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AN AGENT BASED APPROACH FOR COORDINATION OF ENERGY ALLOCATION AND DEMAND IN CYBER-PHYSICAL SYSTEMS

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ABSTRACT

Energy efficient systems are receiving worldwide attention in response to the negative effects of global warming. Energy efficient systems are concerned with allocation of adequate resources in the Energy Domain to meet the energy demand in possibly several Process Domains. In allocation, a balancing problem arises when the energy resources demanded by the Process Domains do not match the resources allocated in the Energy Domain. This situation may lead to suboptimal process performance and inefficient usage of energy. Solving this allocation problem requires a coordination and control mechanism that can balance allocation and demand between multiple coupled subsystems. In this paper, we propose a novel agent-based software system for solving this type of cooperative control problem. The system performs energy allocation for several Process Domains while considering the individual requirements of each domain. In case of resource inadequacy the proposed solution is able to handle the resulting conflicts according to domain specific requirements for system operation. The efficacy of the proposed approach is demonstrated through simulation. Our results show that it is possible to create a coordination mechanism that can achieve a global stable state for energy allocation and demand between multiple coupled systems.

KEYWORDS

Multi-Agent Systems, Negotiation Strategies, Cooperative Control, Cyber-Physical Systems

1. INTRODUCTION

Energy efficiency and the reduction of carbon footprints are receiving attention in response to an increased demand for energy resources, which results in negative effects such as global warming. This fosters a need for designing energy efficient Cyber-Physical Systems (CPS). CPS encompasses systems, which integrate computational algorithms and communication with physical processes. These systems act independently, co-operatively or as ”systems-of-systems” composed of interconnected autonomous systems originally developed independently to fulfill dedicated tasks (Francoise 2014). The individual components of such systems and subsystems are coupled to exchange data with each other and influence each other. This coupling of multiple autonomous systems (physical and cyber) provides far-reaching benefits in terms of more efficient hybrid systems that provide new capabilities in interoperability, resilience etc. To be considered energy efficient, a CPS must provide effective allocation of energy resources in the Energy Domain to meet the demands of energy-intensive processes in the Process Domain to avoid suboptimal system performance due to allocation imbalances. In order to cope with this problem, a coordination and control mechanism is needed that can balance energy allocation and demand.

The main contribution of this paper is a coordination mechanism that unifies the properties of cooperative control strategies and multi-objective multi-issue negotiation protocols in order to achieve a group objective among self-interested agents in each coupled domain.

The remainder of the paper is organized as follows. Section 2 presents related work. Section 3 presents how our framework performs intra-domain and inter-domain negotiation to achieve an agreement state, i.e., a system state in which energy allocation and energy demand is balanced. Section 4 presents case study. Section 5 describes experiments for bilateral and multilateral negotiation and finally Section 6 draws conclusions and discusses some future research directions.

2. RELATED WORK

As the task of balancing energy allocation and demand addresses the system as a whole, the problem can be viewed as a cooperative control problem. Cooperative control strategies have been studied very widely. The cooperative control problems are formulated as formation and non-formation control problems (Li & Duan 2014). Formation control strategies such as the ones proposed in (Wang 1991; Rezaee et al. 2013; Lin et al. 2013) employ leader-following approaches, where the leader agent pursues the group objective and followers are supposed to follow their leader. This approach seems therefore infeasible for solving the allocation problem as followers (Process Domain) are required to follow the energy allocation given by their leader (Energy Domain). There is no negotiation and the leader has no knowledge of the actual energy demand of its follower. Balancing allocation and demand requires feedbacks between the Energy Domain and Process Domain to avoid a situation in which the leader allocates too much or too little energy to the Process Domain.

Contrary to formation control problems, non-formation control problems are typically solved using distributed control, based on different cooperative control strategies. Several attempts (Ren et al 2005; Bauso et al. 2003; Tanner et al. 2003) have been made to solve agreement problems using cooperative rather than self-interested agents. In state of the art of cooperative control strategies, all agents in the group know about the group objective. The group of agents cooperates in the sense that they all want to maximize the group objective. However, real world problems are often more complex, with individual objectives, which may be in conflict with each other or with the group objective.

Several techniques have been proposed in the literature for achieving a consensus among conflicting individual goals in order to fulfill a group objective. For instance, (Klein et al. 2003) proposed bilateral multi-issue negotiation involving non-linear utility functions. But Klein et al. considered a single domain to deal with complex (non-linear) problems. (Ito et al.

2008) proposed an auction-based protocol where agents propose bids and a mediator is responsible for finding the overlaps among generated bids. However, this approach has a major scalability issue, as it imposes an upper limit on the number of bids, agents can generate depending upon the number of agents participating in the auction. Later (Marsa Maestre et al. 2009) extended their work in (Ito et al. 2008) by employing a technique called Q-factor to balance agents' individual utility and agents' social utility. The author reduces but does not fully eliminate the scalability problem by employing probabilistic search in the deal identification phase. (Fujita et al. 2012) proposed a novel secure and fair mediator protocol for non-linear negotiations. The protocol finds the fairest Nash Bargaining solution using approximated fairness. (Aydogan et al. 2014) proposed a mediator-based protocol with feedback for multilateral negotiation scenarios. The mediator generates the estimated utilities from the preferences of negotiating agents by observing their feedback during negotiation to determine the final agreement.

The main limitation of the state of the art mediator-based negotiation protocols dealing with non-linear complex problems is that they only address negotiation involving interdependent issues within a single domain. These approaches haven't addressed negotiation problems where interdependent issues are distributed across multiple coupled control domains. Balancing the allocation of energy resources to the coupled Process Domains requires negotiation between coupled domains in order to coordinate the interdependent issues of energy allocation and demand distributed across the different control domains.

3. MULTI-OBJECTIVE MULTI-ISSUE NEGOTIATION

The agent-based coordination and control mechanism proposed here for balancing the allocation and demand among coupled domains extends the work of (Sørensen et al. 2011; Clausen et al. 2014) on Controleum. Controleum is a generic framework for multi-objective multi-issue intra-domain negotiation. The extension proposed here allows for inter-domain negotiations spanning several subsystems, each controlling a separate problem domain.

3.1 Intra-domain Negotiation

The Controleum negotiation process bears similarities with the negotiation process presented by (Fujita et al. 2012) in which a negotiation defines a context consisting of N concern agents, $\boldsymbol{a} = (a_1, a_2, \dots, a_N)$, which negotiate over a set of M issues, $(s_1, s_2, \dots, s_M)$. The negotiation context has a Mediator Agent (MA), which is responsible for managing the negotiation process. The MA searches for a contract that satisfies the preferences of the Concern Agents (CAs).

The negotiation process is shown in Figure 1. In step 1, the MA initiates the negotiation by generating a population of random contracts. A contract is defined as a vector of M issue values $\mathbf{s} = [s_1, s_2, \dots, s_M]$. Then, in step 2, the MA presents the contracts to each CA for evaluation. Each CA responds to the MA by assigning a cost to each contract in the population. The cost describes the degree to which the proposed contract adheres to the preferences of the CA.

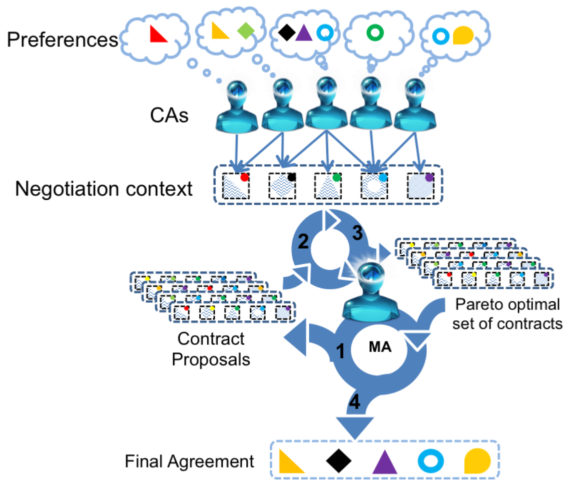

Figure 1. Conceptual illustration of Controleum framework

A lower cost means a better fitness for the agent. Each agent $a_n, n \in \boldsymbol{N}$ defines a cost function, for each issue $s_j, j \in \boldsymbol{M}$, over which the CA wishes to negotiate. The cost of agent a_n for a contract s_c defined as q_{a_n, s_c}, is the summarized values of that agent's cost for each issue in s_c addressed by that agent. The MA uses the Pareto criteria to select the contracts that can be added to the Pareto optimal set of contracts. In step 3, the MA generates the next population of contracts by performing crossover and mutation on randomly selected contracts from the Pareto set. Step 2 and 3 are repeated until the negotiation terminates. The negotiation terminates, in step 4, when a predefined number of negotiation rounds is reached or when a time limit is met. At termination, the MA selects a final contract. To select the final contract, the cost of each agent is normalized for each contract in the Pareto set. After normalization, the sum of the normalized cost is computed for each contract. The lower the sum, the better the contract. The contracts are then sorted according to their costs. Finally, the first contract in the sorted population is selected as the final contract.

If there is a conflict between the preferences of negotiating agents, there is a risk that the consequences are unevenly divided between participants in the negotiation (Clausen et al. 2015). In order to avoid this a selection strategy based on Approximated Fairness (Fujita et al. 2012) has been implemented. This selection strategy ensures that in case of a conflict each agent will concede equally to find a compromise. Approximated Fairness selects the final contract $\boldsymbol{s}_f$ from the Pareto set P_f with the smallest approximated fairness value specified in equations (1), (2) and (3), where v_{s_c} is the approximated fairness value for contract $\boldsymbol{s}_c \in P_f$, $q_{a_n, \boldsymbol{s}_c}$ is the cost of agent a_n for contract $\boldsymbol{s}_c$, $q'_{a_n s_c}$ is the normalized cost for agent a_n for contract $\boldsymbol{s}_c$ and q_{avg, s_c} is the average of the normalized cost for all agents with respect to contract $\boldsymbol{s}_c$.

$$\boldsymbol{s}_f = min_{s_c \in P_f}\left(v_{s_c}\right)$$

$$v_{s_c} = \sum_n^N \frac{\left(q'_{a_n, s_c} - q_{avg, s_c}\right)^2}{N} \tag{1}$$

$$q'_{a_n,s_c} = \frac{q_{a_n,s_c} - q_{a_n,min}}{q_{a_n,max} - q_{a_n,min}} \tag{2}$$

$$q_{a_n,min} = min_{s_c \in P_f}(q_{a_n,s_c}),\ q_{a_n,max} = max_{s_c \in P_f}(q_{a_n,s_c})$$

$$q_{avg,s_c} = \frac{\sum_n^N (q'_{a_n,s_c})}{N} \tag{3}$$

To ensure that negotiating parties always reach an agreement in case where conflict of preferences exists e.g. in a situation where a set of subsystems require more than the available resources, we have introduced the concept of priority in the selection strategy above. A priority is a numeric value ranges from 0 to 10. The lower the value, the higher the priority is. The priority mechanism is shown in Pseudo code 1. The priority scheme will guarantee the selection of a negotiation contract, which satisfies agents with a higher priority before it considers agents with a lower priority.

Pseudo code 1. Priority Scheme

contracts = getAllContracts()
for i := high_prio to low_prio
C = selectConcernsWithPriority(i)
contracts = contracts.getApproximateFairContracts(C);
end for

3.2 Inter-domain Negotiation

In a CPS, multi-objective multi-issue negotiation problems may involve interdependent issues, which are distributed across multiple control domains. This situation may arise e.g. when one subsystem consumes a resource allocated by another subsystem. In this case, the amount of resources consumed by the first subsystem must match with the amount of resources allocated by the other subsystem to maintain global system stability. To support this scenario, Controleum has been enhanced to support inter-domain negotiation through the addition of two types of agents: Subsystem Agents (SAs) and System Constraint Agents (SCAs). SAs are introduced to represent the connected subsystems. SAs are a special case of CAs with the unique property that their minimizing function has a dynamic input variable. This dynamic input variable represents the current best candidate contract from the perspective of a connected subsystem. As the inter-domain negotiation evolves, this input variable changes to reflect the updated perspective of the connected subsystem.

SAs have knowledge of the subsystem they represent, and thus, have the ability to compare contracts proposed in the negotiation in which they are present with a candidate contract from the subsystem it represents. The SA will return a cost value reflecting, how well the contract offered in the negotiation matches with the candidate contract from its subsystem. If the cost is 0, the current best candidate contract of the connected subsystem matches the proposed contract. During inter-domain negotiation, SAs ensure that the preferences of subsystems are represented in each negotiation round and a Pareto-frontier is generated, where their preferences are reflected. This is how, we guarantee that the coupled domains converge i.e. reach a stable state in the negotiation.

SCAs are introduced as part of the conflict solving mechanism of the framework. Specifically, SCAs force connected subsystems to reach an agreement in case of conflicts, by finding an absolute compromise between their candidate contracts. As a result, the minimizing function of SCAs has two dynamic input variables representing the best candidate contracts of the two subsystems it connects. The SCA calculates the mean of the preferences of the two subsystems it connects to solve the conflict and is represented in both systems. This means, that the SCA is able to map values of the issues connecting the two domains, in order to compare them.

In the enhanced Controleum framework, the MA has the responsibility of selecting the best candidate contract in each negotiation round to make this candidate contract available as an input for the SAs and SCAs in connected subsystems. The candidate contract selected by the MA in each coupled control domain represents the issue values over which agents negotiate. When the negotiation terminates, the final contract is selected in each domain.

In case of conflicts between SAs and CAs, a decision needs to be made on how to deal with this conflict. One could choose to prioritize subsystem 1 over subsystem 2, subsystem 2 over subsystem 1 or make a compromise between subsystem 1 and subsystem 2. In the latter case the SCAs are needed for two reasons: First, this ensures that the type of compromise we want is represented on the Pareto frontier. Second, in order to select this compromise, we need to be able to prioritize the agent reflecting this objective. The final contract in each domain complies with the group objective and guarantees that coupled domains finally reach an agreement i.e. guaranteed match between interdependent issues. The essence of the proposed coordination mechanism is the bidirectional information exchange and cooperation between coupled domains. This process of communication and cooperation will lead the whole system to a state, where energy allocation is equal to energy demand.

4. CASE STUDY

The ornamental horticulture industry in Denmark produces ornamental pot plants. The production of ornamental pot plants in the northern hemisphere depends on green houses because of low temperature and light conditions in the winter season. Denmark has approximately 1700 plant and ornamental nurseries in business today. According to the current production practices (Gadtke 2010), the majority of profit from the horticulture industry comes from plants that are produced in greenhouses. The greenhouses are energy intensive and require the use of large amounts of energy. To ensure an environmental and production optimal operation, energy resources must be used efficiently and process performance must be considered. In this regard, focus is on concepts and technologies that facilitate both energy efficiency and process performance.

Consider a scenario as shown in Figure 2, where a Combined Heat and Power plant (CHP) is connected to a number of greenhouses in an ornamental nursery. The CHP constitutes the Energy Domain and the greenhouses constitute the Process Domains. CHP production, also known as cogeneration, is the simultaneous production of electricity and heat.

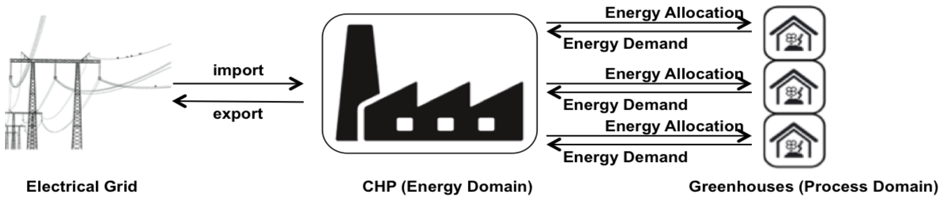

Figure 2. Conceptual drawing of the coupled physical systems

In the scenario, the CHP is responsible for allocation of electricity to the greenhouses in an ornamental nursery. The greenhouses require electricity for providing artificial lighting during the winter season when natural light levels are low. The CHP must therefore allocate just enough electricity to each greenhouse, allowing them to provide the required amount of lighting to reach production goals. Each domain has domain specific concerns. The Process Domain is concerned with climate parameters such as CO_2, air temperature, lighting and other factors influencing the production of plants. The Energy Domain, on the other hand, is concerned with generation limits on the CHP plant as well as electricity market prices. There can be different situations, for example,

1. In case of low electricity prices, all electricity is bought from the public electricity market, since there is no economic incentive in producing electricity locally. When market prices are high, the CHP plant starts local production in order to decrease the amount of electricity bought from the electricity market. Any surplus production not consumed by the greenhouses can be sold to the electricity market, in order to increase profit.
2. In case of extreme prices or when external electricity supply is unavailable, the Energy Domain is forced to perform an allocation, which does not exceed the capacity of the CHP plant.

For better illustration of the properties of our approach, we have chosen to focus on allocation of electricity for artificial light. So, in order to balance the allocation of electricity to each greenhouse, allocation and demand need to be coordinated through negotiation.

Figure 3 shows how the Energy Domain and a Process Domain can be modeled using the modified version of Controleum. The Energy and Process Domains are connected through physical subsystems e.g., lighting subsystem. The group objective is to achieve a state of agreement between the coupled Energy and Process Domains in terms of balancing energy allocation and energy demand. The Energy Domain includes one Allocation Concern Agent (ACA), one Process Subsystem Agent (PSA) and one System Constraint Agent (SCA) that negotiate over a single issue reflecting an energy allocation plan.

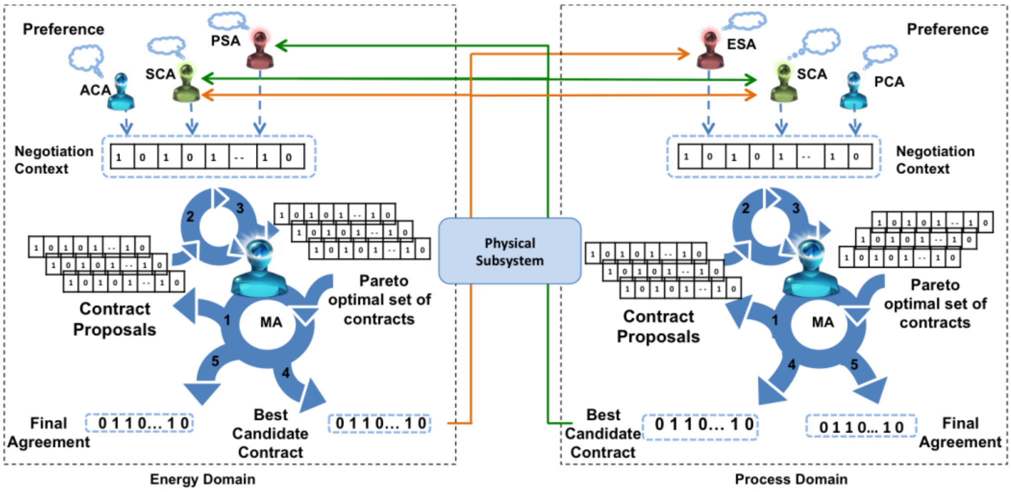

Figure 3. Conceptual illustration of bilateral inter-domain negotiation in Controleum

The candidate contract selected by the MA in the Energy Domain represents an energy plan. An energy plan is an hourly allocation of energy to the Process Domain for an entire day. The value of a time slot in the energy allocation plan issue is 0 or 1 MWh. The Process Domain also includes one Production Concern Agent (PCA), one Energy Subsystem Agent (ESA) and one SCA, which likewise negotiate over a single issue reflecting a light plan. The candidate contract selected by the MA in the Process Domain represents the light plan. A light plan reflects a light schedule that describes when artificial light is on or off in the Process Domain for an entire day. The value of the time slot in the light plan is (on/off). The SCAs exhibit similar behavior in each coupled domain.

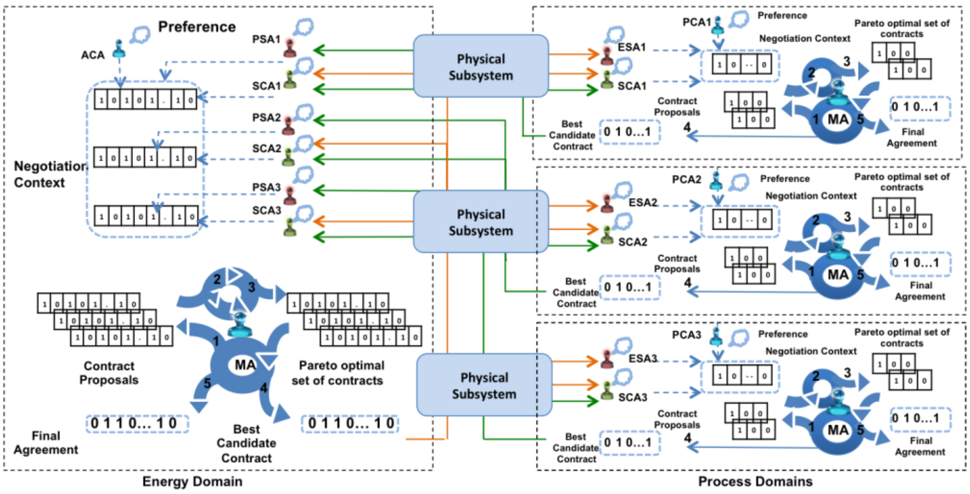

Figure 4. Conceptual illustration of multilateral inter-domain negotiation in Controleum

Figure 4 shows how the bilateral negotiation of Figure 3 has been extended to a multilateral negotiation. Now the Energy Domain includes one ACA, three PSAs and three SCAs. The ACA negotiate over three issues reflecting energy allocation plans, one for each Process Domain. The Process Domains are identical and have same number of agents and issues as described in Figure 3.

ESA: Each ESA represents the preferences of the Energy Domain in the Process Domain and negotiates over one issue representing the plan for using artificial lighting. This light plan is converted to an energy demand plan by the ESA in each Process Domain. The energy demand for "off" hours in the light plan is mapped to 0 MWh in the energy plan, while the energy demand for "on" hours in the light plan is calculated by computing the total load of the lamps, which are installed in the greenhouse. In our case, the total lamp load is achieved by multiplying installed lamp effect (100 W/m^2) with the size of the greenhouse (100m * 100m=10000m^2), which corresponds to an energy demand of 1 MWh. For illustrative purpose we assume that all lamps are switched on at the same time. However, conceptually the framework supports multiple levels. The energy demand plan is defined as $d_n = [d_{1,n}, d_{2,n}, \dots, d_{t,n}]$. Each ESA has a Preference e_n, which represents the energy allocation made in the Energy Domain and is defined as $e_n = [e_{1,n}, e_{2,n}, \dots, e_{t,n}]$. The cost function of each ESA returns a value, which corresponds to the absolute difference of cumulative values of e_n and d_n, as defined in equation (4).

$$q_n = \left|\sum_i^t e_{i,n} - \sum_i^t d_{i,n}\right| \tag{4}$$

PSA: Each PSA represents the preferences of a Process Domain in the Energy Domain and negotiates over one issue, the energy allocation plan for the particular Process Domain. The energy allocation plan issue for PSA agent $n \in N$, where N is the number of PSAs in the negotiation context, is defined as $e_n = [e_{1,n}, e_{2,n}, \dots, e_{t,n}]$, where t defines the number of time slots defined in the energy allocation plan issue. During negotiation, each PSA is assigned a Preference d_n, which represents the current best guess for the light plan of the Process Domain it represents. This is converted into an energy plan using the same conversion method as the ESA. The cost function of each PSA returns a value, which corresponds to the absolute difference of cumulative values of e_n and d_n, as defined in equation (5).

$$q_n = \left|\sum_i^t e_{i,n} - \sum_i^t d_{i,n}\right| \tag{5}$$

SCA: Each SCA is responsible for finding the mean of the preferences of the domains they are represented in. The SCA in the Energy Domain negotiates over energy allocation plan issue e_n, where the SCA in the Process Domain negotiates over light plan issue. Each SCA has a Preference, which represents the mean of preferences of coupled domains defined as $v_n = [v_{1,n}, v_{2,n}, \dots, v_{t,n}]$. This preference is calculated after converting the light plan of the Process Domain into an energy demand plan following the same method as the ESA. The cost function of SCA in the Energy Domain returns a value, which corresponds to the absolute difference of cumulative values of v_n and e_n, as defined in equation (6).

$$q_n = \left|\sum_i^t v_{i,n} - \sum_i^t e_{i,n}\right| \tag{6}$$

The cost function of SCA in each Process Domain returns a value, which corresponds to the absolute difference of cumulative values of v_n and d_n, as defined in equation (7).

$$q_n = \left|\sum_i^t v_{i,n} - \sum_i^t d_{i,n}\right| \tag{7}$$

ACA: The ACA negotiates over the accumulate energy allocation of the energy allocation plan issues for all Process Domains, defined as $y = \sum_n^N e_n$, to ensure that the combined allocation does not exceed CHP capacity. It has a Preference, $= [p_1, p_2, \ldots, p_t]$, which represents total CHP capacity. The cost function of the ACA is shown in equation (8).

$$q_n = \begin{cases} \sum_i^t y_i - \sum_i^t p_i & _{if\ y_i > p_i} \\ 0 & _{otherwise} \end{cases} \quad (8)$$

Following this equation, an ACA will try to suppress the combined cumulative electricity allocation for all Process Domains, y, until it is equal to or less than p.

PCA: The PCA negotiates over a light plan defined as $l_n = [l_{1,n}, l_{2,n}, \ldots, l_{t,n}]$ to ensure that sufficient amount of artificial light is switched on to achieve the production goal. It has a Preference, which represents the preferred number of hours, the lamps need to be switched on in order to achieve the production goal defined as $h_n = [h_{1,n}, h_{2,n}, \ldots, h_{t,n}]$. The cost function of PCA returns a value, which corresponds to the absolute difference of cumulative values of l_n and h_n, as defined in equation (9).

$$q_n = \left| \sum_i^t l_{i,n} - \sum_i^t h_{i,n} \right| \quad (9)$$

5. EXPERIMENTS

Initially we consider a bilateral negotiation between two coupled domains. The Energy Domain is coupled with a single Process Domain as shown in Figure 5.

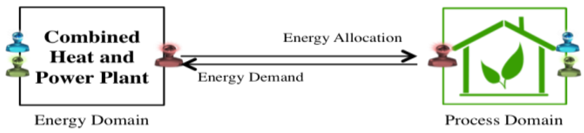

Figure 5. Conceptual drawing of two coupled domains

Next we establish multilateral negotiation among multiple coupled control domains. The Energy Domain is coupled with multiple Process Domains as shown in Figure 6.

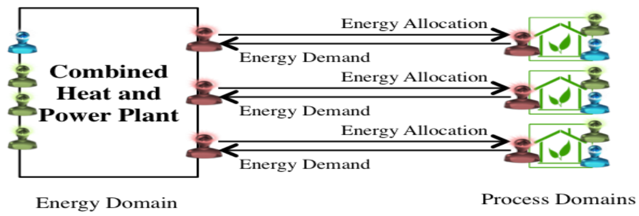

Figure 6. Conceptual drawing of multiple coupled domains

In order to simulate the bilateral and multilateral negotiation needed in each of the different situations described in section 4, we have considered the following sets of scenarios:

Scenario 1. Process Domain prioritized over Energy Domain: in this scenario, the Process Domain cannot divert from its electricity demand and the Energy Domain must adapt to the demand of the Process Domain in case of initial resource insufficiency. However, no surplus resources should be allocated, in the case the demand is less than the available resources.

Scenario 2. Energy Domain prioritized over Process Domain: in this scenario, the Energy Domain cannot allocate more than its total capacity and the Process Domain must adapt to the allocation made in case of resource insufficiency. However, no surplus resources should be allocated, in the case the resources are greater than the demand.

Scenario 3. Absolute compromise between Energy Domain & Process Domain: Here both domains are able to adapt to the perceived preferences of the counterpart. However, no surplus resources should be allocated, in the case the demand is less than the available resources. But a compromise should be made in case of resource insufficiency, so that both domains concede equally in absolute terms.

In each scenario, two experiments are conducted: One with sufficient energy resources to meet demand and other with insufficient energy resources to meet demand. During inter-domain negotiation, the domain specific concern agents (ACA and PCAs) in each domain are assigned a high priority, priority value 0, the ESAs and PSAs are assigned a lower priority of 1 and the SCAs are assigned a priority of 2. This configuration is chosen to exchange actual preferences of coupled domains through subsystem agents during inter-domain negotiation as shown in Table 1. When the negotiation has completed, the selection strategy imposes new configurations in case of a conflict in each set of experiments. In scenario 1, the PSA in the Energy Domain is prioritized over ACA to ensure that the preferences of Process Domain are never compromised. In scenario 2, the ESA in the Process Domain is prioritized over PCA to fulfill the preferences of Energy Domain and to force Process Domain to follow the preferences of Energy Domain. In scenario 3, the SCAs in both Energy Domain and Process Domain are prioritized to find the mean of the preferences of the coupled domains as shown in Table 1.

Table 1. System configuration

<table>
<tr><th rowspan="2">S#</th><th rowspan="2">Scenario</th><th colspan="2">During Inter-domain Negotiation</th><th colspan="2">Selection of Final Outcome After Inter-domain Negotiation</th></tr>
<tr><th>Energy Domain</th><th>Process Domain</th><th>Energy Domain</th><th>Process Domain</th></tr>
<tr><td>1</td><td>Process Domain prioritized over Energy Domain</td><td rowspan="3">ACA (0)
PSA (1)
SCA (2)</td><td rowspan="3">PCA (0)
ESA (1)
SCA (2)</td><td>PSA (0)
ACA (1)
SCA (2)</td><td>PCA (0)
ESA (1)
SCA (2)</td></tr>
<tr><td>2</td><td>Energy Domain prioritized over Process Domain</td><td>ACA (0)
PSA (1)
SCA (2)</td><td>ESA (0)
PCA (1)
SCA (2)</td></tr>
<tr><td>3</td><td>Absolute compromise between Energy Domain & Process Domain</td><td>SCA (0)
ACA (1)
PSA (1)</td><td>SCA (0)
PCA (1)
ESA (1)</td></tr>
</table>

To validate the efficacy of the proposed coordination mechanism, each experiment is repeated 100 times to address possible random behavior of the Genetic Algorithm (GA) used by the MA to generate the population of contracts.

5.1 Bilateral Negotiation

In case of bilateral negotiation, for the first experiment, the total CHP capacity in the Energy Domain is 24 MWh across 24 hours and the cumulative energy demand of the Process Domain is 18 MWh. In the second experiment, the cumulative CHP capacity in the Energy Domain is 18 MWh and the cumulative demand of Process Domain is 24 MWh. These values are chosen arbitrarily to simulate the cases described in each of the two experiments described in section 5.

5.1.1 Process Domain Prioritized Over Energy Domain

Figure 7 shows outcome of the inter-domain negotiation between the two domains. Figure 7a shows the experiment with sufficient resources. At the beginning of negotiation round 1, the MA makes initial allocation of 15 MWh in the Energy Domain for an energy demand of 18 MWh.

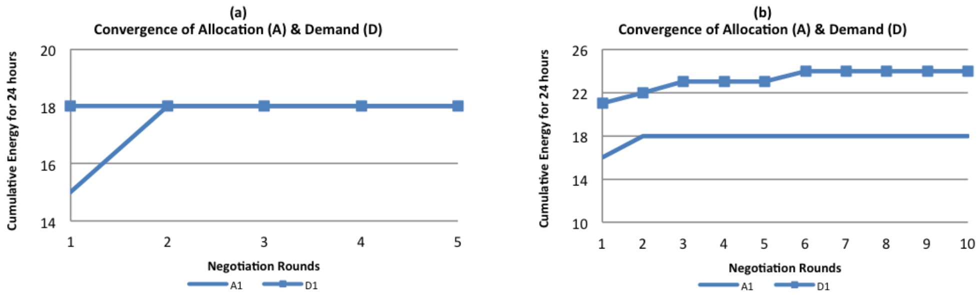

Figure 7. Bilateral convergence of coupled domains (a) Resources>demand (b) Resources<demand

The ACA in the Energy Domain is able to increase its allocation but will not increase allocation beyond CHP capacity. As negotiation process progresses, the PSA in the Energy Domain will contribute to coordinate energy allocation with the demand of coupled Process Domain. This coordination will lead the system towards a state of agreement where energy allocation is exactly equal to the energy demand of the Process Domain. At negotiation round 2, the amount of energy allocated in the Energy Domain matches with the demand of coupled Process Domain. Table 2 shows that coupled domains converge and also reach an agreement during inter-domain negotiation.

Table 2. Simulation results for state of convergence & agreement

Experiment		State of Convergence		State of Agreement	
		Allocation	Demand	Allocation	Demand
		MWh	MWh	MWh	MWh
Process Domain prioritized over Energy Domain	Res.>Dem.	18	18	18	18
	Res.<Dem.	18	24	24	24
Energy Domain prioritized over Process Domain	Res.>Dem.	18	18	18	18
	Res.<Dem.	18	24	18	18
Absolute compromise between Energy Domain & Process Domain	Res.>Dem.	18	18	18	18
	Res.<Dem.	18	24	21	21

In case of insufficient resources (Figure 7b), the MA makes initial allocation of 16 MWh in the Energy Domain, where the MA makes an initial demand of 21 MWh in the Process Domain. As expected, the PCA in the Process Domain does not deviate from its energy preference in response to this. Similarly, the Energy Domain approaches the demand of the Process Domain but does not exceed the CHP capacity. It can be seen from Figure 7b that a conflict exists in the system after negotiation. The data in Table 2 shows how the conflict is resolved by the selection strategy based on system configuration 1 in Table 1, where allocation is increased in the Energy Domain to meet the demand of the Process Domain.

5.1.2 Energy Domain Prioritized Over Process Domain

This experiment yields the same results for inter-domain negotiation both in case of sufficient and insufficient energy resources with respect to demand as shown in Figure 7a and 7b respectively. This is expected, as the preferences and the agents are the same. The only variable changed is the selection strategy for selecting final negotiation outcome after inter-domain negotiation. Here a selection is made according to the system configuration 2 in Table 1, in which the Process Domain reduces its demand in order to match the energy allocated in the Energy Domain.

5.1.3 Absolute Compromise between Energy Domain And Process Domain

Again the result of the negotiation is same as the two previous experiments. Table 2 shows the outcome of the experiment using the selection strategy based on system configuration 3 in Table 1, which prioritizes the SCAs to reach a compromise. In case of sufficient resources, as expected, the Process Domain gets an amount of electricity that matches its demand. In case of a conflict, the selection strategy, which prioritizes the SCAs, will force each domain to make a compromise of 3 MWh in order to reach an agreement.

5.2 Multilateral Negotiation

In case of multilateral negotiation, there are three PSAs and three SCAs in the Energy Domain, one for each coupled Process Domain. We have used the same system configuration (Table 1) for the selection of the final outcome in the experiments with multilateral negotiation as in the experiments with bilateral negotiation.

In case, where sufficient energy resources are available with respect to demand, we have defined the CHP capacity to be 24 MWh across 24 hours and the cumulative energy demand of the Process Domains to be 18 MWh across the same period. The individual energy demand preference of each Process Domain is defined as 3, 6 and 9 MWh respectively. To illustrate a situation with insufficient resources in the system, the total CHP capacity is set to 18 MWh and the cumulative energy demand of all Process Domains is set to 24 MWh. The individual demand of each Process Domain is here defined as 4, 8, and 12 MWh respectively. Again these values are arbitrarily chosen, in order to simulate the scenarios explained in the previous section. However, we have chosen different levels for the Process Domains, in order to show the capability of the framework to handle heterogeneous demands.

5.2.1 Process Domain Prioritized Over Energy Domain

Figure 8 shows the result of the inter-domain negotiation among multiple coupled control domains. Figure 8a shows the result of the experiment with sufficient resources. In the beginning of negotiation round 1, the Energy Domain makes random initial energy allocations of 7, 6 and 5 MWh respectively for each Process Domain. The Process Domains makes demands of 3, 6 and 9 MWh respectively. As the negotiation progresses, the PSAs in the Energy Domain will contribute to coordinate the allocations proposals generated by the MA. The negotiation between ACA and PSAs ultimately converge towards allocations and demands of 3, 6, 9 MWh respectively at negotiation round 7. It can be seen in Table 3 the coupled domains not only converge but also reach an agreement during inter-domain negotiation.

The result of the experiment with insufficient resources is depicted in Figure 8b. The initial allocations proposed by the Energy Domain for each Process Domain are 11, 4 and 8 MWh respectively. The demands made by each Process Domain are 4, 8 and 12 MWh respectively. As the negotiation progresses the PSAs in the Energy Domain try to coordinate allocations and demands in the Energy Domain. However, as can be seen from Figure 8b a fixed gap of 2 MWh exists between allocation and demand of each coupled Process Domain from negotiation round 83. This is because, the selection strategy based on Approximated Fairness ensures that all agents are treated equally and therefore all Process Domains concede on fair basis to bridge the gap of the conflict as shown in Figure 8b. At the end of inter-domain negotiation, according to the system configuration 1 in Table 1, a selection is made forcing the Energy Domain to deviate from its preference with a cost of 6 in order to resolve the conflict between allocation and demand. The result is depicted in Table 3.

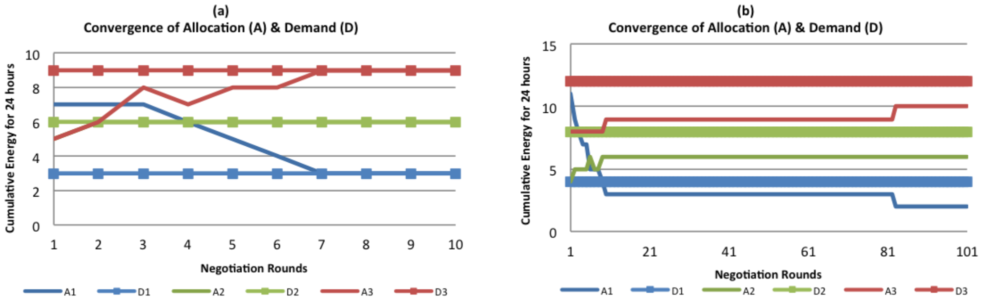

Figure 8. Multilateral convergence of coupled domains (a) Resources>Demand

(b) Resources<Demand

5.2.2 Energy Domain Prioritized Over Process Domain

This experiment yields the same results during inter-domain negotiation as depicted in Figure 8a and 8b respectively. Again, this is due to the fact that the only variable, which changes, is in the selection of the final negotiation outcome. In order to solve the conflict, which arises in the case of insufficient resources, we use the selection strategy based on system configuration 2 in Table 1, which makes the Process Domains compromise in order to adhere to an allocation. The result is shown in Table 3, where the Process Domains are conceding by a cost of 2 in order to meet the allocation of 18 MWh.

5.2.3 Absolute Compromise between Energy Domain And Process Domain

As with the previous experiment, we observe the same behavior depicted in Figure 8a and 8b during inter-domain negotiation. Here we apply the selection strategy based on system configuration 3 in Table 1, which prioritize the SCAs in to find a compromise in terms of allocation and demand. The result can be seen in Table 3. The contract selected by the MA in each domain is the one that fully satisfy SCAs such that the PCAs in each Process Domain made a total compromise of 3 and ACA in the Energy Domain made a compromise of 3.

Table 3. Simulation results for state of convergence & agreement

Experiment		State of Convergence								State of Agreement							
		Allocation (MWh)				Demand (MWh)				Allocation (MWh)				Demand (MWh)			
		C	A1	A2	A3	**C**	D1	D2	D3	**C**	A1	A2	A3	**C**	D1	D2	D3
Process Domain prioritized over Energy Domain	Res.>Dem.	**18**	3	6	9	**18**	3	6	9	**18**	3	6	9	**18**	3	6	9
	Res.<Dem.	**18**	2	6	10	**24**	4	8	12	**24**	4	8	12	**24**	4	8	12
Energy Domain prioritized over Process Domain	Res.>Dem.	**18**	3	6	9	**18**	3	6	9	**18**	3	6	9	**18**	3	6	9
	Res.<Dem.	**18**	2	6	10	**24**	4	8	12	**18**	2	6	10	**18**	2	6	10
Abs. compromise b/w Energy Domain & Process Domain	Res.>Dem.	**18**	3	6	9	**18**	3	6	9	**18**	3	6	9	**18**	3	6	9
	Res.<Dem.	**18**	2	6	10	**24**	4	8	12	**21**	3	7	11	**21**	3	7	11

6. CONCLUSION AND FUTURE WORK

Cooperative control strategies and multi-issue negotiation protocols have been studied widely. In this paper, we proposed a novel inter-domain coordination mechanism, which unifies the properties of both cooperative control strategies and multi-objective multi-issue negotiation protocols. Our experimental results show that our proposed coordination mechanism is able to coordinate a system consisting of multiple control domains using both bilateral and multilateral negotiation. We have illustrated, how cases with insufficient system resources result in conflicts between preferences of coupled domains. We further demonstrated three different approaches to solve this type of conflict: One, which forces demand processes to follow allocation, one which forces allocation to follow system demand, and one which find a compromise between demand and allocation. It is observed from the results that the presence of SCAs is important in case where we need to find an absolute compromise between the coupled domains to solve the conflicts. The SCAs enforce the coupled domains to deviate equally from their preferences in order to reach a final agreement. We also see, that the SAs play a major role in all cases, as they are responsible for propagating the preferences of one subsystem in the connected subsystem during inter-domain negotiation. In cases where one subsystem should have preference over another subsystem, the SAs are further used to solve the conflicts, as the task of balancing demand and allocation is handled by the SAs to help coupled domains to reach an agreement. Each experiment has been repeated 100 times in order to negate random effects from the genetic algorithm used by the MA in the negotiation.

We plan to test the approach presented in this paper on different domains, in order to see if the model presented for inter-domain negotiation and conflict solving is generic in terms of applicability. Further we plan to extend the existing experiments to a real life setting, with multiple local concerns.

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