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Challenges for process system engineering in infrastructure operation and control

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Abstract

The need for improving the operation and control of infrastructure systems has created a demand on optimization methods applicable in the area of complex networked systems operated by a multitude of actors in a setting of decentralized decision making. This paper briefly explores the applicability of multi-level optimization and multi-agent model predictive control in infrastructure system operation and stresses their importance for capacity and system management in the energy and transport sectors.

Keywords: infrastructure systems, multi-agent systems, optimization, model predictive control.

1. Introduction

Our society and economy have come to rely on services that depend on networked infrastructure systems, like highway and railway systems, electricity, water and gas supply systems, telecommunication networks, etc. Malfunctioning and service outages entail substantial social costs and hamper economic productivity. Instead of ensuring robustness by installing redundant capacity, more intelligent control of the existing infrastructure capacity seems a more affordable and promising strategy to ensure critical infrastructures' reliability of service. However, the multitude and variety of nodes and links in modern infrastructure networks as well as the multitude and variety of owners, operators, suppliers and users involved have created enormously complex systems. This complexity hampers the optimization of the overall system performance, due to our limited understanding of infrastructure systems as well as to practical limitations in steering the actors' operational decision making.

The process systems engineering (PSE) area defined by Grossmann and Westerberg (2000) is concerned with the *improvement of decision making for the creation and operation of the chemical supply chain.* As chemical process systems, at the level of individual plants and at the level of the industrial enterprise, are networked systems and the PSE field has enabled tremendous advances in their optimization, it is interesting to explore to what extent the methods from PSE may be applied to infrastructure system operations. The urgent need for improving the performance of infrastructures creates a great demand for innovative optimization and control methods.

2. Infrastructure characterization

The physical network of an infrastructure system and the social network of actors involved in its operation collectively form an interconnected complex network where the actors determine the development and operation of the physical network, and the physical network structure and behavior affect the behavior of the actors. An infrastructure can thus be seen as a complex socio-technical system, the complexity of which is defined by its multi-agent/multi-actor character, the multi-level structure of the system, the multi-objective optimization challenge, and the adaptivity of agents and actors to changes in their environment. Their non-linear response functions in combination with the complex system structure often lead to unpredictable dynamic behavior of the system.

Like industrial enterprise systems, infrastructure systems can be viewed as multi-level systems, whether hierarchically interconnected or decentralized, with a number of operational regimes at the various system levels. Usually, at each level of the decomposed system local performance objectives are defined which should, preferably, not be restricted to the optimization of local goals, but rather aim at optimally contributing to the overall goal. However, the relation between local and overall system performance objectives may be rather fuzzy, especially since the overall objective is often not defined in detail and concerned with a longer time horizon. The local objectives are generally more detailed, concerned with a shorter time horizon and often with the specific interests of an individual actor (e.g. a business unit). To facilitate an overall optimization of the performance of the system as a whole, a kind of coordinator may be required to supervise local decision making in its relation to the overall goal. Unlike the situation of an industrial enterprise, central coordination or supervision is lacking in the practical situation of many infrastructure industries in liberalised markets. Especially in these situations it is a challenging task to develop a method for decentralized optimisation that can be implemented by subjecting the actors to a proper incentive system.

As a conceptual model of infrastructures as socio-technical systems we will use the concept of multi-agent systems composed of multiple interacting elements, Weiss, 1999. The term *agent* can represent actors in the social network (e.g. travelers taking auto-nomous decisions on which route to follow to avoid road congestion or companies involved in the production of gas or the generation of power) as well as a component (e.g. a production plant, an end-use device, a transformer station) in the physical network. In all these cases we see that the overall multi-agent system has its own overall objective, while the agents have their own individual objectives. To safeguard adequate functioning of the infrastructure the actions of the individual agents must be steered towards an acceptable overall performance of the system in terms of e.g. availability, reliability, affordability and quality of service. An indispensable form of system management is capacity management, which deals with the allocation of scarce network capacity to the various suppliers and users (c.q. end-use appliances) of the system.

3. Optimization of multi-agent systems: infrastructure capacity management

Capacity management at the operational level addresses day-to-day and hour-to-hour capacity-allocation issues, which relates to how the flows (of goods, gas, electricity) are directed over the network. In the gas sector, international trade flows through the national grid may not hamper an adequate supply of gas to national users by excess use of transport capacity or quality conversion capacity. In the transport sector, intelligent road capacity allocation principles are designed to achieve more balanced capacity utilization in time and space, i.e. to minimize congestion. In dynamic road pricing schemes price levels for tolls are dynamically varied over space and time depending on the traffic conditions in the network and the policy objectives of the road authority policy objectives. A challenging question is what kind of operational models are needed to accommodate optimal distributed dynamic pricing schemes. The problem of distributed dynamic pricing is not unique for the highway infrastructure. Similar issues are found in the operation of next generation electric power systems with many small scale distributed generating units, such as gas turbines, photovoltaics, wind turbines, fuel cells or micro combined heat & power (micro-CHP) units. These distributed technologies have many advantages, e.g. high fuel efficiency, modular installation, low capital investment and relatively short construction time (Cardell, 2000). However, distributed generation in a competitive electricity market creates major uncertainties to the operation of the system: as (millions of) power users can switch to the role of power producers, the amount and quality of power produced in such a distributed system can vary enormously. Similarly, wind power fluctuations can pose management problems related to the frequency stability and the desired voltage profile. As a consequence of distributed power generation new control techniques need to be developed and implemented in order to guarantee power availability and quality (such as frequency, bounds on deviations, stability, and elimination of transients for electricity networks, and so on), so as to meet the demands and requirements of the users. As the input patterns and demands may vary over time, the network control system needs to be equipped with an agent-based coordination framework. An agent-based approach is also of a great value for control of cascading failures in electricity grids (Hines, 2005). Analogous problems and solutions related to system management can be found in decentralized traffic control concepts (Negenborn, 2006).

The value of an agent-based approach for industrial supply chain management is also evident, see Aldea (2004), Julka (2002). Industrial business processes such as inventory management, planning, scheduling, production and logistics are still often optimized in isolation without proper consideration of their impact on the overall performance at the enterprise level. A multi-agent system with intelligent agents can emulate business processes under a variety of business communication scenarios and makes it possible to evaluate various alternative strategies for their contribution to local and overall goals.

4. Decentralized Decision Systems for infrastructure operation

In a decentralized decision system the objectives and constraints of any decision maker may be determined in part by variables controlled by other agents. In some situations, a single agent may control all variables that permit it to influence the behavior of other decision makers as in traditional hierarchical control. The extent of the interaction may depend on the particular environment and time dimension: in some cases agents might be tightly linked, while in others they have little effect on each other, if any at all. For decision making in such systems two important aspects can be distinguished: a set of individual goals and ways of how to reach them, and a set of linkages allowing agents to interact.

4.1. Multi-level optimization

In a multi-level optimization problem several decision makers control their own degrees of freedom, each acting in a sequence to optimize own objective function. This problem can be represented as a kind of leader-follower game in which two players try to optimize their own utility function $F(\boldsymbol{x},\boldsymbol{y})$ and $f(\boldsymbol{x},\boldsymbol{y})$ taking into account a set of interdependent constraints. The leader optimizing F defines an optimal $\boldsymbol{x}$, so that this term for the objective function of the follower is constant, and $f(\boldsymbol{x},\boldsymbol{y})$ may be in principle replaced by $f(\boldsymbol{y})$. However, due to the iterative structure of this decision process $\boldsymbol{y}$ can still be still represented as a function of $\boldsymbol{x}$. For example, to influence the amount of electricity produced by small distributed generators in the imbalances market price-based incentives may be used. Then, small distributed generators such as micro-CHP equipped households can decide on their supply of electricity to the distribution network while still fulfilling their own electricity (and heat) demands. This can be formulated as a bi-level decision making problem with respect to the price signals to be designed to steer the distribution network- household interaction in the distributed electric power sector (Houwing, 2006). If distributed generation by households takes off, dynamic pricing schemes will be needed to influence decisions of households with respect to e.g. micro-CHP power level and amount of discharged heat, in order to maintain system balance at the distribution network level:

(Upper level)
Min {objective of the electricity supplier w.r.t. operational costs} s.t. constraints on frequency stability and voltage
Subject to:
(Lower level)
Min {operational costs of household} s.t. network and physical constraints.

Analogously, a dynamic pricing model with dynamic route and departure time model can be formulated as a bi-level programming problem, see Figure 1:

(Upper level)
Min {objective of the road authority e.g. congestion} s.t. constraints on tolls
Subject to:
(Lower level)
Max {utility function of travelers} s.t. network constraints

where the upper level describes the overall road performance and the lower level the user-specific objective (utility) function. The aim of the road authority is to optimize system performance by choosing the optimal tolls for a subset of links, within realistic constraints and subject to the dynamic route and departure time choice, that is, the travel behavioral part.

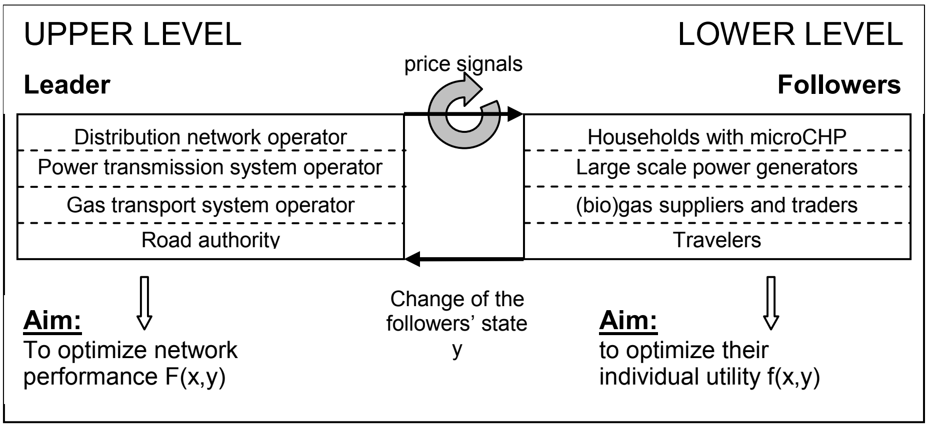

Figure 1. Schematic representation of bi-level decision problem examples found in energy and transport infrastructures

Solving multi-level problems may pose formidable mathematical and computational challenges. Even in the linear case the bi-level programming problem is a non-convex optimization problem which is NP-hard. General multi-level programming problems with an arbitrary number of levels, in which the criteria of the leader and the follower can be nonlinear and/or discrete, are most challenging to solve. In recent years, however, remarkable progress was made in developing efficient algorithms for this class of decision problems (see Bard, 1998). Still, solving the problems as encountered in dynamic road pricing and dynamic pricing of distributed power generation using conventional mathematical optimization techniques seems to be inefficient for complex networks. Therefore, it is useful to consider heuristic methods (e.g. genetic algorithms) to solve such complex problems in the operation of multi-agent multi-level infrastructure systems. Applying multi-level optimization to decentralized decision making on infrastructure system operation is a promising approach to cope with a layered decision structure. In industrial plant operation, however, only a few applications of multi-level optimization were found; see Ryu (2004) and Heijnen (2005).

4.2. Multi-Agent Model Predictive Control

In this section we take a close look at a particular approach used in the PSE area to solve an optimal control problem, namely Model Predictive Control (MPC), see e.g. Maciejowski (2002). This method from the PSE area has become an important approach to finding optimization policies for complex, dynamic systems. MPC has found wide application in the process industry, and recently has also started to be used in the domain of infrastructure operation, e.g. for the control of road traffic networks, power networks, and railway networks. MPC approximates the dynamic optimal control problem with a series of static control problems, removing the dependency on time. Advantages of MPC lie in the fact that the framework handles operational input and state constraints explicitly in a systematic way. Also, an agent employing MPC can operate without intervention for long periods, due to the prediction horizon that makes the agent look ahead and anticipate undesirable future situations. Furthermore, the moving horizon approach in MPC can in fact be considered to be a feedback control strategy, which makes it more robust against disturbances and model errors. The main challenge when applying MPC to infrastructure operation stems from the large-scale of the control problem. Typically infrastructures are hard to control by a single agent. This is due to technical issues like communication delays and computational requirements, but also to practical issues like distributed ownership, unavailability of information from one subsystem to another and restricted control access. The associated dynamic control problem is therefore typically broken up into a number of smaller problems, see Figure 2.

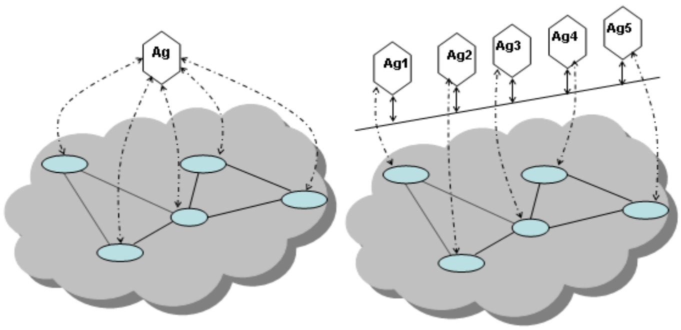

Figure 2. Single-agent versus multi-agent control of a complex network

However, since the sub-problems are interdependent, communication and collaboration between the agents is a necessity. A typical multi-agent MPC scheme therefore involves for each agent the following steps: (1) obtain information from other agents and measure the current *sub*-system state; (2) formulate and solve a static optimization problem of finding the actions over a prediction horizon N from the current decision step *k* until time step *k+N*. Since the sub-network is influenced by other sub-networks, predictions about the behavior of the sub-network over a horizon are more uncertain. Communication and cooperation between agents is required to deal with this; (3) implement the actions found in the optimization procedure until the beginning of the next decision step. Typically this means that only one action is implemented; (4) move on to the next decision step *k*+1, and repeat the procedure, see Camponogara (2002). Determining how agents have to communicate to ensure that the overall system performs as desired is a huge and urgent challenge (e.g. considering the problem of large transient flows in national electricity transmission grids as a result of large scale wind power generation abroad) that still requires a substantial amount of research. Hines (2005) and Negenborn (2006) describe many possible approaches.

5. Conclusions

In this paper we have considered challenges for process system engineering in infrastructure system operation and control. The relevance of optimization models as decision-supporting tools is very high for many players in the world of infrastructure. In all systems that exhibit interactions and interdependencies between subsystems, where multiple functionality plays a role, where capacity allocation in a complex and dynamic environment is an issue, feasible concepts of decentralized optimization are called for. As a particular challenge we pointed out the application of multi-level optimization and model predictive control in a multi-agent setting of decentralized decision making on infrastructure system operation. Besides computational complexity, a formidable challenge here is posed by the design of communication and cooperation schemes that enable agents to come to decisions that are both acceptable locally and ensure an overall system performance in respect of social and economic public interests. The design of markets and an appropriate legislative and regulatory framework to steer individual actors' decision making towards public goals and to enforce adequate communication and collaboration schemes may be beyond the world of PSE, but will certainly be inspired by applicable PSE optimization strategies.

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