

Dynamic Resource Allocation Withself- | Interested Agents in the Upstream Oil & Gas Industry

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ABSTRACT: This paper analyzes resource allocation between principal-agent (and between agent-agent) in the upstream oil & gas industry. In the model, we incorporate the parties' preferences as we outline a principal-agent model. Further, we optimize the resource allocation between the parties as they are self-interested with the use of incentive-based contracts with risk and rewards. Our optimization determines that to realize the highest profit, the principal and the involved agents should avoid any agents' becoming dominant. Hence, the volume of sourced items from the agents should not vary too much. We further outline the on-boarding process of new agents in the network and how the network needs to compensate for the potential loss for some of the agents if the network should fulfill the incentive-compatibility condition.

Keywords: Resource allocation, incentive-based contract, mechanism design theory, principal-agent theory, optimization.

1. INTRODUCTION

This article deals with opportunistic behavior involving a principal and several agent's (and between the involved agent's) in the upstream oil & gas industry. There are two main strategies to minimize opportunistic behavior: (a) measurement of the agents' effort and (b) reduction of goal conflicts between the involved parties (Ouchi, 1979). This paper addresses both. Bako and Brynjolfsson (1992) outlined how incomplete contracts' incentive implications will affect the number of agents, and further how incentives related to quality can lower the number of agents. Further, they outlined a model that optimizes the number of total suppliers, where they found an optimum between high coordination cost (transaction cost) when there are many agents, and the risk of opportunistic behavior when there are few agents. They also argued that the number of agents decreases when incentives focus on increased quality (Bakos & Brynjolfsson, 1992). However, that study does not take into consideration the involved agents' preferences, e.g., they analyze neither how

the agents value the network compared to alternative outside options nor the resource flow from the agents to the principal.

As we want to analyze how the agents value the network compared to outside options, and analyze the resource flow from the agents, we start with mechanism design theory. We outline the mechanism design literature that addresses the decentralized optimization problem with self-interested agents where there is private information regarding their different outcomes and preferences. The mechanism design theory purpose is to reveal true information (preferences) in an environment with asymmetric information, and how this information-revealing problem is a constraint to social decisions. In the mechanism design literature, incentive compatibility and the revelation principle will be of high importance for good cooperation. The revelation principle argues for the value of designing a mechanism where the agent will give away his true information and preferences. Incentive compatibility is present if no agent finds it advantageous to abort from the mechanism.

abort from the mechanism. Then we have a Pareto improvement, meaning that an actor can increase his utility value without compromising other actors. In this paper, we outline two theorems. The first theorem emphasize that the relationship is at risk if one or more agents hold a dominant position. The additional value the workload deviation creates is only marginal, strengthening the argument that one or more dominant agent is not optimal. Ensuring a low deviation from the average resource allocation (e.g., 10–20%) allows the relationship to evolve without any parties becoming dominant and behaving opportunistically. This ensures that the network evolves positively without any significant reduction in profit.

Further, we have outlined a principal-agent model for how incentive-based contracts with risk and rewards can be used to secure incentive compatibility and participation constraint on a drilling project. One of the paper’s main contribution is an example of performing an optimization of resource allocation among four agents, and later extending it to six agents. Theorem 2 shows how the on-boarding of new agents affects the level of sourced items for the other agents. The existing agents will accept the new agents if the relationship fulfills the requirements of incentive compatibility and participation constraints.

This article is organized as follows. Section 2 gives a briefly introduces mechanism design—a game-theoretical approach. Section 3 outlines the methodology. Section 4 outlines a general introduction to the Oil & Gas industry. Section 5 introduces the mechanism design theory, using the study of adverse selection. Section 6 outlines the study of moral hazard using the principal-agent model under incentive-based contract with risk and rewards. Section 7 outlines an optimization example. Section 8 concludes.

2. A BRIEF INTRODUCTION TO MECHANISM DESIGN-A GAME THEORETICAL APPROACH

Game theory can be employed to study a system of agents acting opportunistic or agents who are bounded rational (the rationality of individuals is limited by their information, their lack of time, and their cognitive limitations of their minds) when participating in some form of bilateral cooperation. Game theory and economic theory often involve Pareto improvement. Pareto improvement is when a player increases his utility value without compro-

mising other actors. If a player increases his utility so that it affects other players negatively, it signals Pareto inefficiency. The goal in game theory is often to aim for a Pareto optimal allocation of resources, meaning that none of the involved actors can increase their utility by forming alliances.

2.1 Basic definitions

We will now explain the basic definition regarding game theory through an example involving a principal and an agent working together. The definitions and terms are based on Fudenberg & Tirole (1991), Osborne & Ariel (1994) and Maskin (2007).

The *type* of an agent determines the preferences of an agent, and is influenced by the different outcomes of a game. We outline the importance of *type* when we discuss mechanism design in the next section, as *type* will affect the design of the mechanism. Suppose an operator who owns a petroleum license (a principal) is collaborating with a service company (agent i) that performs dedicated work related to a drilling project for this operator, where agent

i receives a particular outcome (outcome x_1). Let

$\theta_i \in \Theta_i$ be the type of agent i , for a set of possible types Θ_i . The preferences of agent i in relation to

outcome $x_1 \in X$ can be expressed as a utility function that can be further expressed as a parameter of

the *type*. Let $u_i(x_1, \theta_i)$ be the utility for an agent i

in outcome $x_1 \in X$ given type θ_i . Suppose agent i chooses to leave the present relationship for the benefit of a collaboration having a different relationship

with a different outcome (outcome x_2). If the payment to agent i from x_2 is better than the payment

from x_1 , we say that x_2 “dominates” x_1 in the first collaboration. A specific collaboration “dominates” agent i if he can benefit by leaving the partnership for another partnership. Hence, agent i prefers outcome

x_2 above x_1 when $v_i(x_1, \theta_i) < v_i(x_2, \theta_i)$.

Otherwise, agent i prefers x_1 .

The agent’s choices for all given situations constitute a *strategy*. Hence, let $s_i(\theta_i) \in S_i$ be the strategy of agent i given type θ_i , where S_i is a set of all pos-

sible strategies available to agent i . In addition to the above-mentioned *pure* strategy (e.g. agent i interact with one operator), agent i 's strategy can be mixed (e.g., agent i interacts with other operators (principals) at the same time and can obtain outside information used to benchmark and value the situation differently). Hence, obtaining individual information can give them an advantage over the operator. However, we argue that the core of a Pareto cooperative game evolves based on the fact that no subgroups within the partnership can do better by leaving the partnership. Hence, using the information for his own interest will not benefit the agent. This is evident in the next sections, where we further outline the mechanism design problem with focus on the social choice function, incentive compatibility, and the revelation principle.

3. METHODOLOGY

This optimization was designed to explore the benefit of implementing an incentive based contract in the oil & gas industry. Further, the study aims to optimize the resource flow from involved agents to the principal. The examples were chosen based on interviews with key-employees in the industry, where resource allocation was highlighted as a problem due to unsatisfying incentive models. This has been outlined in an earlier paper where the problem was described in more detail through an embedded multiple case study (Sund, 2008). Multiple case studies are particularly useful when studying relationships between companies because they provide an understanding of the latent factors that can produce contradictory views between parties (Hedstrom & Swedberg, 1998). The optimization conducted in this paper is a replication of that study and the purpose of our framework is to outline a mechanism that aims to reveal the true information (preferences) in an environment with asymmetric information. We challenge this problem by setting up a mechanism where all the involved agents find it advantageous to reveal their true preferences because of the constraints related to incentive compatibility and participation. Hence, we can optimize the resource allocation between the agents by involving some additional constraints and regulating the relationship with the use of incentive-based contracts with risks and rewards. We choose this study approach because of the limited understanding of how inter-organizational collaboration occurs and evolves (Davies et al., 2006). It is a preferred methodology when the theories are well known and understood,

but the underlying theoretical logic (and the relationship between the theories) is limited (Davis et al., 2007a; Davis et al., 2007b). The results depicted in table 8 and 11 in section 7 will be analyzed using Excel solver. Hence, we want to find specific values for specific cells in a spreadsheet model that optimizes a certain object. In our examples, this means to optimize the number of resources that has been allocated from the agents based on their total profit of contributions. Hence, we need to define the target cells, often described as objective or goal, and further define the changing cells, or cells that can be changed to optimize the target cells. At the end, we involve the constraints depicted in table 6 in section 7 (Winston, 2007).

4. GENERAL INTRODUCTION TO THE UPSTREAM OIL & GAS INDUSTRY

This paper models an optimal bilateral inter-organizational strategy for the upstream oil & gas industry, hence referred to as the drilling environment. The relationship between the operator (defined as a principal owning a petroleum license) and the agent (defined as a significant service provider for that principal) can greatly affect productivity and cost efficiency. The study of motivating and controlling cooperative action is known in the literature as principal-agent analysis (Salanié, 1998). The principal-agent literature addresses problems arising when the agent works for his own goals rather than the principal's (Milgrom & Roberts, 1992; Salanié, 1998). This is especially relevant if the agent has private information, and the principal finds it hard to monitor and observe the agent's actions, as the principal can only evaluate its own outcome (Barney & Hesterly, 1996).

As the drilling environment is recognized to have asymmetric information, the service provider knows more about the tasks that should be performed than does the operator. The principal-agent literature argues that this can lead to strategic misrepresentation and opportunistic behavior. This can be avoided by the principal's offering an incentive scheme that pays the agent according to the value realized (Gintis, 2009). Further, the principal-agent theory argues that there has to be at least a minimum surplus to the actors, or they will consider joining other collaborative environments. The service provider often experiences an incentive constraint as the operator maximizes its profit subject to an individual rationality constraint (participation constraint). For example, lack of incentive compatibility between the

parties may force the service provider to consider outside options. On the other, if the parties have incentive compatibility, they may be willing to share their private information with other involved parties (Milgrom & Roberts, 1992).

Our paper focuses on the mechanism (service contract) that regulates the general relationship between the operator and the service provider in drilling activities. In this much used mechanism, quality and speed are often seen as conflicting, but can affect each other positively. An input factor is considered time-critical in the drilling process if their recovery rate upon failure depends on the use of existing infrastructure, and losses may occur if the input factor is delayed (Sund & Hausken, 2009).

On the Norwegian Continental Shelf (NCS is the continental shelf over which Norway exercises sovereign rights. Stretching 200 nautical miles from the Norwegian coast, its major parts are the shelves of the North Sea, Norwegian Sea and Barents Sea (The United Nations Convention on the Law of the Sea, 1982), almost all service provider relationships with the operator are regulated through a fixed-price contract, with no or few incentives related to operation. Incentive-based contract that incorporate risk and reward (e.g. financial payment) related to perfor-

mance are not common used. This contract pays a negative reward (penalty) if the agent does not meet the standards been agreed up on, and pays a positive reward if the agent reach the goals been agreed up on. As the agent financial results are related to performance, the agent becomes more dependent of the other parties. Hence, the party that can contribute with the highest value will be the decision maker rather than the actor with formal ownership of the process (Sund & Hausken, 2009).

Cost, investment, and production level on the NCS

The drilling environment is recognized to pose increased complexity with time, as there are often up to 40 different teams involved in a drilling project. Complexity is believed to be one of the main reasons for the increase in drilling costs for one field completion from \$140,000 in 2004 to nearly \$500,000 in 2007. At the same time, the daily productivity increased from 102 average drilled meters in 2002 to 111 meters in 2003, before leveling off at around 80 meters since 2004 (Osmundsen, Sørnes, & Toft, 2008).

Below, we outline the investment level and production level on the NCS. Further, we give an example for how the production level can develop and how it differentiates production and gross income. Table 1 depicts the investment level on the NCS.

Table 1 Accrued and estimated investment costs for extraction of crude petroleum and natural gas 2005-2010 (In NOK million)¹

	2005	2006	2007	2008	2009	2010*
Field development						
Fields on stream	19,518	21,316	30,762	35,184	40,104	28,833
	34,395	39,013	46,003	57,617	65,222	73,485

* Estimates

The quality of the drilling process, which might last 100 days, affects the productivity of the well for possibly 15 years.² A possible relationship between quality and productivity is depicted in table 2:

¹ www.ssb.no

² Average length of operation before shutdown is 13.75 years on the NCS. Source: www.npd.no

Table 2 Hypothetical estimated production of barrels of oil per day (b/d)

Quality of drilling	Estimated production in b/d for 15-year life of well
High	12,000 b/d
Middle	10,000 b/d
Low	8,000 b/d

The effect of the implied cumulative production on gross income is depicted in table 3:

Table 3 Effect of production level on gross income

Estimated b/d per day	High = 12,000	Middle = 10,000	Low = 8,000
Number of barrels in			
15 years of production	65,700,000	54,750,000	43,800,000
Differentiation in barrels		10,950,000	10,950,000
Differentiation in gross income*		\$686,565,000	\$686,565,000

* Average oil price in 2009 is \$62.7. Source: www.ssb.no

This example considered only the result of the drilling process and how it affects the production phase, and did not take into consideration later investments that might increase productivity at an additional cost. The well's productivity might also be influenced by the geological structures and maturity of the field, for example, shale production/brown fields. However, this paper's focus is the influence of the drilling process on production for new fields (green fields). Table 4 depicts how the net total petroleum production on the NCS has declined,³ despite the increased investment and cost of drilling activities as shown in table 1.

Table 4 Net total production of oil on the NCS from 2002 to 2009

Year	Net total petroleum production in Sm ³ (thousands)
2002	173,649
2003	165,475
2004	162,777
2005	148,137
2006	136,577
2007	128,277
2008	122,673
2009	115,453

³ Net total petroleum production in 1000 Sm³. Source: www.npd.no, www.ssb.no

Tables 1 and 4 demonstrate asymmetry between investment in the drilling phase and productivity in the production phase. For example, higher investment in the drilling phase does not necessarily lead to better productivity in the production phase. In table 3, we argue that the different quality in the production phase will affect gross income. This statement has been verified through discussion with several key employees from different operators and service providers on the NCS. In this paper, we argue for the importance for the incentive-based contract with risk and rewards as a mechanism to increase the productivity on drilling projects, and thereby affect the productivity in the production process.

5. MECHANISM DESIGN-THE STUDY OF ADVERSE SELECTION

Mechanism design has received increased attention since its noteworthy contributors Leonid Hurwicz, Eric Maskin, and Roger Myerson were awarded the 2007 Nobel Memorial Prize in Economics. The theory of mechanism design affects adverse selection positively as the mechanism tries to reduce opportunistic behavior to a minimum. Adverse selection is defined as a pre-contractual information asymmetry that gives conditions under which the principal cannot be certain that the agent accurately performs the agreed-upon work. Some authors refer to the application of adverse selection models as the “mechanism design problem” (Salanié, 1998). Central to mechanism design is the decentralized optimization problem, in which self-interested agents possess private information regarding their own outcomes and preferences (Salanié, 1998). In many situations, collective decisions are made without the involved agents’ personal preferences, as they are not publicly observable. This indicates that the agents must be relied upon to reveal their private information, as the setting is characterized by incomplete information. Later in this paper we evidently outline how there is a motivation for the agent to reveal their private information. The agents private information is revealed through implementation of an optimal system-wide solution. As noted earlier, $\theta_i \in \Theta_i$ is the agent i type and determines his preferences over different outcomes; i.e., $v_i(x, \theta_i)$ is the utility of agent i given type θ_i for outcome $x \in O$.

Therefore, we seek to understand how the agent’s

private information is elicited and if and how this information revelation problem constrains how social decisions can respond to individual preferences. We define this as the mechanism design problem (Mas-Colell, Whinston, & Green, 1995).

5.1 The Social Choice Function

The social choice function is a system-wide goal in mechanism design, and its purpose is to create a mechanism that selects the optimal outcome given agent types. Hence, we outline some definitions related to the social choice function and their properties (Arrow, 1963; Dasgupta, Hammond, & Maskin, 1979; Mas-Colell et al., 1995; Myerson, 1981; Parkes, 2001).

Definition 1.1 Social choice function f : $\Theta_1 \times \dots \times \Theta_I \rightarrow X$ that, given the agent types $\theta_1, \dots, \theta_I$, assigns a collective choice $f(\theta_1, \dots, \theta_I) \in X$.

Hence, given the agent types, $\theta = \theta_1, \dots, \theta_I$, it would be proper to choose outcome $f(\theta)$. The goal of mechanism design is to implement “game rules,” i.e., possible methods and strategies to try to select an outcome based on the agents’ strategies, and thereby implement this solution to the social choice function regardless of the agents’ self interest.

Properties of Social Choice Functions

The properties of the social choice function will affect mechanism design. The social choice function has to be Pareto optimal, indicating it implements outcomes none of which is strongly preferred (compared to other outcomes) by a subset of agents. The social choice function is important to mechanism design as it has to be Pareto optimal, even the agents have quasi-linear utility functions.

Definition 1.2 Agent i quasi-linear utility function with type θ_i is of the following form

$$u_i(o, \theta_i) = v_i(x, \theta_i) - p_i$$

where o defines the choice $x \in K$ from the relevant set and the payment from agent p_i . The valuation

function, $u_i(x)$, for an agent with quasi-linear preferences is defined by its type. Hence, each choice value is defined by $x \in \mathcal{K}$, where \mathcal{K} represents their allocations, and the payment is represented by the transfer. For example, side-payment makes it easy to transfer utility across the involved agents. We argue that the agent is risk neutral because the agent is willing to pay as much as he values the item and therefore his utility will be the same as his expected value.

5.2 Mechanisms

The mechanism design concept tries to set up a mechanism where there are a number of self-interested agents with private information regarding their preferences, and thereby come up with an optimal system-wide solution to a decentralized optimization problem. Below are some definitions related to mechanism design and their properties (Dasgupta et al., 1979; Mas-Colell et al., 1995; Maskin, (2007); Myerson, 1981).

Definition 1.3 A mechanism $\Gamma = (S_1, \dots, S_I, g(\cdot))$ defines the set of strategies S_1 available to each agent, and an outcome function $g: S_1 \times \dots \times S_I \rightarrow X$, hence, $g(\cdot)$ is the outcome from the mechanism implementation for the strategy profile $s = (s_1, \dots, s_I)$.

The mechanism defines available strategies, and based on agents' strategies, a method is used to select the final outcome.

Given mechanism Γ , with the outcome function $g(\cdot)$, we say that a mechanism implements a social choice function $f(\theta)$ if the outcome with equilibrium agent strategies is a solution for the social choice function that is aligned with the agents' possible preferences.

Properties of Mechanisms

Describing the properties of a mechanism requires defining the solution concept and each agent's domain of preferences as quasi-linear, risk neutral, etc. With respect to the implementation of a mechanism (see definition 1.5) and the properties of a social choice function (see definition 1.1), we argue that the

property of a mechanism is the same as the property of a social choice function when implemented in a mechanism. That is, a mechanism Γ is Pareto optimal if it involves a Pareto optimal social choice function $f(\theta)$. Another property of a mechanism is the individual-rationality often addressed as the "voluntary participation/participating constraint." This constraint indicates that the agent is not forced to participate in the mechanism. This constraint will affect the expected utility the agents receive from participating.

Let $\bar{v}_i(\theta_i)$ be the expected utility of agent i realized through an outside option instead of the mechanism

of type θ_i . The most common definition of individual rationality is interim individual rationality, in which the agent knows his own expected utility and has little if any information regarding the preferences of the other agents, but can expect them to be at least its own expected outside utility. When the agent can withdraw from participation once it has knowledge about the outcome, an *ex post* individual rationality is the most appropriate solution. In this situation, the agent's utility from participating has to be at least the same as the outside utility for all agents involved in the mechanism. Often agents must chose to participate before they know their true preferences, which is addressed as *ex ante* individual rationality. Hence, the expected utility, average preferences for participating in the mechanism must be at least the agents' expected utility when he is not participating. If not, the agent may choose not to participate.

5.3 Mechanism Implementing the Social Choice Function

Hence we outline an mechanism Γ with an outcome $g(\cdot)$ where Γ involves the social choice function $f(\theta)$ as long as the social choice function creates an equilibrium positive for all the involved agents' preferences (Mas-Colell et al., 1995):

Definition 1.4 A mechanism Γ is considered to be rational for all the agents' preferences, θ_i , when it implements a social choice function $f(\theta)$.

$$u_i(f(\theta_i, \theta_{-i})) \geq \bar{u}_i(\theta_i)$$

Hence, $u_i(f(\theta_i, \theta_{-i}))$ is expected utility of agent i resulting from his outcome given knowledge about

the other agents' preferences θ_{-i} , and $\bar{u}_i(\theta_i)$ is the expected utility for the agent if he decides not to participate. E.g., the mechanism is individual rational if the agent can at any given time realize more utility when participating compared to not participating if the agent has prior knowledge about the other agents preferences.

Definition 1.5 A mechanism $\Gamma = (S_1, \dots, S_I, g(\cdot))$ implements social choice function $f(\cdot)$ if there exists an equilibrium strategy profile $(s_1^*(\cdot), \dots, s_I^*(\cdot))$ of the game created as a consequence of Γ so that $g(s_1^*(\theta_1), \dots, s_I^*(\theta_I)) = f(\theta_1, \dots, \theta_I)$ and this is relevant for all $(\theta_1, \dots, \theta_I) \in \Theta_1 \times \dots \times \Theta_I$.

Hence, we argue that a mechanism implements a social choice function $f(\cdot)$ if the equilibrium realized through the game is created by using the mechanism that has the same output $f(\cdot)$ for every given types profile $\theta = (\theta_1, \dots, \theta_I)$.

The problem with definition 1.5 is that it assumes that there exist multiple equilibriums and that the agents will select the equilibrium that the mechanism designers prefer. Also, with respect to the so-

cial choice function $f(\cdot)$, an agent may find it disadvantageous to reveal their information truthfully. We show in section 6 that this is not correct, as this problem can be treated as an optimization problem.

5.4 Incentive Compatibility and the Revelation Principle

The revelation principle simplifies the identification of all the available social choice functions that can be implemented. Under weak conditions, the

revelation principle can be set up as a mechanism that is incentive compatible and directly reveals the agent's type (direct-revelation mechanism). This captures the value of designing a mechanism, as the agent will give away their true information and preferences. The direct mechanism that always has an equilibrium should be preferred to one that does not create an equilibrium, because the latter may permit free-riding by some of the agents. If the agent's dominant strategy is truth telling, we have a straightforward mechanism. Incentive compatibility is present if every agent finds it disadvantageous to abort from the mechanism. In the revelation principle, each agent is asked to reveal their true type,

and as we know $(\hat{\theta}_1, \dots, \hat{\theta}_I)$, the agent will choose $f(\hat{\theta}_1, \dots, \hat{\theta}_I) \in X$. Hence, the agent will reveal their direct type and create a mechanism as defined (Dasgupta et al., 1979; Hurwicz, 1973; Mas-Colell et al., 1995; Maskin, (2007); Myerson, 1981; Parkes, 2001; Vickrey, 1961):

Definition 1.6 The direct revelation mechanism is one where $\Gamma = (\Theta_1, \dots, \Theta_I, g(\cdot))$ is a constraint for the strategy set $\sum_i = \Theta_i$. This is relevant for all i , and involves an outcome rule $g = \Theta_1 \times \dots \times \Theta_I \rightarrow O$, as it choose an outcome $g(\hat{\theta})$. The direct revelation mechanism is realized based on the agents' reported preferences $\hat{\theta} = (\hat{\theta}_1, \dots, \hat{\theta}_I)$.

Hence, the agent will reveal his true preferences θ_i , based on his reported type $\hat{\theta}_i = s_i(\theta_i)$. We can now outline the mechanism where truth telling is an optimal strategy for the agent.

Definition 1.7 A social choice function $f(\cdot)$ is implemented truthfully and is to be considered to be incentive compatible when $(s_1^*(\cdot), \dots, s_I^*(\cdot))$ as $s_i^*(\theta_i \in \Theta_i)$ and we can find all $i = 1, \dots, I$. This is evident if the involved agents' truth telling gives equilibrium according to the mechanism $\Gamma = (\Theta_1, \dots, \Theta_I, g(\cdot))$.

The next section presents an example where we

model the principal-agent relationship using an incentive scheme to see how payment amount affects the agent's effort.

6. THE PRINCIPAL-AGENT MODEL-THE STUDY OF MORAL HAZARD

The last section outlined the impact of adverse selection and how it affects the involved agents' behavior when cooperating. This section examines the impact of moral hazard in a principal-agent model. Moral hazard is post-contractual opportunism, or a condition under which the principal cannot be sure that the agent has put forth maximal effort, as its effort is difficult to observe. Hence, we want to outline and include a worked example and use the drilling environment for the oil & gas industry as a case example. As adverse selection and mechanism design define the possibilities and constraints that regulate the relationship between principal-agents and agent/agents pre-contractual, the moral hazard (post-contractual) opportunistic behavior is that occurring within the project, and hence similar to a principal-agent model. Because the two different opportunistic behaviors, adverse selection and moral hazard, are interrelated, we argue that adverse selection must be considered when modeling the principal-agent solution.

6.1 Worked example

This section explores a dynamic transaction model seen as a bilateral cooperation process between a principal and an agent. Consider a situation on a drilling project where the operator (principal) will hire a service provider (agent) to perform some kind of work. The Norwegian Continental Shelf often has up to 40 different teams working on one drilling project (Osmundsen et al., 2008). As the different team members has different preferences, this has lead to increased complexity, and this complexity is believed to largely account for cost's having more than tripled from 2004 to 2007 (Osmundsen et al., 2008).

Therefore, we argue that the implementation of an incentive-based contract binding the parties on a drilling project will lead to higher first-time quality due to reduction of moral hazard and adverse selection.

The case model

Our model defines a principal-agent problem and determine a Pareto optimal contract where there are problems with information revelation and challeng-

es with respect to moral hazard between an operator and a service provider. We also want to show that the principal-agent model needs to consider challenges related to adverse selection addressed in section 4. Hence, the social choice function, incentive compatibility, and the revelation principle outlined in section 4 will be addressed, especially in section 6. The general principal-agent model used in our example was developed by Milgrom and Roberts (1992) and further extended to fit our example.

Example

Our example assumes the principal to be risk-neutral, hence concerned with the quality and the final payoff from the project overall. We assume the agent to be risk-averse. (The risk-neutral agent is considered at the end of this section, where we take into consideration a small financial risk.) Hence, the agent will try to contribute as little as possible if there is no upside benefit.

The agents wage w (income) and contribution b give the following utility function:

$$u(w, b) = \sqrt{w} - (b - 1) \quad (1)$$

Hence, w 's decreasing marginal utility function is

$$1/(2\sqrt{w}) \quad (2)$$

Our model uses two levels of contribution: $b = 1$ and $b = 2$. The former indicates that the agent's contribution is costly when exceeding 1 and represents a risk-averse agent. The principal goal is to get the agent to accept an appropriate level of contribution of work, and not consider outside options. This is done by rewarding the agent with at least as much as he could receive by participating in an outside collaboration, similar to the methodology outlined in the mechanism design concept in the last section. The agent's expected utility is defined as u . Our example sets u to 1. We also align the agent's income with the value he creates for the principal. Other factors that affect the contribution that either the principal or the agent can observe or affect should also be considered.

In our example, we set $b = 1$ and the income equal to 15 with a probability 2/3, $b = 2$ with income of 45 with a probability of 1/3, as observed in table 5.

Table 5 Probability of outcome

Behavior	Income	
	I = 15	I = 45
b = 1	p = 2/3	p = 1/3
b = 2	p = 1/3	p = 2/3

When $b = 1$, we calculate the income to be $(2/3) \times 15 + (1/3) \times 45 = 75/3$, and when we increase the level to $b = 2$, the expected income rises to $(1/3) \times 15 + (2/3) \times 45 = 105/3$. Hence, the contribution b effectively increases the probability of a higher outcome realized by the agent.

The agent bears no risk because he would receive a fixed payment w irrespective of outcome or even if he does not contribute with contribution level $b = 1$. If the principal could observe b , he would demand $b = 2$, and pay nothing for $b = 1$. Eq. 3 gives the payment needed for the agent to accept the contract instead of joining an outside option.

$$\sqrt{w} - (b - 1) = \sqrt{w} - (2 - 1) \geq 1, \quad \text{or} \quad w \geq 4 \quad (3)$$

As observed, if the agent should accept the contract, the payment w has to be at least 4. In our model, the principal will not give away more than necessary, hence the agent receives $105/3 - 4 = 93/3$. If the principal wants the lowest contribution from the agent, the principal would pay $b = 1$ to the agent, and the agent would receive utility of $72/3$. The additional w for the extra contribution is $4 - 1 = 3$ to the principal, but the alternative payoff would be $(105 - 75) = 30/3 > 3$. Hence, the principal will find it feasible to pay for the extra contribution from the agent.

In a situation where the level of outcome is observable but not the level of effort, the principal cannot determine the outcome based on the agent's effort. Still there can be some relation between effort and outcome as effort affect outcome. Their affection on each other could also be a misrepresentation, as the outcome could be higher through luck, or lower as outside disturbance out of the agents control can affect the outcome negatively. Creating a purpose for

the agent to work hard can be done by giving him better payment for high effort than low effort (measured by outcome as effort affect outcome), indicating the agent needs to take on some financial risk.

In this next example, the agent needs to receive $b = 2$ when the principal wants high effort, and the outcome needs to be better compared to when the agent chooses $b = 1$.

Under an incentive based contract, the agent receives:

l , when the outcome is 15 and,

h , when the outcome is 45

The agent's expected utility by choosing $b = 1$ is

$$(2/3)(\sqrt{l} - 0) + (1/3)(\sqrt{h} - 0) \quad (4)$$

Or, the agent's expected utility by choosing $b = 2$ is

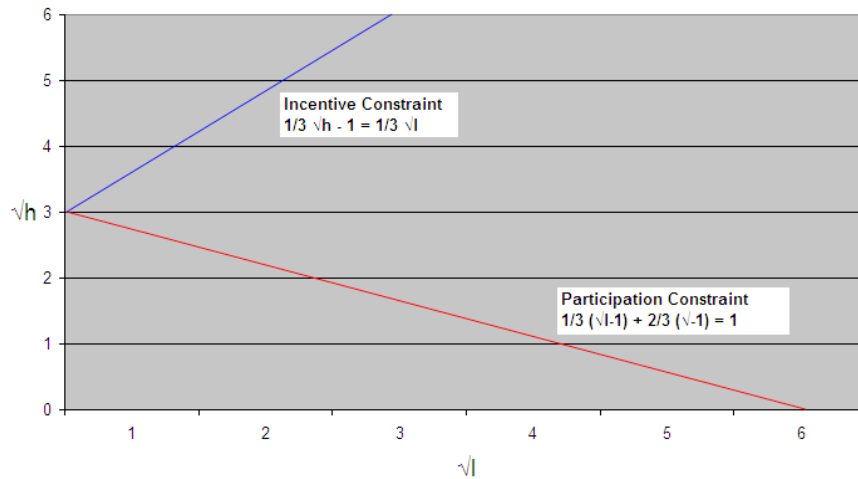
$$(1/3)(\sqrt{l} - 1) + (2/3)(\sqrt{h} - 1) \quad (5)$$

The agent must receive at least as much or more for the high contribution compared to low contribution level. Expression 6 addresses the agent incentive compatibility constraint, the same constraint as outlined in the incentive compatibility model (mechanism design/adverse selection) outlined in definitions 1.1 to 1.7. Incentive compatibility means that the agent must not be worse off by exerting extra effort, the same principle we outlined in section 4 where we argued that the incentives should be positive for all involved parties, or some of the participants would consider joining other relationship.

$$(2/3)(\sqrt{l} - 0) + (1/3)(\sqrt{h} - 0) \leq (1/3)(\sqrt{l} - 1) + (2/3)(\sqrt{h} - 1) \quad (6)$$

Expression 6 shows a constraint in the incentive scheme, affecting high contribution negatively. In addition, we will make the participation constraint consistent with the incentive compatibility problem. If the participation constraint is violated, the agent will reject the contract and will not participate in the collaboration. As the incentive constraint increases, the participation constraint decreases, as seen in fig. 1.

Fig. 1- Incentive constraint (\sqrt{h}) and participation constraint (\sqrt{l})



The incentive constraint can be reduced to the following form.

$$(1/3)\sqrt{h} - 1 \geq (1/3)\sqrt{l} \quad (7)$$

The payoff needs to increase significantly higher when contribution increases ($b = 2$), compared to ($b = 1$).

Expression (6) can also be reduced to a simpler term for the participation constraint, where the outcome with low utility needs to be higher than the outside option. Hence, we set the outside option equal to 1.

$$(1/3)(\sqrt{l} - 1) + (2/3)(\sqrt{h} - 1) \geq 1 \quad (8)$$

The challenge for the principal is to find two positive values of l and h , as the agent is risk adverse, that will lead the agent to accept downside (negative) incentives. Downside risk for agents can be included in a principal-agent model, and be seen as an incentive for increased cost efficiency and productivity (Sund & Hausken, 2009).

Above the top (blue) line in the upper left area in fig. 1, the combination of h and l meets the incentive constraint. At this point, the agent will be motivated to perform at the expected level with a combination of h and l payment. Above the lower (red) line and below the top line, the combination of h and l satisfies a participation constraint. The principal wants $l = 0$ and $h = 9$, with a return of $(1/3) \times (15 - 0) + (2/3) \times (45 - 9) = 87/3$. The return is less than the earlier return of $93/3$. This is because the principal has to pay additional 2 (from 4 to 6) to the agent. Using $b = 2$ will impose extra cost for the principal, as the agent has to take on performance risk.

If the principal is comfortable with $b = 1$, there are no incentives for the principal to provide extra payment to the agent. The agent will accept the payment as long as the payment, $b = 1$, is at least equal to any outside option. The principal will use the incentive scheme with $b = 2$ as long as the output is higher than an incentive scheme where $b = 1$. As the agent has a payment of $b = 1$ the principal's payoff is $(2/3) \times (15 - 1) + (1/3) \times (45 - 1) = 72/3$. This is lower than when applying $b = 2$. Therefore $b = 2$ contribution level should be preferred.

In this example, we evidently show that there is a positive payoff for the principal to use $b = 2$ in relationship with the agent as it motivates for higher contribution level. In the next section, we want to optimize the resource flow among multiple agents in a drilling project having a principal-agent relationship.

7. OPTIMIZATION EXAMPLE

This section extends the example in section 6. We will outline a principal-agent relationship with the aim of optimizing the resource allocation among multiple agents in a drilling project. Further, we want to analyze how the agents evaluate the network compared to outside options, and analyze the resource flow from the agents. We will do this by implementing a social choice function and incentive compatibility in the resource allocation among the agents. Given these two constraints, the mechanism will create a revelation principle. This will be evident given that the agents accept a new volume and payoff in the network when they optimize an alternative resource allocation rather than choosing to leave for an alternative relationship.

The additional constraints are outlined in Table 6. The operator sets these constraints in conjunction with the service providers. To achieve optimization, they need to be satisfied. For example, there should at any time be at least four agents involved, so that no agent can become too dominant. Too few agents can lead to opportunistic behavior as they enter a dominant position because of economics of scale, whereas too many agents could lead to high coordination and transaction costs (Bakos & Brynjolfsson, 1992). Another constraint is that no agent’s resource allocation can deviate from the agreed number of sourced items by more than a predefined percentage (e.g., if there are four agents and the principal wants to adopt 800 units, the average is 200 (800/4) per agent. If the maximum deviation is set to 10%,

an agent could source at maximum 220 and at minimum 180 units to the principal). We will later argue that the allowed deviation affects incentive compatibility and the participation constraint. Conflicting with these two constraints could lead some of the involved parties to optimize the resource bundle value, and thereby only one agent would source all the volume. We will also show how this optimization will encourage the on-boarding of new resources. Moreover, agents will still reveal their preferences because the mechanism creates incentive compatibility and offers a secure participation by implementing an incentive-based contract with risks and rewards where the final payoff is shared by all involved parties.

Table 6 – Additional constraints

Minimum of four service providers involved
Maximum and minimum % deviation from average resource allocation for every four agents (average resource allocation is $1000/4 = 250$)

To make our example as realistic as possible, the agents need to bundle resources and sell resource packages to the principal. Table 7 depicts an example of how agents might combine resources to form bundles. The principal asks for resource bundles consisting of 12 resource units. The specific terms of the bundle decides what kinds of resource units the

agent has to choose. The revenue is set from historical data and/or in conjunction with the principal and agents. We argue that this will mean they reveal their true information because trying to hold back true information or bluff would affect not only the other agents but also themselves given that their payoff depends on the overall performance on the project.

Table 7 – The four agents’ resource revenue, profit, cost and combination of resources to form a resource bundle

	Agent 1	Agent 2	Agent 3	Agent 4
Agents’ resource revenue				
Revenue of resource 1	\$220 00	\$140 00	\$160 00	\$220 00
Revenue of resource 2	\$140 00	\$160 00	\$140 00	\$110 00
Revenue of resource 3	\$160 00	\$180 00	\$155 00	\$130 00
Agents’ resource costs				
Cost of resource 1	\$80 00	\$65 00	\$90 00	\$80 00
Cost of resource 2	\$100 00	\$120 00	\$75 00	\$95 00
Cost of resource 3	\$140 00	\$130 00	\$135 00	\$120 00
Agents’ use of different resources to create a bundle				
Use of resource 1	2	4	3	4
Use of resource 2	4	3	3	4

Use of resource 3	6	5	6	4
Total profit of resource bundle	\$560 00	\$670 00	\$525 00	\$660 00

Table 8 illustrates how resource allocation can be optimized by using Excel solver. Further, in Table 8, we outline how any change in the percentage deviation from the number of average sourced bundles affects the profit and how much the resource allocation will deviate between the involved agents. Below, we relate

the results to incentive compatibility and participation constraint as outlined in the mechanism design theory in section 4. The numbers in Table 8 follow the numbers in Table 7. We have excluded the revenue and costs of the resource bundle in our table.

Table 8 – The four agents’ profit contributions and the result of the bundle allocation optimization with 0–50% deviation from the average number of sourced resource bundles

Principal requested sourcing volume is 1000 bundles in total					
Agents	Agent 1	Agent 2	Agent 3	Agent 4	Total
Result of resource bundle optimization with 0% deviation from the average (250 bundles)					
optimization with 0% deviation from the average (250 bundles)	250	250	250	250	1000 bundles
Total profit of contribution from the agents*	\$140,000	\$167,500	\$131,250	\$165,000	\$603,750
Result of resource bundle optimization with 10% deviation from the average (250 bundles)					
optimization with 10% deviation from the average (250 bundles)	225	275	225	275	1000 bundles
Total profit of contribution from the agents	\$126,000	\$184,250	\$118,125	\$181,500	\$609,875
Result of resource bundle optimization with 20% deviation from the average (250 bundles)					
optimization with 20% deviation from the average (250 bundles)	200	300	200	300	1000 bundles
Total profit of contribution from the agents	\$112,000	\$201,000	\$105,000	\$198,000	\$616,000
Result of resource bundle optimization with 30% deviation from the average (250 bundles)					
optimization with 30% deviation from the average (250 bundles)	175	325	175	325	1000 bundles
Total profit of contribution from the agents	\$98,000	\$217,750	\$91,875	\$214,500	\$622,125
Result of resource bundle optimization with 40% deviation from the average (250 bundles)					
optimization with 40% deviation from the average (250 bundles)	150	350	150	350	1000 bundles

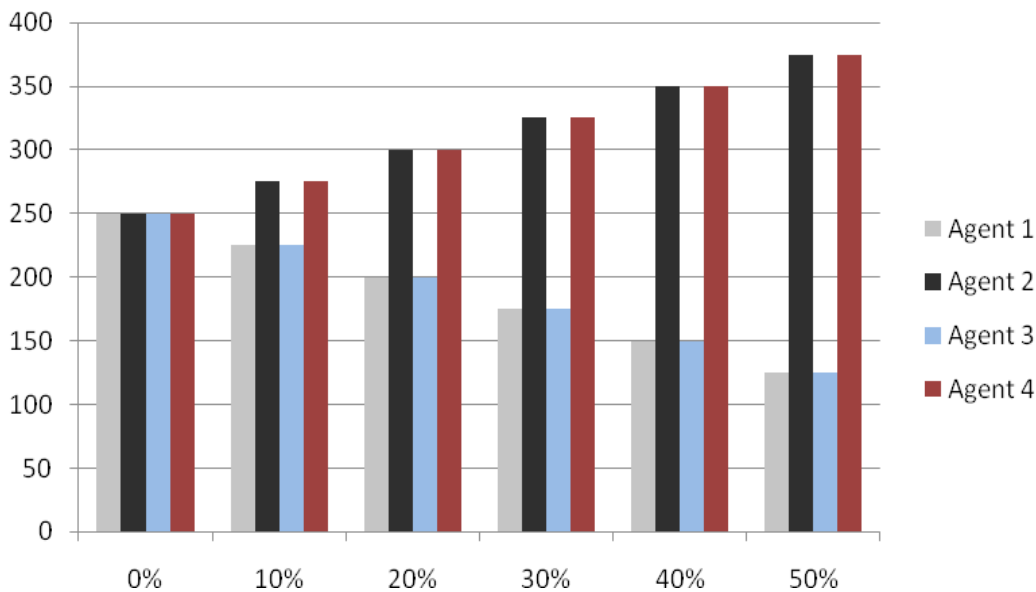
Total profit of contribution from the agents	\$84,000	\$234,500	\$78,750	\$231,000	\$628,250
Result of resource bundle optimization with 50% deviation from the average (250 bundles)	125	375	125	375	1000 bundles
Total profit of contribution from the agents	\$70,000	\$251,250	\$65,625	\$247,500	\$634,375

* The total profit contribution from the agents is the agents’ total profit from the resource bundle in Table 7 multiplied by the result of the resource bundle optimization from each agent outlined in Table 8.

Figure 2 follows the data in Table 8 regarding the number of units in each agent’s bundle under each deviation constraint. There is a major deviation from the average when the percentage increases from 0% to 50%. We argue that an increase in the percentage deviation from the average sourced volume conflicts with the constraints outlined in Table 6 because it can lead one or more service providers to enter into

a dominant position and exploit their economics of scale. We argue that one should have as little deviation related to sourced volume from the agents as possible because it ensures stability in the relationship. Opportunistic behavior through one or more agents gaining a dominant position could affect negatively the total profit.

Figure 2 – Number of units in each agent’s bundle under each deviation constraint



In Table 9, we outline how the total profit changes as the deviation from the average sourced resource bundles change in percentage terms. In addition, we outline how the increase in profit evolves as a percentage.

Table 9 –The four agents’ profit contribution and change in profit as the allowed deviation increases

Deviation from average	0%	10%	20%	30%	40%	50%
Total profit	\$603,750	\$609,875	\$616,000	\$622,125	\$628,250	\$634,375
Change in profit (%)	1.0101%	1.0100%	1.0099%	1.0098%	1.0097%	

When change in deviation from the average resource allocation increases by 10%, profit only increases by approximately 1%. We argue that one should not risk the relationship by placing one or more agents in a dominant position since the profit only increases marginally.

Theorem 1: The relationship is at risk if one or more agents hold a dominant position. The additional value the workload deviation creates is only marginal, strengthening the argument that one or more dominant agents is not optimal. Ensuring a low deviation from the average resource allocation (e.g., 10–20%) allows the relationship to evolve without any parties becoming dominant and behaving opportunistically. This ensures that the network evolves positively without any significant reduction in profit.

Proof: Follows from Figure 2 and Table 9.

Theorem 1 follows from Figure 2 and Table 9, where we outline how the profit increases only marginally when the deviation increases significantly (from 0%–50%). Hence, we argue that the risk of the involved parties being exposed to opportunistic behavior by one or more dominant parties grows as the deviation increases. Keeping a low deviation

(e.g., 10–20%) prevents any of the involved parties exploiting the situation for their own benefits.

Our next example follows Table 7 but increases the number of agents from four to six to analyze a situation for on-boarding new resources on the project. Hence, the principal asks for additional resource bundles from 1000 (average: $1000/4 = 250$) to 1350 (average: $1350/6 = 225$).

Table 10 follows Table 7 with the same constraints and conditions as in Table 6 (except total sourced bundles have increased from 1000 to 1350). Our goal in this example is to analyze a situation where two additional agents are involved. We earlier argued that there has to be incentive compatibility for agents to reveal their preferences. If there is no incentive compatibility, the incentive will create a participating constraint. Participation constraints because of a lack of incentive compatibility in this situation occurs when the new incentives are lower than the old ones. For example, if one agent receives better conditions before the new agents were on-boarded, it can be a participation constraint for the agent and he could decide to join other networks.

Table 10 – The six agents’ resource revenue, profit, cost and combination of resources to form a resource bundle

	Agent 1	Agent 2	Agent 3	Agent 4	Agent 5	Agent 6
Agents’ resource revenue						
Revenue of resource 1	\$220 00	\$140 00	\$160 00	\$220 00	\$145 00	\$110 00
Revenue of resource 2	\$140 00	\$160 00	\$140 00	\$110 00	\$145 00	\$180 00
Revenue of resource 3	\$160 00	\$180 00	\$155 00	\$130 00	\$210 00	\$190 00
Agents’ resource costs						
Cost resource 1	\$80 00	\$65 00	\$90 00	\$80 00	\$90 00	\$80 00
Cost resource 2	\$100 00	\$120 00	\$75 00	\$95 00	\$95 00	\$100 00
Cost resource 3	\$140 00	\$130 00	\$135 00	\$120 00	\$120 00	\$120 00

Agents use of different**resources to create a bundle**

Use of resource 1	2	4	3	4	6	3
Use of resource 2	4	3	3	4	3	4
Use of resource 3	6	5	6	4	3	5
Total profit of resource bundle	\$560 00	\$670 00	\$525 00	\$660 00	\$750 00	\$760 00

Table 11 illustrates how resource allocation can be optimized by using Excel solver. Further, in Table 11, we outline how any change in the percentage deviation from the number of average sourced bundles affects the profit and how much the resource allocation will

deviate between the involved agents. Below, we relate the results to incentive compatibility and participation constraint. The numbers in Table 11 follow the numbers in Table 10. We have excluded the revenue and costs of the resource bundle in our table.

Table 11 – The six agents’ profit contribution and the result of the bundle allocation optimization with 0–50% deviation from the average number of sourced resource bundles

Principal requested sourcing volume is 1350 bundles in total							
Agents	Agent 1	Agent 2	Agent 3	Agent 4	Agent 5	Agent 6	Total
Result of resource bundle optimization with 0% deviation from the average (225 bundles)	225	225	225	225	225	225	1350 bundles
Total profit of contribution from the agents*	\$126, 000	\$150, 750	\$118, 125	\$148, 500	\$168, 750	\$171, 000	\$883,125
Result of resource bundle optimization with 10% deviation from the average (225 bundles)	203	247	203	203	247,5	247,5	1350 bundles
Total profit of contribution from the agents	\$113, 400	\$165, 825	\$106, 313	\$133, 650	\$185, 625	\$188, 100	\$892,912
Result of resource bundle optimization with 20% deviation from the average (225 bundles)	180	270	180	180	270	270	1350 bundles
Total profit of contribution from the agents	\$100, 800	\$180, 900	\$94, 500	\$118, 800	\$202, 500	\$205, 200	\$902,700

Result of resource bundle optimization with 30% deviation from the average (225 bundles)	157	293	157	157	292,5	292,5	1350 bundles
Total profit of contribution from the agents	\$88,200	\$195,975	\$82,687	\$103,950	\$219,375	\$222,300	\$912,488
Result of resource bundle optimization with 40% deviation from the average (225 bundles)	135	315	135	135	315	315	1350 bundles
Total profit of contribution from the agents	\$75,600	\$211,050	\$70,875	\$89,100	\$236,250	\$239,400	\$922,275
Result of resource bundle optimization with 50% deviation from the average (225 bundles)	112	337,5	112	112	337,5	338	1350 bundles
Total profit of contribution from the agents	\$63,000	\$226,125	\$59,063	\$74,250	\$253,125	\$256,500	\$932,063

* Total profit of contribution from the agents is the agents' total profit from the resource bundle in Table 10 multiplied by the result of the resource bundle optimization from each agent outlined in Table 11.

Table 11 follows Table 9 because the profit increases only marginally (by approximately 1%) for every 10% deviation from the average number of sourced resources. Incentive-based contracts with risk and rewards can ensure future participation even if the network chooses to on-board new agents. They would also ensure that the agents reveal their true preferences and information because there are benefits for all involved parties to do so. This would only occur if the incentive creates an incentive compatibility situation. The optimization outlined above, we argue, creates incentive compatibility under the given conditions because the agents generate significantly more profit and the relationship is regulated by an incentive-based contract with risk and rewards. In the mechanism design theory in section 5, we argue for the importance of the "voluntary participation constraint." This constraint indicates that the agent is not forced to participate in the mechanism, and further that this constraint will affect the expected utility the agents receive from participating. Hence, the expected value for the agent must be equal or greater than it will if not participating. Otherwise, the agent may choose not to participate. Incentive compatibility is present if every agent finds it disadvantageous to abort from the mechanism.

Table 11 depicts that agent 4 receives less bundles to source than before the new agents were on-boarded. When the percent deviation is, e.g. set to 10%, agent 4 could source 275 bundles. However, after the network on-boarded the two new agents, agent 4 receives less bundles to source (203 bundles). Sharing the profit after their contribution will most probably lead agent 4 to resist the new solution according to the mechanism design literature outlined in section 5. Hence, we argue that to ensure Pareto improvement, agent 4 needs to be compensated for its loss as in the principal-agent model outlined in section 6 (at a level implying agent 4 will still find it advantageous to participate in the network). If on-boarding the two new agents affects negatively agent 4, it signals that the partnership is Pareto inefficient and, as a consequence, the agent could leave the network to find more profitable outside options.

Theorem 2: On-boarding new agents affects the level of sourced items for the other agents. The existing agents will accept the new agents if the relationship fulfills the requirements of incentive compatibility and participation constraints.

Proof: Follows from Tables 8 and 11 and sections 5 and 6.

Theorem 2 follows from the central design problem outlined in section 5 and deals with the decentralized optimization problem with self-interested agents where there is private information regarding their different outcomes and preferences. Our goal is to create a mechanism in an environment with asymmetric information involving the involved agents' preferences.

If the new agents contribute significantly more value, the existing agents will accept the new agents because the final profit is shared by all involved parties. If they contribute with less value, they would probably not be on-boarded. If some of the agents receive less volume to source when on-boarding new agents, they have to be compensated for their loss. If they are properly compensated for their loss, the network can still have incentive compatibility and, as a result, the involved parties will reveal their true preferences and information. If not compensated, they will leave the network, hold back information, bluff or behave opportunistically, affecting the network negatively. The new agents' value contribution for the network needs to be significantly higher than the old network's value after the agents receiving less volume have been compensated. If not, the network will not fulfill the requirement of the participation constraint.

We consider this mechanism to be strong because it creates an equilibrium that is acceptable to all agents after on-boarding the two new agents as they still want to participate in the network. This solution is a Pareto optimal mechanism that solves the problem of private information, moral hazard and adverse selection between the involved parties.

8. CONCLUSION

We wanted to deal with the two main challenges related to opportunistic behavior: (a) the measurement of the agents' effort and (b) the reduction of conflicts of interests between the involved parties (Ouchi, 1979). In this article, we have managed to do so through a framework that deals with the decentralized optimization problem with self-interested agents.

The purpose of our framework is to outline a mechanism that aims to reveal the true information (preferences) in an environment with asymmetric information. This information revelation problem is a constraint for the network to evolve. To do so, we set up a mechanism where all the involved agents

find it advantageous to reveal their true preferences because of the "rules" related to incentive compatibility and participation constraints. Hence, we can optimize the resource allocation between the agents by involving some additional constraints and regulating the relationship with the use of incentive-based contracts with risks and rewards. We argue that the agents decrease their profits only marginally when the deviation between their volumes of sourced items is small. At the same time, this will prevent one or more agents entering into a dominant position, thereby risking that they will behave opportunistically. We argue that there is a Pareto improvement because the players can increase their utility value without compromising the other actors. By contrast, by not involving the constraint, one or more agents can source the total amount of resources by themselves because this generates a marginally increased profit in the short-term. This can lead to the agent(s) acting opportunistically and lead to lower profits for all involved parties in the long run. This is also ultimately negative for the opportunistic agents.

If some of the agents receive less volume to source when on-boarding new agents, they have to be compensated for their losses. The network can still have incentive compatibility and, as a result, the involved parties will reveal their true preferences and information. If not compensated properly, they will behave opportunistically or leave the network, affecting negatively the network. The new agents' value contribution needs to be significantly higher than the old network's value after the agents receiving less volume have been compensated. If not, the network will not satisfy the requirement of the participation constraint. As a consequence of conflicting these constraints, the agent will value the network less because their social choice function creates a negative equilibrium. This situation has no incentive compatibility and the agent will most probably leave the network because the participation constraint is conflicted.

We argue that a resource allocation given the conditions and method outlined in this article will lead to an attractive and more "democratic" allocation that ultimately leads to higher profits for all involved parties. As a consequence, the network will gain a competitive advantage over other networks. Further, the network will, as a result of its higher profit, attract the best resources and further strengthen its position.

Finally, we need to consider important limitations. First, we could use quantitative data obtained from

the industry (relevant companies). This could lead us to verifying the input data in our models. We agree this would be helpful for our analysis. Yet, we argue that the lack of quantitative data from the industry does not affect the quality of our findings as our goal is to optimize the resource flow between parties on a drilling project with constraints. The constraints would function the same way regardless of the information (if it was obtained from the industry or not). Secondly, we can use other methodologies to complement the optimization. If we conduct a case study, we can elicit the parties preferences and benchmark their preferences with the result of our optimization. We agree that this will benefit our study, but it is not necessary. In the methodology section we argue that our results are verifiable as we refer to similar results obtained in an embedded multiple case study.

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