# Multi-layered Satisficing Decision Making in Oil and Gas Production Platforms

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**Abstract.** From a control perspective, offshore oil and gas production is very challenging due to the many and potentially conflicting production objectives that arise from the intrinsic complexity of the oil and gas domain. In this paper, we show how a multi-layered multi-agent system can be used to implement a satisficing decision-making process for allocation of production resources. Through simulations using real-world production data, we illustrate that this satisficing decision-making process performs better than existing control systems applied on marginal fields, even though satisficing decision making often only provides near-optimal solutions.

**Keywords:** Multi-agent systems, Emergence, Satisficing, Multi-objective, Production Systems.

## 1 Introduction

The background for our research is oil and gas production at marginal (i.e. small in total oil and gas volume) fields in the Danish sector of the North Sea, more precisely the Siri Area. The Siri Area consists of three fields (Siri/Stine, Nini, and Cecilie). Oil and gas fields are typically owned by several companies (partners) to reduce the economic risk. Within the group of partners, one partner is normally the field operator. At the Siri Area, DONG Energy E&P is the operator. The operator has the daily responsibility for production and maintenance of the production platform's installations.

From a production perspective marginal fields are very challenging since they mature more rapidly, i.e. in the range of months, than larger fields that mature in the range of years. Furthermore, marginal fields may typically go through the full life-cycle from installation to abandonment in less than a decade. As a consequence of the rapid maturing, the production scheme of marginal fields has to be revised more frequently than those of regular fields. Simply applying the same relatively fixed production scheme as is used at regular fields would result in suboptimal production. The application of a relatively fixed production scheme is further challenged by the fact that the growing global request for oil and gas advances technological achievements

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which allow marginal fields to evolve beyond their original abandon point. This is also the case for the Siri Area, where the Siri production platform in 2004 became host for the first tieback project, such that it now consists of the main production platform Siri, three unmanned satellite platforms Nini, Nini East, Cecilie, and one subsea installation Stine. The focus of this paper is on the intrinsic complexity of the oil production platform and the oil production processes, with their indirect cross-production resource dependencies among production equipment and processes like water injection, gas handling, and tanker export. Indirect cross-production resource dependencies may result in unforeseen interactions, like bottlenecks and fluctuations, which cause the production scenarios to become very dynamic and complex. To avoid bottlenecks and fluctuations, process operators typically decrease the production throughput to increase process stability. By inspecting historical production logs at Siri, it is found that production throughput is frequently lowered and often goes on unnoticed for a long period before intervention happens, which results in unnecessary loss of production. This loss of production can be avoided if the production scheme is continuously adjusted to the dynamics of the field, a process which involves the three decision layers of a production platform: 1) The strategic production-decision layer handling the planning with goals in the range of weeks/days; 2) The tactical production-decision layer handling the allocation with goals in the range of days/hours; 3) The operational production-decision layer handling the local optimization with goals in the range of hours/minutes.

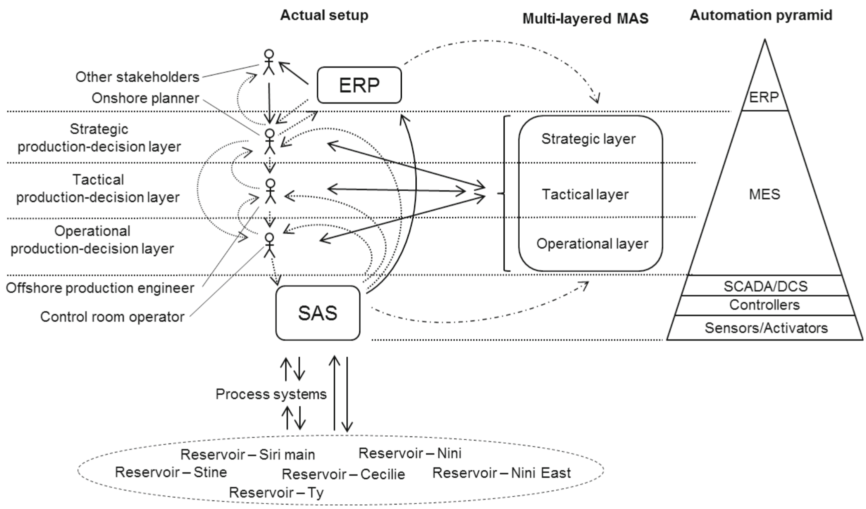


**Fig. 1.** Simplified data infrastructure at the Siri Area

Fig. 1 depicts a simplified data and control infrastructure diagram for the Siri Area, with the following abbreviations: ERP (Enterprise Resource Planning systems) and SAS (Safety and Automation System) [1]. Today, the data flow of integrated operation control systems is directed from the SAS system towards the ERP system and not vice versa. Data from the ERP system are primary used to generate new strategic, tactical, and operational plans, which from a production viewpoint makes the system relatively static. To support a flexible production scheme that automatically adjusts itself to the dynamics of the field, data must flow in both directions.

The rest of the paper is organized as follows: Section 2 presents the related state of the art. Section 3 provides the conceptual overview of our approach and describes its implementation. An experimental evaluation using real production data from the Siri Area is presented in section 4. Finally, section 5 concludes the paper.

## 2 State of the Art

Today, control systems for offshore oil and gas production are programmed in static control structures in well-proven industrial automation systems, i.e., DCS (Distributed Control System) or SCADA (Supervisory Control and Data Acquisition). Optimization is normally done offline, resulting in relatively fixed production schemes. Several internal DONG Energy E&P optimization studies conducted at the Siri Area have indicated that production throughput could be increased if the information systems at the decision layers, i.e., SAS and ERP systems, were better integrated thereby allowing a faster respond to changing field dynamics. The studies have also shown that a production throughput tends to decrease over time without any interconnected change in the related production constraints or objectives.

In general, studies addressing optimization in a mathematically strict sense is only seen in a very few studies, which address optimization of lift gas and slug mitigation, using Advanced Process Control (APC) and Model Predictive Control (MPC) as discussed by Bonavita et al. [2]; Artificial Intelligence in Petroleum Engineering discussed by Mohaghegh [3], and Real-Time Optimization (RTO) discussed by Bieker et al. [4]. The focus of these studies is optimization of subsystems and none of them, to the best of our knowledge, can handle online optimization of a complete installation. A few preliminary decision-support-control and distributed optimization systems by Ølmheim et al. [5] and Wartmann et al. [6] have also been tested in the oil and gas production domain, but only in simulation scenarios and only addressing confined parts of the process installation. None of the mentioned control approaches seems to have the ability to provide a high degree of flexibility for handling the changing high-level operational conditions at rapidly maturing marginal fields with limited data models, process data, and shared resources.

To meet the challenges of controlling a dynamic offshore oil and gas production environment in the range of minutes/hours/days (daily production issues) through months/years (field maturing issues), a multi-agent system with the characteristics of natural decomposition of action, perception, and distributed problem solving seems a promising approach as it provides the required flexibility. One of the first approaches in applying a multi-agent system to control production can be found in the ARCHON project [7] that proposed to encapsulate entities with cognitive layers [8]. Multi-layered multi-agent systems as we use them are not as such a new idea; some early work in this direction is the ASIC system developed by Boissier et al [9]. The ASIC architecture consists of three layers: command, adaptation, and decision. A three-layer model was also proposed in the work of Chappin et al., for conceptualization and formalization of agent behaviour in a socio-technical system for operational decision making in electricity markets [10]. Finally, Barbuceanu et al. followed a similar approach for organizing the supply chain in manufacturing as a network of cooperating, intelligent agents, each performing one or more supply chain operations [11]. In the context of control, the work of Sørensen et al. [12] shows how multi-agent systems can be used to prevent interactions among independent control objectives sharing resources in the same controlled environment, by searching for alternative resource allocation solutions that are acceptable to the requirements of all control objectives.

Building on state of the art, we propose a new application of multi-layered multi-agent systems to bridge the gap between SAS and ERP in complex offshore oil and gas production by developing a multi-layered multi-agent system that integrates the individual decision layers present in the automation pyramid of an oil and gas production platform. The open nature of multi-agent systems provides the necessary flexibility to meet the evolution of marginal fields, as new agents addressing changed production conditions can be added whenever the need arises. That is, the proposed multi-layered multi-agent system can adapt to new operational conditions, as it supports dynamical introduction and removal of control agents, each representing different production objectives, without the need to inspect or modify existing control agents. This dynamic control is possible as the infrastructure of the multi-layered multi-agent system takes responsibility for coordinating potential interactions among control agents dynamically.

## 3 The Approach and Its Key Criteria

In the production system domain, the focus is usually on “optimization”, but for many real-world problems only limited models are available due to system complexity; so, in a mathematically strict sense, no optimization is performed, as there is no knowledge with regards to location of a global production optimum. Based on literature studies and in the light of the interviews given by oil-and-gas-production engineers, we argue that it is not “optimization” that is done today in oil and gas production, but merely manually tuning of process parameters based on human experience. Based on this observation, our approach aims to find solutions to allocation of production resources that satisfy the production objectives and constraints at a given time in the best possible way within a given time frame. Our approach is inspired by the economist Simon who introduced the concept of ‘satisficing’ as an approach to decision making [13]. The word ‘satisficing’ is a combination of the two words: ‘satisfy’ and ‘suffice’. In [14], satisficing in the context of decision making is defined as:

> *“Examining alternatives until a practical (most obvious, attainable, and reasonable) solution with adequate level of acceptability is found, and stopping the search there instead of looking for the best-possible (optimum) solution”.*

Satisficing decision making seems to be a useful approach in the development of complex control systems when no global model can be established to determine a global optimum. By using satisficing decision making, the aim is to find the best-possible solutions for allocation of resources to production processes that both satisfy and suffice all production objectives and constraints. Since decision making in the oil-and-gas-production domain is multi-layered, it is necessary to find satisficing solutions not only within each decision layer but also across all decision layers. As shown in Fig. 1, the decision-making process is scattered across the strategic, tactical, and operational layers. Ideally, decision-making within one layer should be coordinated with decision making within adjacent layers in order to find solutions that bring the whole production platform to a state of satisficing equilibrium.

Today, the flow of control typically propagates from the strategic layer through the tactical layer down to the operational layer, with no or very little feedback to upper layers, in case the lower layers cannot meet the demands of the decisions made at the upper layers. That is, any assumptions an upper layer may hold about the effects of its decisions at lower layers may be broken without the upper layer knowing about it, which may lead to suboptimal or even wrong subsequent decisions at the upper layer. Those unnoticed broken assumptions between multi-layered decision layers can be avoided, if they are made explicit by providing feedback from lower layers to higher layers. Such a feedback mechanism can be established based on Jackson's work on problem frames [15]. We use Jackson's concept of entailment relations [16] to discover broken assumptions. An entailment relation is a tuple ($S, W \vdash R$), where:

1. Specifications $S$ are implemented as a computer program.
2. The World $W$ or the set of domain properties as seen by $S$.
3. $\vdash$ is the semantic for entailment.
4. $R$ is the user Requirements.

As the entailment relation ($S, W \vdash R$) is defined for a single problem context, we have to extend the concept of entailment to cover nested sub-problems in order to use it for a multi-layered decision-making process. This can be done by defining a nested entailment relation that propagates information from lower decision layers to upper decision layers. In the nested entailment relation the world $W$ at the upper layer $L1$ will be given by an entailment relation ($S, W \vdash R$) at the lower layer $L2$. I.e., in the entailment relation ($S_{L1}, W_{L1} \vdash R_{L1}$) at layer $L1$ , $W_{L1}$ will be given by an entailment relation ($S_{L2}, W_{L2} \vdash R_{L2}$) at layer $L2$, and $W_{L2}$ at layer $L2$ will be given by an entailment relation ($S_{L3}, W_{L3} \vdash R_{L3}$) at the lower layer $L3$ and so on, until entailment is terminated when the bottom layer is reached. When implementing the concept of entailment in a multi-agent system, each specification in the set $S$ becomes an agent, the world $W$ becomes the agents' world model and the entailment $\vdash$ of requirements $R$ becomes the goals of the agents. In a control context, $W$ usually expresses inputs and outputs of the control system. When the chain of nested entailment relations holds, we define the system to be in a state of satisficing equilibrium. The possible size of the satisficing equilibrium state space depends on the flexibility in the requirements $R$.

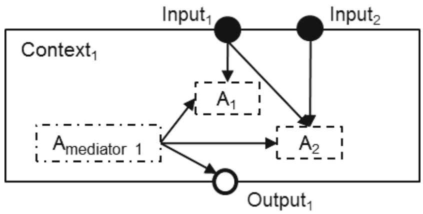


**Fig. 2.** Negotiation context

Agents belonging to the same entailment relation are grouped into a negotiation context with one mediator agent responsible for the negotiation process. Fig. 2 depicts a single negotiation context (solid rectangle) with agents $A_1$ and $A_2$ (dashed rectangles). The world $W$ is represented by $\text{Input}_1$, $\text{Input}_2$ and $\text{Output}_1$. The arrows indicate the direction of data flow. There is at least one negotiation context for each decision layer.

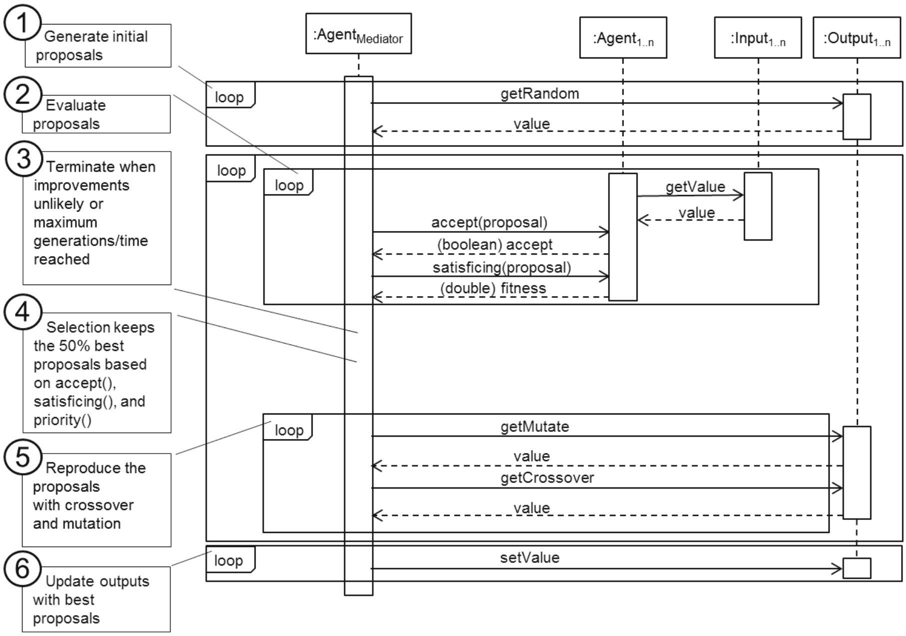


**Fig. 3.** UML sequence diagram of negotiation process

The negotiation process is an incremental process that converges towards a satisficing solution, if one exists. In searching for a satisficing solution, the mediator uses a genetic algorithm. Implementation details concerning the genetic algorithm can be found in [12]. The negotiation process is divided into six steps as shown in Fig. 3.

1. The mediator agent generates an initial set of proposals (e.g. 200) for allocation of production resources.
2. The mediator agent presents each proposal to the agents by message *accept* and they reply whether they can accept the proposal. They furthermore respond to a message *satisficing* about how satisfied they are with each specific proposal. Satisficing is here expressed as a percentage to which the proposal fulfils the agent's goals.
3. The mediator agent continues the negotiation process as long as it has not converged towards a solution and the end of the control loop's time period is not reached. The negotiation process is said to have converged, and a satisficing solution found, when no new proposal can be generated, that is any better than a previous proposal. When the negotiation process terminates, the mediator agent jumps to step 6.
4. The mediator agent selects the best 50% of the proposals based on acceptance, priority and the returned fitness values.
5. The mediator then generates the missing 50% proposals using the genetic algorithm's crossover and mutation functions. The mediator then loops to step 2.
6. Finally the mediator updates all outputs with accepted solutions.

In case no satisficing solution could be found, the entailment relation of the negotiation context is said to be broken. Broken entailments are typically caused by allocation conflicts over shared production resources. E.g. in Fig. 2, $Output_1$ is shared by agents $A_1$ and $A_2$. Many of these resource-allocation conflicts may emerge, because agents by default are considered equally important. However, in any non-trivial control system the importance of individual agents may change depending on the actual operational state. This state-dependent change in agents' importance is handled by supporting dynamic prioritization of individual agents. Important agents are given higher priority than less important agents. By default the priority of all agents is set to 5. In the current implementation, we have chosen to use a priority range from 1-10 (1 = highest and 10 = lowest). In selection of the best 50% of the proposals, the mediator favours proposals accepted by agents with higher priorities.

Furthermore, to acknowledge the fact that some agents' requirements may be more critical, from a safety point of view, than others, agents' requirements can either be modelled as 'hard' or 'soft'. A 'hard' requirement is a requirement that always have to be satisfied, and a 'soft' requirement is a requirement that it is desirable to satisfy. For instance, in the oil and gas production domain the complete production platform is protected by the safety system, so the outer bounds of the solution space are set by the safety system. The constraints in the safety system have to be mapped to hard requirements to avoid production shutdowns, as eventual shutdowns are very expensive due to slow start-ups and thereby lost production. Examples of safety system constraints can be minimum/maximum temperatures, tank-levels, pressures etc. Another group of hard requirements is related to business logic/policies like in the Siri Area where each of the three oil fields (Siri/Stine, Cecilie, and Nini) are processed in separate separators even though a mixed field mode could give a better throughput. Production-related issues like optimizing flaring over water injection are 'soft' requirements. The set of 'hard' requirements confines the search space for finding a satisficing solution. Hence a satisficing solution to the allocation of production resources is a solution that fulfils all 'hard' requirements and provides the best-possible solution for all 'soft' requirements.

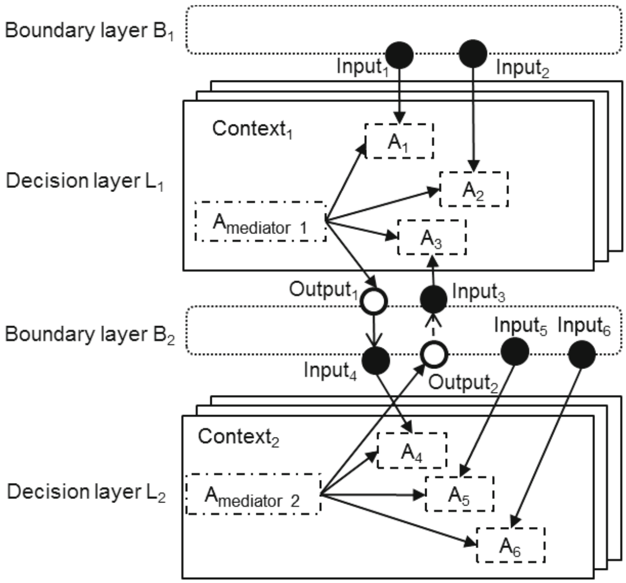


**Fig. 4.** Agent interactions between negotiation contexts on different layers

Each decision layer may contain one or more negotiation contexts that are connected to negotiation contexts in adjacent decision layers through the inputs and outputs of a boundary layer, as shown in Fig. 4. The boundary layer provides the necessary feedback mechanisms for delegating broken entailment relations between decision layers, thereby ensuring that the system is in a constant search for a satisficing equilibrium. Using the inputs and outputs of the boundary layer $B_2$, the feedback mechanism links the entailment relation ($S_{L2}$, $W_{L2} \vdash R_{L2}$) for Context$_2$ at decision layer $L_2$ to the world $W_{L1}$ of Context$_1$ at decision layer $L_1$. In Fig. 4 the negotiation Context$_1$ at decision layer $L_1$ is connected to the negotiation Context$_2$ at decision layer $L_2$. When the negotiation process of Context$_1$ terminates, mediator $A_{\text{Mediator 1}}$ passes on the best solution to decision Layer $L_2$ in the form of Output$_1$. Output$_1$ is through boundary layer $B_2$ provided as input Input$_4$ at decision layer $L_2$. Mediator $A_{\text{Mediator 2}}$ now seeks for a solution at decision layer $L_2$, and feedback to decision layer $L_1$ is through a domain property of the world $W_{L1}$ (marked with a dashed arrow between Output$_2$ and Input$_3$) in the boundary layer $B_2$. Hence, agent $A_3$'s world $W$ entails Context$_2$ based on Input$_3$. Thus, in case the entailment relation ($S_{L2}$, $W_{L2} \vdash R_{L2}$) at decision layer $L_2$ is broken, due to the value of Input$_4$, it is propagated back to decision layer $L_1$ through the nested entailment relation between Output$_2$ and Input$_3$.

The design of the feedback mechanism also ensures propagation of any change in the operational state of $Context_2$, for instance in case agents are prioritized, inputs change, a new solution is found, etc. As an example, if agent $A_4$ is given a higher priority than $A_5$, this may impact $Output_2$; the feedback via the domain property of $W_{L1}$ will impact $A_3$. $A_3$ will seek to influence $Output_1$; this process will continue until a satisficing equilibrium is found or a conflict is identified. In the next section, the experiment illustrates the use of both feedback and priority. To ensure stability of the multi-layered negotiation process in search for a satisficing equilibrium, we use the basic rules of thumb on closed-loop control, expressing that the inner loop (lower decision layer) is twice as fast as the outer loop (upper decision layer).

## 4 Experiments

To validate our approach, we have chosen the export-to-tanker scenario at the Siri platform, as this scenario involves all three decision layers. The experiment extends our previous findings [17, 18]. In the export-to-tanker scenario, the oil is exported to a shuttle tanker from a temporary storage tank on the seabed. Due to limited electrical power resources at the Siri platform, one of the major power consumers has to be stopped during the export-to-tanker scenario, i.e., either a gas compressor or a water injection pump. The gas compressors are used to handle produced gas either for use as fuel or lift gas (lift gas is used to get the wells to flow due to low pressure in the reservoirs). Water injection is used as pressure support in the thin sandstone production layers in the reservoirs in order to maintain an economically-feasible production. The water injection system consists of three 2 MW pumps. Fig. 5 shows negotiation contexts (solid rectangles) that are directly involved in the experiment. Names of negotiation contexts at the strategic layer are related to resource allocation concerns, whereas at the tactical layer they are related to systems, and at the operational layer they are related to production equipment.

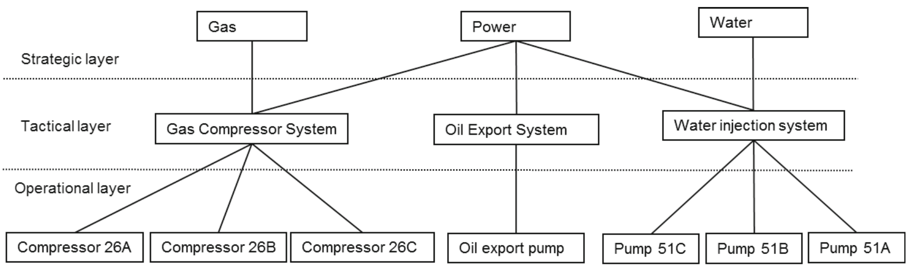


**Fig. 5.** Experiment negotiation context diagram

The export-to-tanker scenario is triggered by the *Oil export system* at the tactical layer, and by requesting power from the *Power* negotiation context. The *Power* negotiation context contains the following agents: *Ensure power for water injection* (priority 6), *Ensure total power* (priority 3), *Ensure power for gas compression* (priority 4), *Maximize total power allocated* (priority 6), *Ensure power for export* (priority 5). The *Power* mediator agent starts a negotiating process to find a new power plan. As the flare is to be kept at a minimum due to the environmental impact and the appertaining regulations, the agent *Ensure power for gas compression* has been assigned with a higher priority than the agent *Ensure power for water injection*. Based on the agents' priorities, we expected that a water injection pump would be stopped during the export-to-tanker scenario.

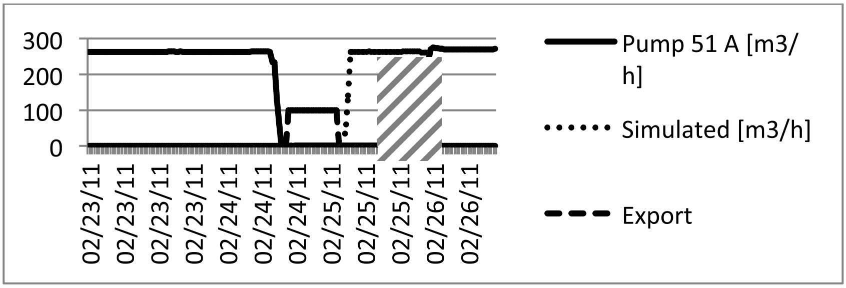


**Fig. 6.** Real production data - Export to tanker

Fig. 6 shows real production data for the export-to-tanker scenario executed manually at the Siri platform on 24-01-2011. The dashed line indicates when the export-to-tanker scenario took place. During this export the water injection pump 51A (solid line) was manually stopped. The manual start of water injection pump 51A was postponed by a day (solid line) without a technical reason, resulting in an unnecessary loss of production. A simulation using our approach shows that the water injection pump would have been automatically started one day earlier (marked with the dotted line). This earlier start gives a better water injection performance than the manually operated system. The increase in the water injection volume is marked by the hatched area. Our simulation run of the real production data is shown in Fig. 7. The three layers from Fig. 5 and their respective negotiation contexts are mirrored in the GUI.

In Fig. 7 agents are coloured depending on how satisfied they are with a solution. Satisfied agents are green (dark grey), and dissatisfied agents have shades ranging from yellow (light grey) to dark orange (medium grey). In the simulation, the agent *Ensure power for water injection* turns orange (medium grey) when the export-to-tanker scenario starts, as the agent *Ensure power for export* has higher priority. Similarly, the agent *Ensure pump capacity for Siri* turns orange as the power allocation for the Water injection system is insufficient to maintain full pump capacity. Later on, when the export-to-tanker scenario stops, the *Power* negotiation context will again allocate the necessary power for the water injection system, and the agents *Ensure power for water injection* and *Ensure pump capacity for Siri* will turn green again.

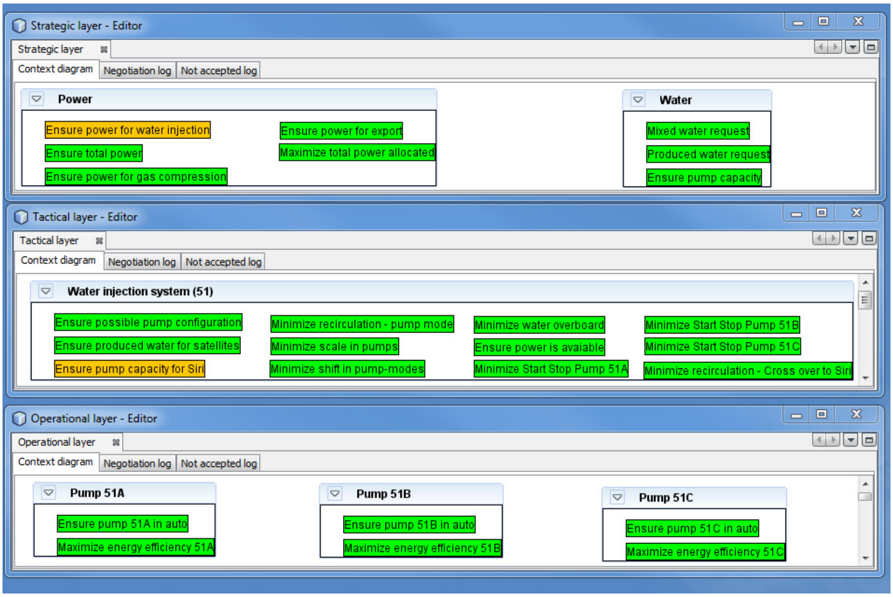


**Fig. 7.** Simulation's run for export-to-tanker scenario

## 5 Conclusion

In this paper, we have presented a new application of multi-layered multi-agent systems for supporting decision making across the three layers of control in offshore oil and gas production. The proposed approach provides a new level of flexibility that meets the need for dynamic evolution of marginal oil and gas fields.

We have shown that a satisficing decision-making process implemented as a multi-layered multi-agent system can perform better than manually controlled systems, as is currently the state of the art within the oil-and-gas-production domain. Hence, we believe that the proposed approach possesses the capability to face the continuously changing operational conditions of marginal oil and gas fields in the North Sea.

From an architectural perspective the proposed multi-layered multi-agent-system approach is not bound to the oil and gas domain, and it seems reasonable that the approach can be mapped to other control domains which possess a similar layered structure for decision making.

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