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IFAC-PapersOnLine 48-30 (2015) 251–256

Multi-Agent based Distributed Optimization Architecture for Energy-Management Systems with Physically Coupled Dynamic Subsystems

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Abstract: This paper introduces a special architecture for realizing multi-agent based distributed optimization for large scale dynamic systems. By combining advanced environments for multi-agent implementation and fast non-linear dynamic optimization according to a newly devised Mediator-based architecture, optimal operation of large scale power and energy management systems becomes possible. The architecture allows overcoming typical problems like convergence issues, especially high exchange of information between agents due to tightly coupled physical subsystems. Two application examples are introduced and considered schematically: first application is a Building EMS for energy optimization by controlling A/C and other energy consuming devices inside a building, and the second application is a Mediator based distributed energy matching system (for demand side). In the first application, a distributed model predictive control strategy is deployed while dividing the system (i.e. Building EMS in this context) into separate independent yet coupled subsystems. In the second application, the whole demand side is divided into several aggregators where these aggregators perform distributed energy matching within them while having their local energy optimized. In both of these applications, Mediators are introduced to occasionally intervene into the optimization. Multi-agent framework is deployed for performing the distributed optimization in both of these applications.

Keywords: Multi-Agent Architecture, Distributed Optimization, Distributed Model Predictive Control, EMS, BEMS, x-Management System.

1. INTRODUCTION

The computation of optimal schedules and optimal real time control commands of large scale dynamic (nonlinear) systems as they may occur in the electric energy and/or heat energy related field poses problems for central computing architectures since the needed computing time grows nonlinearly (in the worst case exponentially) with the system order. Distributed optimization paradigms can be used in this case to reduce the computational burden on single local optimizers. Distributed approaches usually rely on information exchange between local optimizer of the subsystem and a series of local optimization cycles in order to achieve the convergence to the global (overall) optimum. This is a consequence of the fact that the subsystems in the general case are coupled and the local optimization of one subsystem depends to some degree on the result (internal states) of some other subsystem(s). The couplings within the subsystems can be physically defined (e.g. Building HVAC system) or informatically outlined (e.g. distributed energy optimization in demand-side management).

For real time control of physical system, the Model Predictive Control (MPC) scheme which is based on optimization has been emerged and due to the advent of fast efficient algorithms and fast computing hardware it has been applied from the domain of managing slow chemical reaction processes (Morari et al. (1999)) and similar processes in the process industry to extremely fast real time control applications such as vehicle car dynamics control (Houska et al. (2011)). Distributed optimization such as multi-agent based optimization with/without synchronization as computational paradigm has been successfully combined with Model-Predictive Control (Maestre et al. (2014)).

This paper shows a design for a special distributed optimization (also valid for distributed MPC) architecture, which is based on Multi-Agent based distributed optimizers for large scale dynamic systems with the introduction of a so called Mediating unit. Especially, large scale heterogeneous systems are considered, meaning systems that consist of subsystems, which are very different from each other.). A special software agent (the *Mediator*) that reduces the intervention in the distributed management (optimization, operation and control of single subsystems) as much as possible but intervenes in case of necessity in order to guarantee convergence, optimality and safety of the overall process is introduced. In order to elucidate the effectiveness of the proposed framework, we have considered two distinctive (yet similar in architectural point of view) application domains. The first one is a real Building Energy Management System (BEMS) containing many subsystems (e.g. zones, and/or floors), while the second one is Demand-side Energy Management containing many subsystems (e.g. aggregators, prosumers/consumers). As of now, we do not provide the experimental results. The results and detailed analysis will be in follow-up contributions.

2. SYSTEMS' BRIEF DESCRIPTIONS

The BEMS system (1^{st} application system) contains multiple floors or what we call thermal regions (a space consisting of several thermal zones). In multi-agent distributed

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Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2015.12.386

optimization tightly coupled systems (ex. the coupling could be an energy flow) are difficult to treat since they lead to a high communication overhead and to a high number of needed optimization cycles (as a consequence the advantage compared to a central optimum operation computing approach is negligible, not existent or even turned into a disadvantage). The coupling in BEMS HVAC system as an example could be the common air supply temperature of thermal regions and the heat flow between neighbouring regions. Depending on the topology of building structure and floor, this physical type of coupling can be very pronounced. The *Mediator* based architecture should allow the distributed approach still to be superior to a central architecture out of different considerations (ease of implementation, fast real time computation of needed commands for subsystems and convergence to optimal operation or at least convergence to suboptimal operation or fail safe operation in reasonable time even in the case of tightly coupled physical subsystems).

As for the second application example, the model of distributed energy matching operation among several energy aggregators is considered (for demand side energy management). The aggregators (operate under the *Mediator*) are assumed to have limited physical connectivity (via power line) among them. Such operation requires information and power exchange within the physically linked aggregators. The *Mediator* is in control of initiating the distributed operation as well as maintaining the energy and information exchange with Utility grid. The *Mediator* takes the advantage of Microgrid Coalition Formation method, which takes aggregators' energy status (i.e. the difference between total supply and total demand inside an aggregator) and forms optimal coalitions, (Chakraborty et al. (2015)) for energy exchange with minimized distribution power loss. Based on the coalition, the *Mediator* occasionally updates the communication network map of associated aggregators. The *Mediator* maintains a learning based method that continuously learns about the formed coalitions and associated belief network map. Therefore, the modification in communication network map only takes place when there is a significant change in belief network happens (i.e. in formed coalitions). In such way, the *Mediator* only occasionally intervenes into the distributed operation.

3. FORMULATIONS TOWARDS DISTRIBUTED OPTIMIZZATION

A typical optimization problem to be solved in an energy management system can be described as following (deterministic formulation for central computing):

$$
\begin{aligned}
&\min_{\mathrm{u}(t)} \int_{t_0}^{t_1} P(\mathrm{x},\mathrm{p},\mathrm{u},t)\,dt \\
&\textit{with} \\
&\dot{\mathrm{x}} = f(\mathrm{x},\mathrm{p},\mathrm{u},t) \\
&\textit{and} \\
&\mathrm{h}(\mathrm{x},\mathrm{p},\mathrm{u},t) = 0 \\
&\mathrm{g}(\mathrm{x},\mathrm{p},\mathrm{u},t) \le 0
\end{aligned}
\tag{1}
$$

where x are the states (e.g. SOC values of energy storage, temperatures, voltages for the 1st application and energy transaction with Utility for the 2nd application), p the parameters, u are the input commands (e.g. on/off of devices, temperature set-points, charge/discharge power of electric storage, energy to be exchanged with aggregators, local customers) and h, g are the equality and inequality constraints (respectively) of the problem describing physical topology and/or Demand Response (ex. temperature comfort constraints for the 1st application) and energy supply/demand limits(as for the 2nd application).

The application specific objective functions with constraints are presented in Appendix A. As of the 1st application, the model is expressed with the state evolution equation and depending on the problem with some of the equality and inequality constraints (differential-algebraic system). And for the 2nd application, a multi-objective optimization function is devised that will attain the energy transaction minimization with utility while maximizing local energy exchange (within the aggregators and inside particular aggregator).

3.1 Distributed optimization

The generic optimization problem defined in (1) is, by convention, a centralized optimization problem. As the system size grows, (e.g. the number of floors as well as number of thermal zones with associated states for 1st application; while number of customers as well as the number of aggregator), the centralized optimization suffers the curse of dimensionality. Moreover, due the diversifications of the subsystems, having a centralize control architecture for managing the whole problem space is inefficient. Therefore, the distributed system (as well as optimization) is the possible remedy. However, the transformation between the centralized optimization problem to a distributed (working under multi-agent framework) implementation are of different kinds; depending on the type of problem at hand the state evolution equation, the constraints, the equality and inequalities can be split or are already split by the topology itself. So the coupling of the sub-systems can be expressed as:

· Coupling by subsystem states that enter the state evolution equation of another subsystem

· Coupling by subsystem outputs that enter the state evolution equation of another subsystem

· Coupling by subsystem common inputs (common resource, etc.)

· Coupling by common supra subsystem in- and/or equality constraints

· Coupling by energy information that needs to be transferred between two particular aggregators

3.2 Partitioning of overall system into subsystems

For the 1st application of BEMS domain, a division of that system (energy system) comes from very basic topological or other relevant properties of the system at hand or consideration from operation. Fig. 1 shows such a partitioning. Each physical subsystem (rectangles) has a local