the simulation are specified in Table 1.

In the simulation we suppose that tasks arrive in accordance with a nonhomogeneous Poisson process $\{N(t), t \geq 0\}$ with a bounded intensity function $\lambda(t)$. Here $N(t)$ denotes the number of events that occur by time t and the quantity $\lambda(t)$ indicates how likely it is that an event will occur around the time t. We use the thining or random sampling approach [20], which assumes that $\lambda(t) \leq \lambda$ for all $t \leq T$, where T is the simulation time (2000 working hours (1 year) for this case study). Furthermore, for $T \leq 1000$: $\lambda_{A1}=\lambda_{A2}=\lambda_{B1}=\lambda_{B2}=0.05$ and for $T > 1000$: $\lambda_{A1}=\lambda_{A2}=2 * 10^{-5}$; $\lambda_{B1}=\lambda_{B2}=0.05$.

Table 1. The characteristics of the task types A1/A2 (create a simple/complex web illustration) and B1/B2 (create a simple/complex Flash animation) used in the simulation

Type	A1	A2	B1	B2
Required skill(s)	S1: 2	S1: 4	S2: 1	S2: 4
Average (max) duration (hours)	14 (18)	30 (38)	12 (15)	50 (60)
Extra time delay per skill (hours)	S1: 2	S1:4	S2: 3	S2: 8
Material reward	10	20	7	25
Intrinsic reward	1	3	1	4
Development increment	S1:0.1	S1:0.2	S2: 0.08	S2: 0.2

Organization modeling

The firm has two high level long-term goals with the same priority: "it is required to maintain a high profit level" and "it is required to maintain a high level of satisfaction of the employees". These goals are imposed on the organizational structure that comprises the role Manager and the generalized role Task Performer. The latter is instantiated into specific roles-instances associated with the tasks received by the firm. An instantiated role is assigned to one of the agents representing the employees using the following policy: Agents that can be potentially allocated to a role should be *qualified* for this role. An agent is qualified for a role under two conditions: (1) the agent is not involved into the execution of any other tasks; (2) agent possesses the skills required for the task associated with the role; and the level of development of these skills will allow to the agent to finish the task before the task deadline (i.e., maximum duration). To formalize these conditions, for each task and agent characteristic a predicate is introduced. Some of these predicates are given in Table 2. To express the temporal aspects of the agent qualification rule the language TTL is used [22]. TTL specifies the dynamics of a system by a trace, i.e. a temporally ordered sequence of states. Each state corresponds to a particular time point and is characterized by a set of state properties that hold in this state. State properties are defined as formulae in a sorted predicate logic using state ontologies. A state ontology defines a set of sorts or types (e.g., TASK, AGENT), sorted constants, functions and predicates (see Table 2). States are related to state properties via the satisfaction relation |=: state(γ, t) |= p, which denotes that state property p holds in trace γ at time t. Dynamic properties are specified in TTL by relations between state properties.

Table 2. Predicates for the formalization of agent-based models

Predicate	Description
task_arrived, task_started, task_finished: TASK	Specifies the arrival, start and finish of a task
role_for_task: ROLE x TASK	Identifies a role for a task
agent_allocated: AGENT x ROLE	Specifies an agent allocated to a role
agent_qualified_for: AGENT x ROLE	Specifies an agent qualified for a role

The agent qualification rule is formally expressed in TTL as follows:

∀γ ∀t:TIME ∀a1:TASK ∀ag:AGENT ∀r1:ROLE ∀tp1: TASK_TYPE
state(γ, t)|= [task_arrived(a1) ∧ role_for_task(r1, a1) ∧ task_type(a1, tp1) ∧
¬∃r2:ROLE r2≠r1 ∧ agent_allocated(ag, r2) ∧ sum([sk:SKILL], ∃VALUE:n, m, k case(state(γ, t)|= task_requires_skill(a1, sk, n) ∧ agent_possesses_skill(ag, sk, m) ∧ m≥0.5∧ task_extra_delay(tp1, sk, k), k • (n-m), 0)) < (task_max_duration(tp1) - task_average_duration(tp1))
⇒ ∀t1:TIME t1>t state(γ, t1)|= agent_qualified_for(ag, r1)

Here in sum([summation_variables], case(logical_formula, value1, 0)) logical_formula is evaluated for every combination of values from the domains of each from the summation_variables; and for every evaluation when logical_formula is true, value1 is added to the resulting value of the sum.

Further, since the firm recognizes the importance of wishes of its employees, a role can be only allocated, when a qualified agent has voluntarily requested the role. Furthermore, the firm established the rule that in case several qualified agents requested a role, then the agent with the earliest previous allocation time among these agents will be allocated to the role. These rules are also formalized using TTL.

For the successful execution of tasks the agents are provided with material rewards on the following basis: 50% of the reward is given to the agent who performed the task and the rest is divided equally among all other employees.

Modeling agents

The firm consists of three members and the manager modeled as agents. As in the most firms of such type, the employees are intrinsically motivated by their work, and pursuit high performance standards. For each agent two high level long-term hard goals are defined that also comply with the organizational goals: g1: it is required to maintain the level of income not less than 50; g2: it is required to maintain the level of intrinsic satisfaction not less than 5.

Two agents ag1 and ag2 possess the skill S1 to perform purely graphical work: agent_possesses_skill(ag1, S1, 4) and agent_possesses_skill(ag2, S1, 3). Here the third argument denotes the level of the skill development. The agent ag3 has the skill S2 to make Flash animations: agent_possesses_skill(ag3, S2, 4). Furthermore, ag1 has the general knowledge related to S2 (agent_possesses_skill(ag1, S2, 0.1)), which however is insufficient for the performance of tasks that require S2. By mutual consent of the firm and ag1 the development goal for ag1 without a strict deadline has been set: it is desired to achieve the level of development of S2 ≥ 0.5. When ag1 decides to gain the minimum level of the skill S2 development that is necessary for the task execution (0.5), s/he will be given one week for the training, during which no other tasks will be assigned to him/her. The motivation of the agents to attain their goals is represented by the motivation models, two examples of which for ag1 are given in Fig. 2.

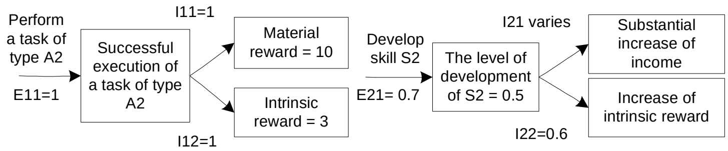

Fig. 2. The examples of two motivation models for the agent ag1 used in the case study

The parameters of the motivation models are defined as follows: Expectancy of an agent ag for the successful execution of a task tk is defined as a weighed average of the quotients $pos(sk_i)/req(sk_i)$ for each skill sk_i required for tk; here $pos(sk_i)$ is the development level of the skill sk_i possessed by ag and $req(sk_i)$ is the level required by tk. Instrumentality for each second level outcome associated with the successful execution of a task is equal to 1 for every agent qualified for this task. This is because the reward system is defined explicitly and the qualified agents have a clear estimation of the intrinsic reward associated with the task. The instrumentality value of ag1 for the skill S2 development is reevaluated in the end of each month and is equal to 1, when n/m > 50, and is equal to n/(m*50) otherwise; here n is the amount of the material rewards provided by the tasks of types B1 and B2 received by the firm up to the current time point, and m is the amount of months of the simulation time (the initial instrumentality value is 0.35). The valence values of second level outcomes change over time. In particular, when the goal g1 of an agent ag is not satisfied, then the valence values of ag for all outcomes related to material rewards will become 1, and the valence values of outcomes related to intrinsic rewards will become 0.5. When g1 is satisfied, then the valence values for material outcomes will decrease to 0.5, and for intrinsic outcomes will increase to 1. An agent generates a request to perform an action specified in a motivation model (e.g., request for a role), when the motivational force associated with this action is greater than 0.5.

The initial income value is 20 for all agents, and the initial intrinsic satisfaction level is 3. Each agent consumes 0.05 units of the received material rewards per day and the amount of the received intrinsic rewards decreases by 0.03 each day.

The simulation is performed using the dedicated tool [1]. Fig. 3a shows how the motivational force of ag1 to attain the skill S2 changes over time. After the time point 1000, when the amount of tasks of type A diminishes significantly, the force transgresses the threshold 0.5, and ag1 begins the attainment of S2. After some time ag1 possesses the skills required to perform the tasks of both types A and B and both his/her goals g1 and g2 become satisfied (see Fig. 3b).

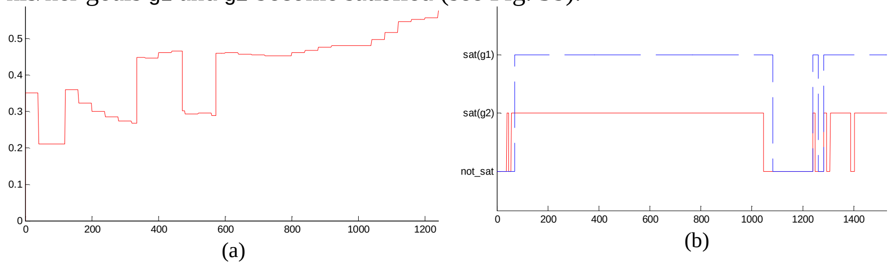

Fig. 3. (a) The change of the motivation force (the vertical axis) of agent ag1 for the attainment of skill S2 over time. (b) The change of the satisfaction of the goals of agent ag1 over time.

4 Conclusion

The paper proposes a formal approach for modeling of agents situated in an (formal) organization that accentuates the intentional and motivational aspects of agent behavior. The proposed quantitative motivation model of an agent based on the expectancy theory allows estimating the agent's motivational force to attain certain (organizational or individual) goals. Since the goal expressions are based on performance measurements, using the proposed approach it is possible to analyze how different organizational factors that affect the parameters of the motivation model influence the organizational or agent performance. An example of such analysis is demonstrated by a simulation case study in this paper.

Based on a large corpus of empirical social studies a great number of dependencies between organizational and environmental factors and the agent's motivation have been identified. These factors and dependencies stem from the different organizational views introduced above and will be further used for modeling and analysis of the behavior of agents situated in different types of organizations.

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