Reducing Hazards in Multiagent Task Delegation

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Abstract. Delegation of tasks is a basic pattern of numerous interactions within multiagent systems. Since agents are selfish and exploit local knowledge about their actions as well as the environment, delegators face the hazard of losing outcome due to self-serving behavior of the "employed" agent. This research work adopts the economic theory of agency to study delegation relationships in multiagent systems and to design a mechanism for task delegation that prevents delegators from losing outcomes in such relationships. The contribution of this work is a mechanism for task delegation considering the economic situation of agents. The paper proposes the results of a simulation study to demonstrate the usefulness and efficacy of the provided artifact.

Keywords: Agency Theory, Multiagent System, Task Delegation

1 Introduction

Raising the flexibility of production lines, logistics networks, and whole business ecosystems is one of the core objectives in the field of Industry 4.0. Shifting tasks from centralized units to local entities is a very promising and important change of paradigms in today's industries. With multiagent systems (MAS), the computer science contributes a useful and in parts already adopted, basic technology to delegate tasks in Industry 4.0 scenarios, e.g. within self-organizing Smart Factories.

Delegation of tasks is a pervasive phenomenon and a major issue in MAS. This importance is reflected by the majority of the definitions of the term "agent" that make explicit references to task delegation [1] and the seminal contract net protocol introduced as a basic mechanism for task delegation into the MAS-community since the early literature [2]. This paper use the term "manager" for the delegating and "contractor" for the adopting software agent. Recent years in MAS research have witnessed interest in mechanisms to decide whether to delegate a task or not and, if yes, to whom a task should be delegated at best. While the first question is answered by different "make-or-buy" decision models, the latter includes the question if the contractor is trustworthy. Solutions to this problem are mutual models of trust, the software agents build up and keep updated (e.g. by learning). Using such models, the manager tries to determine the likelihood that the delegation will fail [3]. Other approaches rely on policies [4] or organizational rules [5]. In light of this fast growing literature, it is important to understand and to mitigate problems in delegation rela-

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When managers cannot monitor contractors and outcomes are influenced by unpredictable external factors, contractors may minimize their effort and attribute poor results to these disturbances. This lack of oversight prevents managers from holding contractors accountable for low performance, risking unfavorable outcomes.

tionships mainly caused by self-interested contractors [1]. Consider a situation in which a manager cannot monitor the contractors' actions. Outcomes are not only influenced by the actions but also by an unpredictable external disturbance that is not verifiably by the manager. The only verifiable signal is the outcome at the end of the relationship. In such situations contractors will minimize their effort because they cannot be monitored and they can excuse low outcomes with disturbances that are beyond their control – even if this is a cheating behavior. Managers cannot infer from outcomes that a contractor's effort was low or high and thus cannot blame contractors for low effort. Subsequently, managers face the hazard of losing outcome.

Economic agency theory (EAT) deals with such situations of task delegation since the early 1970ies and provide formal frameworks and feasible means for analyzing and solving a broad class of problems in delegation relationships for the manager (in terms of agency theory: the principal) [6]. Up until recently, the findings of EAT are not reflected appropriate by the MAS community like this was done with game and decision theory. The present paper at hand sheds more light on the conflicts of interest as well as incentive problems and provides a mechanism for incentive compatible task delegation in MAS. In a task delegation relationship, one software agent (manager) hands over a task to another software agent (contractor). The manager's outcomes are directly related to the actions of the contractors. To perform an action, the contractor has to spend effort. Outcomes are not only affected by the contractors' actions but also by external disturbances not verifiable by the manager. Manager and contractor are able to verify the outcome at the end of the relationship at zero costs in an undisputed way. Agents are self-interested and maximize their own objective function.

in terms of FL, the outcome can be affected by network condition

It is further assumed that managers cannot monitor the contractors' actions – all actions are hidden from the manager. Therefore, the problem of "hidden actions" [7] is addressed. EAT suggests introducing incentive mechanisms into task delegation [6]. To reduce hazards in multiagent task delegation, the paper adopts this suggestion and develops an incentive compatible task delegation mechanism. The mechanism is evaluated by a simulation study that shows evidence for the method's efficacy. *The leading research question in this paper is how such a mechanism has to be designed in order to maximize the manager's outcomes.*

The remainder of this paper is organized as follows. In section 2, the theoretical background is described and approaches in the extant literature are analyzed. In section 3, the research method is introduced. Section 4 outlines the formal framework and proposes a novel task delegation mechanism. In section 5, the experimental setup and the results of the simulation study are provided. Section 6 concludes the paper.

2 Theoretical Background

2.1 Economic Agency Theory

Agency theory has its roots in information economics and deals with delegation relationships characterized by an asymmetric distribution of information about contractor's characteristics, contractor's actions or states of the world [6]. Depending on the type of information asymmetry, the manager faces corresponding problems like hidden characteristics, hidden action and hidden information – all followed by a loss of outcome for the manager. The paper focuses on hidden action as a class of problems where the manager cannot observe the contractors' actions without additional (and therefore costly) means. It is assumed that contractors are self-interested and maximize their own objective function. External disturbances exist as a random component that can't be observed by the managers [6]. This situation is summarized in figure 1 based on seminal papers published in journals rated with A+ or A in the JQ 2-ranking.

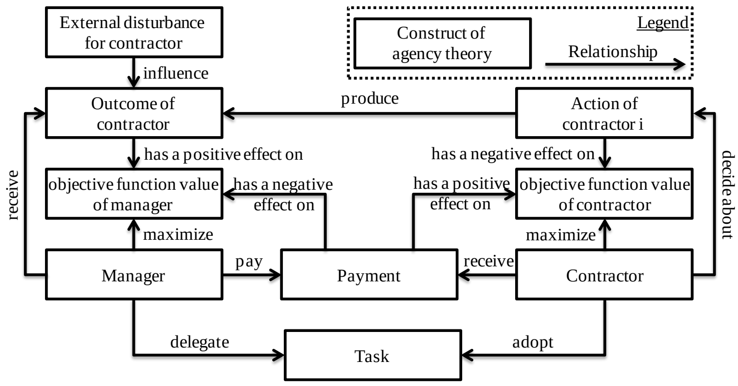

Fig. 1. Agency relationship with hidden action

Economic literature provides numerous variations and advancements of this standard two side, one stage, one period, one contract model with only one signal (outcome).

To give an overview of advanced agency models, relevant economic outlets were searched by appropriate terms (e.g. common agency) to retrieve recent papers published after 2000. Additionally, fundamental papers in agency theory, like [7], were included in the search space. During decades, economists built up a comprehensive knowledge base of delegation patterns exploitable for MAS researchers. So common agency models deal with additional problems evolving from multiple managers delegating tasks to the same contractor [9]. So managers compete with each other for the contractor's resources and had to take into account, that other managers' offers influence the effectiveness of their own offer. In settings with only one manager but more than one contractor (team of contractors), the manager faces the supplementary problems of free riding and production externalities [10]. A combination of both is reached in models with multiple managers and multiple contractors [11]. If the agency relationship is multi-staged, the contractor on one stage is the manager for another contractor on the subsequent stage at the same time. In this environment, the problem of federation is added to the agency relationship [12]. Contractors on subsequent stages are able to federate to the detriment of the manager on the very first stage.

If agency relationships repeat (in a finite or infinite time horizon) all parties are able to learn from previous periods and will adapt their behaviors. This makes it necessary to consider history-dependent preferences for effort spending [13]. In settings in which the manager allocates more than one contract to a contractor at the same

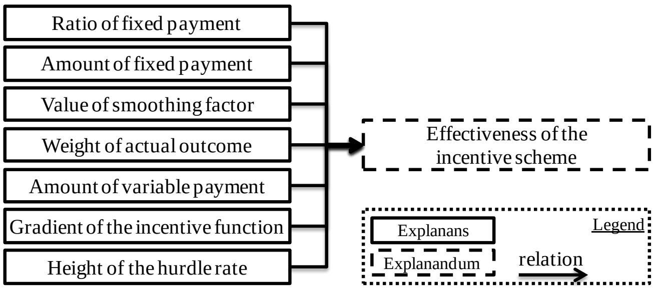

Fig. 2. Cause-effect model for the effectiveness of incentive schemes

time the manager must be aware of the mutual influences between these contracts. If one contract commits the contractor to produce a certain result while another asks for maintenance work, contractors will neglect maintenance if they are paid according to their production outcome [14]. While the contractor in the standard model produces only one verifiable signal (the outcome) multi-signal models assume that there are additional signals that allows managers for evaluating contractors' actions. But this raise questions about weighting or inconsistency of different signals [15].

Up until recently, economists also developed a bunch of means for solving agency problems in different settings and to effectively mitigate hazards for managers. Beside means for allowing to monitor contractors' actions and for unveiling information about external disturbances [15], economists mainly developed methods to incentivize contractors to behave congruent to the managers objectives [16]. Since incentives were identified as the most promising tool to overcome agency problems [17], this work is grounded on this knowledge and introduces incentives schemes in multiagent task delegation mechanisms. Incentives schemes affect the contractor's objective function so that it gets congruent with the objective function of the manager. This is done by a conditioned payment of the contractor depending on the produced outcome. Graphically, this lead to a new directed edge in figure 1 that connects "outcome of contactor" with "payment". A higher outcome induces higher payments. As simple it sounds in the first view the more complex it gets on the operational level of designing the incentive scheme [18]: Who should receive the payment – especially in teams of contractors where outcome cannot be assigned to a specific contractor (team production)? When should the incentive be paid – immediately or in future to avoid shortsightedness of the contractor? Should the incentive payment only be based on the actual outcome or is there a need for including past outcomes – especially in scenarios with highly varying outcomes contractors demand for smoothing? What is the best smoothening filter? Do contractors accept the contract if all risk is shifted to them or is it effective to divide payment into a fix and a variable part? What is an appropriate amount for incentive payments and an appropriate gradient of the incentive function?

Following primarily results from economic research the effectiveness of incentive schemes mainly depends on seven factors [18]. Figure 2 give a brief résumé about incentive literature and provide a cause-effect model for explaining influences on the effectiveness of incentive schemes.

2.2 Task Delegation in Multiagent Systems

Task delegation was one of the major concerns in multiagent research over the past decades. At an early stage, Bond and Gasser identified task allocation as one of the basic problems in distributed artificial intelligence (DAI) and outlined that the avoidance of uncertainty in results or completion is one of the bases for making allocation decisions [19]. With the contract net protocol a seminal pattern for task delegation was introduced into MAS research from the very beginning [2]. Research is mainly focused on the question to which agent a task should be delegated at best. Recent studies proposed a permanently increasing number of market mechanism including auction or negotiation protocols. However, as the principal concern these works suggest solutions for ex ante problems of delegation (selecting the best contractor) – ex post problems arising from the possibility of hidden actions are not in the scope of these approaches and are still an understudied field of research in the main outlets of the community like the AAMAS Journal and Proceedings.

Reflecting the importance of task delegation, Castelfranchi and Falcone suggested a theory of delegation for MAS from a plan-based view on the problem [1]. Although the authors analyzed possible conflicts between manager and contractor caused by a selfish exploitation of asymmetric distributed knowledge, they studiously avoided the whole body of knowledge in EAT dealing with that problem. This is even more surprising since Kraus made this theory accessible for DAI researcher two years earlier in a very comprehensive study [20]. Kraus figured out that in cases where one agent delegates tasks to selfish agents and the delegating agent faces a lack of information about the other agent(s), EAT provides a purposeful framework for task delegation problems in MAS based on incentive mechanisms.

Up to recently several studies are concerned with incentive contracting in MAS. From the viewpoint of mechanism design Shoham and Tanaka investigated the effect of incentives in a public goods game played by rational software agents. The authors show that an incentive mechanism can be established so that agents are willing to contribute to the provision of public goods although this is not individually rational without such an mechanism [21]. As the society in its whole is the delegator, a public goods game is not the standard case of task delegation. Cruz and Simaan studied a more characteristic delegation relationship between a team leader and the members of the team within a MAS. By introducing incentives in a standard leader-follower Stackelberg game, an equilibrium was implemented so that the strategies of the team members were in align with the global objectives of the team leader [22].

Dynamic scheduling of production is an often addressed problem by MAS researchers because inherent advantages of MAS tend to fit to the challenges of this application domain. After a task is delegated by a scheduling agent (manager) to a specific machine agent (contractor), the task might be late due to malicious behavior of the machine agent. Avoiding this hazard, Váncza and Márkus proposed an incentive mechanism for production scheduling based on in-process tardiness penalty [23]. By conducting simulation studies, the authors provide evidence that their penalty mechanism effectively solves the problem of not fulfilling commitments towards the customers due to delays caused by machine agents. Although Váncza and Márkus employs several machine agents, it is not a model with multiple contractors in the sense of EAT since the machine agents are not related to each other and there are no additional problems that arise from multiple contractors.

Recent studies concerning multiagent task delegation more and more rely on the concepts similar with trust, reputation or compliance in social science. Braynov and Sandholm show that in electronic commerce where agents act as buyers and sellers, social welfare, the amount of trade, and the objective functions of agents can be maximized if seller's trust is equal to the trustworthiness of the buyer [24]. To achieve this equality, the authors define an incentive compatible bilateral contract in which agents truthfully report about their trustworthiness. Without being mentioned by the authors, this work strongly relates to the adverse selection problem in markets well known in economic literature and first reported by [25] in 1970. A slightly different approach is provided by Jurca and Faltings as they incentivize rational agent in open, distributed marketplaces to truthfully report about their reputation [26]. The simulation experiments show that defective behavior decreases about approx. 40% when agents are provided with incentives. Hermoso and Cardoso use learning concepts in incentive mechanism for the first time [27]. They show that over time an almost optimal incentive scheme evolves and contractors select the most reliable action. Hermoso and Cardoso do not consider additional problems that arise from the existence of multiple contractors. Thus, it is not a multiple contractor model in the sense of agency theory.

To sum up MAS literature, table 1 shows a classification of the research conducted by the MAS community in terms of agency theory. Therefore, the number of managers and contractors will be examined as well as the assignment of these roles to specific software agents. All works only consider models consisting of a single stage, one contract and one signal. They only differ in the number of participants and periods.

Table 1. Classification of task delegation relationships in MAS research

Paper	*Participants*	*Manager*	*Contractor*	*Periods*
[1]	1:1	delegator	adopter	1
[21]	1: many	"the society"	society member	1
[22]	1:many	team leader	team member	many
[23]	1:1	scheduler	machine	many
[24]	1:1	buyer	seller	1
[26]	1:1	buyer	seller	1
[27]	1:many	service requester	service provider	many

This paper is closely related to the developments in the field of incentive based task delegation in MAS literature as presented above and is also based on the body of knowledge of the EAT. The comprehensive work of [20] is an essential precursor. However, the proposed approaches of incentive based MAS research draws several concerns as they mainly consider 1:1-delegation relationships in a single period in time. Approaches considering a 1:many-relationship with more than one period can be found in [22, 27]. In [22] a standard leader-follower Stackelberg game was used to analyze the problem and to design a mechanism for solving it. But the model is missing stochastic to describe random external disturbances as a crucial element in delegation relationships. The same stands for [23]. The provided approach in this paper differs from existing research as it considers a 1:many-relationship lasting over more than one period and explicitly model stochastic influences during task completion.

3 Research Method

The research is conducted by applying the design science methodology [8] to ensure rigor in design and evaluation. In design, it is ensured by grounding the artifact on proven cause-effect-models and feasible means from the agency theory. Design is furthermore led by well-established methods from system engineering and uses constructs as well as mathematical notations out of the agency theory. To obtain knowledge about the usefulness of the artifact in the appropriate environment scientifically, a simulation study is conducted to evaluate the task delegation mechanism.

The proposed artifact is applied to a MAS operating the on-site logistics of a road construction site during the earth works phase. Considering this, the experiment design consists of two models. The first represents the logistics system of the construction site with its processes and physical conditions while the second model contains the MAS including the task delegation mechanism. The parameterization of the logistics system model was done by using existing empirical data from real world construction sites regarding loading times, driving times etc. [28]. The calibration of the construction site logistics model was done by a specific scenario built up by domain experts to ensure rigor [29]. The model matches the values calculated in this scenario.

4 Incentive Compatible Task Delegation Mechanism

4.1 An Agency Model of Task Delegation in MAS

A contractor $i \in \mathbb{N}$ receives a task from the manager m. In order to fulfill the task, the contractor performs an action $a_{i,t} \in A$ at a specific time $t \in \mathbb{N}$. Thus, A denotes the set of all possible actions of all contractors. Let $e_{i,t}$ be the contractor's effort to perform the action at time t described as a bijective function $e_{i,t}: A \rightarrow \mathbb{R}^{\geq 0}, a_{i,t} \longmapsto e_{i,t}(a_{i,t})$. The possibility of negative efforts is excluded. The payment of the manager to a contractor at a specific time is denoted as $p_{i,t} \in \mathbb{R}^{\geq 0}$ and therefore negative payments (penalties) are excluded, too. Contractors possess an objective function that is partially differentiable, separable and strictly monotone.

$$u_{i,t}: \mathbb{R}^{\geq 0} \times \mathbb{R}^{\geq 0} \rightarrow \mathbb{R}^{2} \tag{1}$$

$$\left(\mathrm{p_{i,t}}, \mathrm{e_{i,t}}\left(\mathrm{a_{i,t}}\right)\right) \longmapsto \mathrm{u_{i,t}}\left(\mathrm{p_{i,t}}, \mathrm{e_{i,t}}\left(\mathrm{a_{i,t}}\right)\right) \tag{2}$$

$$\mathrm{u_{i,t}}\left(\mathrm{p_{i,t}}, \mathrm{e_{i,t}}\left(\mathrm{a_{i,t}}\right)\right) = \mathrm{u_{i,t}}\left(\mathrm{p_{i,t}}\right) + \mathrm{u_{i,t}}\left(\mathrm{e_{i,t}}\left(\mathrm{a_{i,t}}\right)\right) \tag{3}$$

The assumption is that the first derivation with respect to the payment is positive ($\mathrm{u_{i,t}^{p_{i,t}}} > 0$) and the first derivation w.r.t. the effort is negative ($\mathrm{u_{i,t}^{e_{i,t}(a_{i,t})}} < 0$). This means that the payment is judged as positive while the effort is judged as negative. If the second derivation w.r.t. the payment is positive (negative), the contractor is willing to take risks (is risk-averse). If the second derivation w.r.t. the effort is positive (negative), the contractor is eager to work (is work-averse). If the second derivations are equal to zero, the contractor is risk- neutral resp. work- neutral. The script t denotes different values of the objective function but not different function rules. This reflects time consistency of preferences as it is assumed in EAT.

While performing the actions and by spending effort, the contractor produces an outcome $o_{i,t} \in \mathbb{R}^{\geq 0}$. Negative outcomes are excluded from the model. Outcomes are not only influenced by the actions but also by a stochastic external disturbance modeled by a conditional density and distribution function ("production function" f).

$$\mathrm{f}\colon \mathbb{R}^{\geq 0} \times \mathbb{R}^{\geq 0} \rightarrow \mathbb{R}^2 \tag{4}$$

$$\left(o_{i,t}, e_{i,t}\left(\mathrm{a_{i,t}}\right)\right) \longmapsto f\left(o_{i,t}|e_{i,t}\left(\mathrm{a_{i,t}}\right)\right) \tag{5}$$

$$\forall \mathrm{e_{i,t}}\left(\mathrm{a_{i,t}}\right)\colon \int_0^\infty \mathrm{f}\left(\mathrm{o_{i,t}}|\mathrm{e_{i,t}}\left(\mathrm{a_{i,t}}\right)\right)\mathrm{dt} = 1 \tag{6}$$

$$\forall e_{i,t}\left(\mathrm{a_{i,t}}\right)\colon \mathrm{F}\left(o_{i,t}|e_{i,t}\left(\mathrm{a_{i,t}}\right)\right) = \int_0^\infty f\left(o_{i,t}|e_{i,t}\left(\mathrm{a_{i,t}}\right)\right) dt \tag{7}$$

The monotone likelihood ratio property is valid: Let $e_{i,t}^{1,2,3,\dots,\infty}(\cdot)$ be different effort levels resulting from different actions a contractors carries out. It holds that $e_{i,t}^{1}(\cdot) > e_{i,t}^{2}(\cdot) > \cdots > e_{i,t}^{\infty}(\cdot)$ so it can be derived that $\mathrm{F}\left(o_{i,t}|e_{i,t}^{1}(\cdot)\right) \geq \mathrm{F}\left(o_{i,t}|e_{i,t}^{2}(\cdot)\right) \geq \cdots \geq \mathrm{F}\left(o_{i,t}|e_{i,t}^{\infty}(\cdot)\right)$ what leads to a first order stochastic dominance. It is further assumed that there exist only strictly positive possibilities: $\forall e_{i,t}(\cdot), o_{i,t}\colon f\left(o_{i,t}|e_{i,t}\left(\mathrm{a_{i,t}}\right)\right) > 0$. This ensures that every outcome is reachable at every effort level and the manager cannot infer from outcomes that a specific effort level was chosen by the contractor. This, contractors choose their actions by maximizing the objective function:

$$a_{i,t} \in \arg\max_{a_{i,t} \in \mathrm{A}} u_{i,t}\left(p_{i,t}, e_{i,t}\left(\mathrm{a_{i,t}}\right)\right) \tag{8}$$

If payment $p_{i,t}$ is fixed, the contractor is only able to reduce effort by choosing the appropriate action in order to maximize the objective function. Because of the monotone likelihood ratio property this will raise the probability of a lower outcome. Let

$$o_t^m = \sum_{i=1}^{n} \int_0^\infty f\left(o_{i,t}|e_{i,t}\left(\mathrm{a_{i,t}}\right)\right) dt \tag{9}$$

be the overall outcome for the manager received from all $n \in \mathbb{N}$ relationships and let

$$p_t^m = \sum_{i=1}^{n} p_{i,t} \tag{10}$$

denote the overall payment to all contractors of the manager. Then the manager's objective function can be denoted as

$$v_t : \mathbb{R}^{\geq 0} \times \mathbb{R}^{\geq 0} \rightarrow \mathbb{R}^2 \tag{11}$$

$$(o_t^m, p_t^m) \longmapsto v_t(o_t^m, p_t^m) \tag{12}$$

$$v_t(o_t^m - p_t^m) = v_t(o_t^m) - v_t(p_t^m) \tag{13}$$

If it is assumed that the manager is risk-averse, then $v_t'(o_t^m - p_t^m) > 0$ and $v_t''(o_t^m - p_t^m) < 0$ holds. Again, the subscript t describes different values of the manager's objective function at different times and not different function rules what implies the common assumption of time-stable preferences. The manager's maximization problem is formulated by $\max v_t(o_t^m - p_t^m)$. Since o_t^m is beyond the manager's sphere of influence, the only possibility is to vary p_t^m by adjusting the payment rules. As incentive compatible payments were chosen as the solution for the hidden action problem in task delegation, the design of these payment rules is the core of the presented approach and will be described in the subsequent section.

4.2 A Novell Incentive Compatible Task Delegation Mechanism for MAS

Let a payment rule be denoted as a mathematical function that maps a set of payment function parameter $y \in Y \subset \mathbb{R}$ and the smoothed assessment basis $o_{i,t}^*$ for the incentive payment onto a real number greater or equal zero. Thus, $p_{i,t}$ can be reformulated as $p_{i,t} : Y \rightarrow \mathbb{R}^{\geq 0}$ with $(y_1, y_2, \ldots, y_{j \in \mathbb{N}}, o_{i,t}^*) \longmapsto p_{i,t}(y_1, y_2, \ldots, y_{j \in \mathbb{N}}, o_{i,t}^*)$. Seven factors influencing the efficacy of an incentive scheme can be derived from economic theory (see figure 2). Therefore, the set Y consists of seven elements as shown in table 2. Since outcome is produced by a team of contractors, it is assumed that the manager receives an additional signal that allows for identifying the contribution of a single contractor to the overall outcome. Therefore, a contractor's smoothed output $o_{i,t}^*$ is the assessment basis for the incentive payment to this contractor.

Table 2. Parameter of the payment function

Parameter	*Description*	*Domain*
y_1	Ratio of fixed payment	$[0,1] \subset \mathbb{R}$
y_2	Amount of fixed payment	$\mathbb{R}^{\geq 0}$
y_3	Value of smoothing factor	$\mathbb{N}$
y_4	Weight of actual outcome	$[0,1] \subset \mathbb{R}$
y_5	Amount of variable payment per unit of outcome	$\mathbb{R}^{\geq 0}$
y_6	Gradient of the incentive function	$\mathbb{R}$
y_7	Height of the hurdle rate	$\mathbb{R}$

Regarding to the suggestions of EAT, the newly provided payment function contains a fixed and a variable part and the assessment basis is exponentially smoothed. The variable part will only be paid if the assessment basis exceeds a certain hurdle rate. Bringing all together, the payment scheme is defined as

$$o_{i,t}^{*} = \mathrm{y}_4 \mathrm{o}_{\mathrm{i,t}} + (1 - \mathrm{y}_4) \frac{1}{\mathrm{y}_3} \sum_{\mathrm{z}=1}^{\mathrm{y}_3} \mathrm{o}_{\mathrm{i,t-z}} \tag{14}$$

$$p_{i,t}(y_1, y_2, \ldots, y_7, o_{i,t}^{*}) = \begin{cases} y_1 y_2 + (1 - y_1) y_5 o_{i,t}^{*} & \text{if } o_{i,t}^{*} > \mathrm{y}_7 \\ y_1 y_2 & \text{if } o_{i,t}^{*} \leq \mathrm{y}_7 \end{cases} \tag{15}$$

4.3 Incentive Compatibility and Participation Constraint

By relating the payment of the contractor to the outcome the contractor's decision problem is expanded to a decision problem with an expected value of the objective function and needs to be reformulated as

$$a_{i,t} \in \arg\max_{a_{i,t} \in \mathrm{A}} \int_0^{\infty} u_{i,t}\left(p_{i,t}(y_{1,\ldots,7}, o_{i,t}^{*}), e_{i,t}(\mathrm{a}_{\mathrm{i,t}})\right) \cdot f\left(o_{i,t} | e_{i,t}(\mathrm{a}_{\mathrm{i,t}})\right) d\mathrm{t} \tag{16}$$

This decision problem is denoted as incentive compatible within the EAT [30]. Considering a reservation value $r_i \in \mathbb{R}$ the contractor holds with or without taking part in the delegation relationship, the contractor will participate if

$$\forall\, a_{i,t}, o_{i,t}\colon \int_0^{\infty} u_{i,t}\left(p_{i,t}(y_{1,\ldots,7}, o_{i,t}^{*}), e_{i,t}(\mathrm{a}_{\mathrm{i,t}})\right) \cdot f\left(o_{i,t} | e_{i,t}(\mathrm{a}_{\mathrm{i,t}})\right) d\mathrm{t} \geq \mathrm{r}_{\mathrm{i}} \tag{17}$$

4.4 Technical specification

The technical specification is informed by the FIPA Contract Net Interaction Protocol Specification (FCNIP) [31]. As shown in figure 3 on the next page the FCNIP is extended by three more internal steps and one more interaction to match the requirements of the proposed incentive compatible task delegation mechanism.

The call for proposal (cfp) contains a description of the task that needs to be fulfilled and in addition the payment rule according to formula (15). By calculating the participation constraint (formula (17)) the contractor decides whether to refuse the call or to submit a proposal in order to adopt the task. This is slightly different to the FCNIP in which the cfp contains the question about the amount of compensation the manager must provide so that the contractor adopts the task – but this is due to the different perspectives. While the FCNIP focuses on finding the best (e.g. cheapest) contractor, the artifact at hand focus on the ex post-problem of proposing an incentive compatible task delegation to an already identified contractor. Thus, if a proposal is submitted the contractor accepts the payment rule and the manager do not have any reason for rejecting the proposal. However, this possibility still remains in the specification to allow reconsiderations. After accepting the proposal the task is delegated to the contractor. For performing the task, the contractor chose the action according to the decision problem formulated in (16). Then the contractor performs the action,

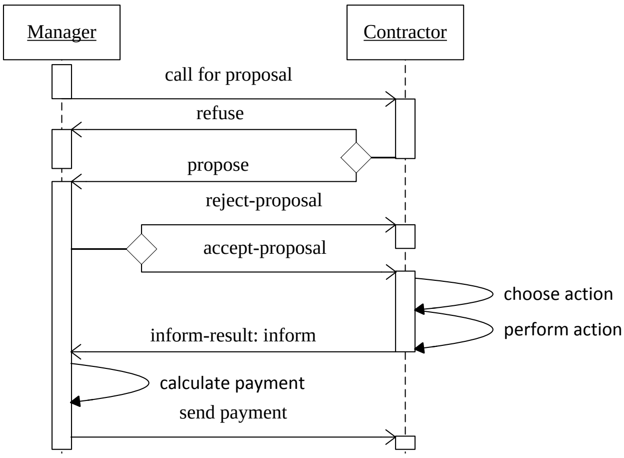

Fig. 3. Technical specification

realizes the external disturbances and produces the outcome. Subsequently, the manager is informed about the amount of outcome. The manager now calculates the payment according to the outcome and sends the payment to the contractor.

5 Evaluation

5.1 Experimental Setup

To provide evidence for the purposefulness of the artifact it was applied in a simulated environment in which the MAS operates the on-site logistics of a road construction site during the earth works phase. The MAS consists of a dispatcher agent (the manager) that delegates transportation tasks to truck agents (the contractors) that produce outcomes by driving to different loading and unloading places on their own decisions in accordance to times for driving, loading, unloading, and waiting and excavators' loading performances. The causal chain between increasing the outcome by increasing payments is explained by formulas (3), (7), and (16). The physical model of the site contains a transportation road network modeled as a graph and waiting queues at loading and unloading places. Variations in loading and unloading performances were modeled as beta distributions based on empirical evidences. The implementation was validated against a specific scenario build up by domain experts and it was tested by code walkthroughs performed by two mutually independent PhD students.

Table 3 shows the simulation plan. The amount of fixed payment (y_2) is in the interval of $[0, 1.2]$ €/minute. That reflects common rental prices for trucks including drivers in Germany. At its maximum the smoothing factor is 480. Since each tick simulates one real time minute, the outcomes of the whole day (8h*60m) are incorporated at maximum. The gradient of the incentive function is between 0.1 and 2.0 and is therefore exponential or linear. The interval of the hurdle rate is determined by the performances of the machines that were chosen for the simulation.

Table 3. Simulation plan

Characteristic	*Description*
Explanandum	Amount of soil being transported (outcome for manager)
Explanantia	$y_{1,\dots,7}$
Interval	$y_{1,4}$ see table 2; $y_2 \in [0,1.2]$; $y_3 \in [1,480]$; $y_5 \in [0.1,1]$; $y_6 \in [0.1,2]$; $y_7 \in [0,3.7]$
Step	$y_{1,4,5,6,7}: 0.1$; $y_2: 0.1$; $y_3: 6$; 1,000 combinations randomly chosen
Duration	480 ticks per run
Runs	100 runs (allows evidence at a level of significance of 0.9999 and a random error of 0.01)

5.2 Results

The simulation experiment was conducted with and without the proposed artifact. Figure 4 and table 4 gives a descriptive overview of the results – numbers in braces describe the baseline case without the artifact. As one can see, using the task delegation mechanism lead to an increase of the outcome of the manager. Analyzing the influences of the parameter of the payment function on the outcome, a multiple correlation analysis shows a correlation of 0.4018 what provides evidence for a medium joint influence of all parameter in their combination.

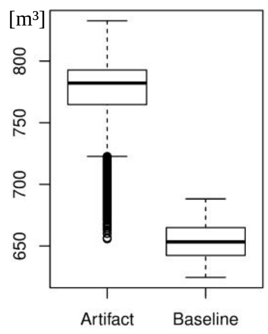

Fig. 4. Box plot diagrams

Table 4. Measures of dispersion and central tendency

Statistic		*Value*	
Arithmetic mean		774.7309	(653.5603)
Quartile			
	0.25	764.6733	(642.4145)
	0.50	782.1081	(653.3393)
	0.75	792.6711	(664.8586)
Variance		690.1779	(238.2371)
Var. Coeff.		0.0339	(0.0235)

The negative spikes in Fig. 4 are caused by the stochastic effects in the physical model of the site as they occur in reality, too. To analyze the influence of a single parameter on the outcome, the correlation coefficients were analyzed pair wise in table 5.

Table 5. Correlations

Correlation of	y_1	y_2	y_3	y_4	y_5	y_6	y_7
with outcome	-0.039	-0.045	0.157	0.015	0.032	-0.039	-0.307

As table 5 shows, the ratio of fixed payment (y_1) as well as the amount of fixed payment (y_2) are negatively correlated with the outcome. This also stands for the gradient of the incentive function (y_6) and the hurdle rate (y_7). The value of the smoothening factor (y_3), the weight of the actual outcome (y_4) and the amount of variable payment (y_5) are positively correlated with the outcome.

5.3 Discussion

Introducing the provided incentive based task delegation mechanism into the simulated multiagent system lead to an increase of the average outcomes for the manager. As the boxplot diagram in figure 4 demonstrates, the use of the artifact also leads to negative spikes – but the lowest value in the experiment using the artifact was higher than the average value of outcomes in the experiment without the artifact. Results also show that the variance of the outcomes as well as the coefficient of variance is increasing. This means that managers will receive higher outcomes on the one hand but also face a higher volatility on the other hand. Since risk neutrality of managers was assumed, the only criterion is the maximization of the outcome.

The multiple correlation of 0.4018 provides evidence for a positive but medium joint influence of all design parameter of the mechanism. Furthermore, the simulation experiment only leads to weak or very weak correlations of the design parameter. This is due to the characteristics of the chosen experimental setting. Earth works suffers from a high influence of stochastic processes on the outcomes. As the simulation was grounded on empirical evidences from real world construction sites, the high impact of random components was transferred into the experiment. So, results show a positive effect of the artifact but stochastic influences still plays an important role.

Regarding the question about how a task delegation mechanism in multiagent systems has to be designed in order to maximize the manager's outcomes, the correlations of the design parameter with the outcome provide advices for system engineering. First, if a fixed payment is offered, the amount should be low – raising the amount of variable payment will lead to higher outcomes. But results indicate that a completely variable payment is not efficient at all. The first 100 results with the highest outcome were achieved at an average ratio of fixed payment of 0.496. Thus a half-and-half payment is advisable. Hurdle rates are means to challenge contractors to raise effort in order to exceed the hurdle. But the higher the hurdle, the more exhausting it gets. If hurdles are only achievable at a prohibitively high effort, contractors will not provide any additional effort. Thus, hurdles have to be kept low. The first 100 results with the highest outcome advice to set the hurdle rates at about 33% of the outcome that can be achieved at maximum effort.

6 Conclusion

This paper presents an incentive based task delegation mechanism grounded on the EAT which is by so far understudied in the field of multiagent systems research. There are two main results of this work. First, the results of the simulation provide evidence for the feasibility and efficacy of the provided artifact in order to maximize outcomes for task delegating agents by aligning the objective functions of managers and contractors. Second, the conducted simulation experiment provides advices for multiagent system engineers for designing incentive compatible task delegation mechanisms. Results indicate that contractors should be paid fixed and variable with a ratio of about fifty-fifty. Hurdle rates are efficient at about 33% of the outcome that can be achieved at maximum effort. The amount of fixed payment is less important than the amount of variable payment. The findings are in line with prior results in the field of agency theory and MAS research as they also provide evidence for the efficacy of incentive based mechanisms in delegation relationships. But this work differs from existing MAS research as it considers a 1:many-relationship lasting over more than one period and explicitly model stochastic influences during task completion.

This research could be extended in expanding the underlying agency model. This can be done in several ways as the state of the art suggests. Agency theory provides numerous variants of models to explain and to design different delegation relationships. As the research in this field is mainly based on mathematical methods, models are often expanded in only one or two directions like shifting from one to more agents or shifting from one to more periods. Using multiagent systems and computer simulations, even complex models will stay analyzable.

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