Technical report

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Z. Lukszo, M. Weijnen, R.R. Negenborn, B. De Schutter

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Z. Lukszo, M. Weijnen, R.R. Negenborn, B. De Schutter. Tackling challenges in infrastructure operation and control -- cross-sectoral learning for process and infrastructure engineers. *International Journal of Critical Infrastructures*, vol. 5, no. 4, pp. 308-322, 2009.

Delft University of Technology, Delft, The Netherlands

Tackling challenges in infrastructure operation and control: cross-sectoral learning for process and infrastructure engineers

Z. Lukszo*, M.P.C. Weijnen
Faculty of Technology, Policy and Management
Delft University of Technology, The Netherlands
email: {Z.Lukszo,M.P.C.Weijnen}@tudelft

R.R. Negenborn, B. De Schutter
Delft Center for Systems and Control
Delft University of Technology, The Netherlands
email: {R.R.Negenborn,b.deschutter}@.tudelft.nl

Abstract

The need for improving the operation and control of infrastructure systems has created a demand for optimization and control methods applicable in the area of complex networked systems operated by a multitude of actors in a setting of decentralized decision making. Because of the analogy between production systems and infrastructures, process systems engineering (PSE) approaches for optimization and control can be applied to infrastructure system operations. This paper explores the applicability of the techniques often used by the PSE community, i.e. 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, MPC

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 have a negative impact on 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 reliability of service of critical infrastructures. 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 due to practical limitations in steering the actors' operational decision making.

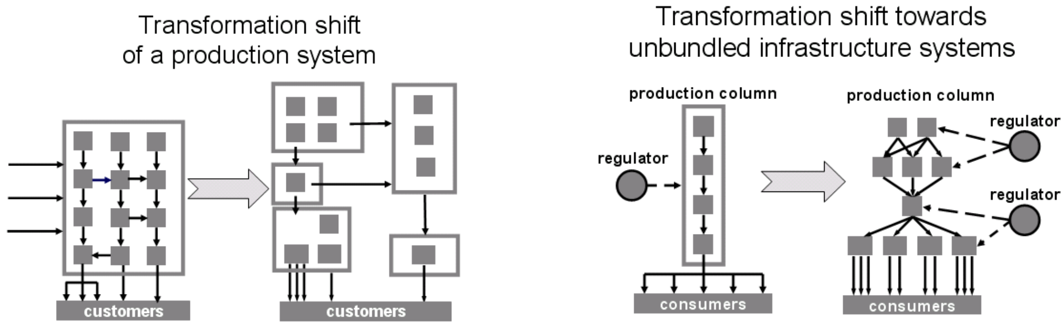

Figure 1: Transformation shift towards more distributed systems in industry and infrastructures

A comparison of networked industrial systems with infrastructure network systems is quite obvious. Considering an industrial system that can be represented as a networked system with inter-related subsystems designed to produce products, a shift toward more distributed production is observed when production units operate quite independently from each other, sharing utilities and supporting activities. More and more, the status quo in industry is characterized by a distributed character of enterprises divided over many sites and further into many plants at one location (Behdani et al., 2009).

In the past the value chain of most infrastructures was vertically integrated with centralized planning and coordination of new capacity and services; however, nowadays, most infrastructure value chains, such as the one for electricity, have been unbundled, with different problem owners for power generation, transport, distribution, and service provision, with different regulators for different parts or different performance aspects of the total system, and market forces steering the security of supply and the quality of service, see Figure 1.

The huge complexity of industrial and infrastructure networks hampers the effective and efficient operation and control of these systems. The challenges for both industrial and infrastructure network systems are similar, i.e.:

- acquiring a deeper understanding of the physical and social network complexity and their interactions;
- dealing with more and more deeply distributed autonomous control of the network behavior;
- coping with new needs for flexibility (in time and functionality) in combination with more stringent demands on capacity utilization, reliability and quality of service, health, safety, and environment;
- dealing with the need for a well-defined decision-making process to guarantee the efficiency and effectiveness of decision making in the shorter and longer term.

The urgent need for improving the performance of infrastructures creates a large demand for innovative optimization and control methods. As industrial process systems, at the level of individual plants and at the level of the industrial enterprises, are networked systems and the process-system-engineering (PSE) field has brought tremendous advances in their optimization and control, it is interesting and relevant to explore to what extent the methods from PSE may be applied to infrastructure system operation. That is the topic of this paper, which is structured following this line of thinking. Section 2 contains a characterization of infrastructures as socio-technical systems, which can be modeled with a model-based paradigm. In Section 3 optimization of multi-agent systems is addressed, to be continued in Section 4 for distributed decision making in more detail. Here two approaches are extensively described: multi-level optimization and distributed multi-level control including illustrative examples from the energy and transport sectors. Section 5 shows how the multi-level optimization can be combined with a distributed model predictive control scheme. Finally, Section 6 concludes the paper by stressing the importance of learning from one another to engineers working on manufacturing optimization control and infrastructure control.

2 Characterization of infrastructures

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 different operational regimes at the various system levels. Usually, at each level of the decomposed system local performance objectives are defined that 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 concerned with a longer time horizon and not defined in detail. 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 liberalized markets. Especially in these situations it is a challenging task to develop a method for decentralized optimization that can be implemented by subjecting the actors to a proper incentive system.

To model 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 autonomous 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 control mechanism of a component (e.g., a production plant, an end-use device, or 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.

3 Optimization of multi-agent systems: infrastructure control issues

Capacity management at the operational level addresses day-to-day and hour-to-hour capacity allocation issues, which relate to how the flows (of goods, gas, electricity) are directed over the network.

In the gas sector, international trade flows through the national grid should be controlled so as not to hamper an adequate supply of gas to national users by excessive use of transport capacity or quality conversion capacity. In the road 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. 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 road 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 and 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 and Ilic, 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 of service (such as frequency, bounds on deviations, stability, 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 the demand 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 great value for control of cascading failures in electricity grids (Hines, 2007; Negenborn et al., 2009a). Analogous problems and solutions related to system management can be found in decentralized traffic (Van Katwijk, 2008), water (Negenborn et al., 2009b), and combined electricity and gas control concepts (Arnold et al., 2009).

The value of an agent-based approach for industrial supply chain management is also evident, see, e.g., Aldea and Bañares-Alcántara (2004), Julka et al. (2002), van Dam et al. (2008). 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 aspects are of the utmost importance: a set of individual goals and ways of how to reach them, and a set of communication links allowing agents to interact. In this paper two approaches known from the PSE domain: multi-level optimization, and single-level multi-agent control, will be discussed to present their applicability for the infrastructure domain.

4.1 Multi-level optimization

In a multi-level optimization problem several decision makers control in a hierarchical system their own degrees of freedom, each acting in sequence to optimize their own objective function. The objective at one level is determined by the decision space of other levels: the decision maker at one level influences decisions at lower levels to improve his own performance criterion after decisions at higher levels have been made.

The problem at each level of the hierarchy can be presented as follows:

$$\min \{f_k(x) : (x^k \mid x^{k+1}, \ldots, x^r)\}$$
$$\text{subject to } x \in S^k \text{ (the level-}k\text{ feasible region)}$$

where the function $f_k(x)$ is minimized over $\mathbb{R}^n$ by varying only the subset x^k of the variables in the decision space $\mathbb{R}^n$, with $k \in \{1, \ldots, r\}$ and r the number of levels:

$$S^k = \{x^* \in S^{k-1} \mid f_{k-1}(x^*) = \min\{f_{k-1}(x) : (x^{k-1} \mid x^{*^k}, \ldots, x^{*^r})\}\ .$$

For two decision makers this problem can be represented as a kind of leader-follower game in which players try to optimize their own utility function $f_1(\mathbf{x}, \mathbf{y})$ and $f_2(\mathbf{x}, \mathbf{y})$ with $(\mathbf{x}, \mathbf{y}) \in \mathbb{R}^n$ taking into account a set of interdependent constraints. The leader optimizing f_2 defines an optimal $\mathbf{x}^*$ so that this term for the objective function f_1 of the follower is constant, and $f_1(\mathbf{x}^*, \mathbf{y})$ may in principle be replaced by $f(\mathbf{y})$. However, due to the iterative structure of this decision process $\mathbf{y}$ can still be represented as a function of $\mathbf{x}$.

For example, to influence the amount of electricity produced by small distributed generators 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 that have to be designed to steer the distribution network-household interaction in the distributed electric power sector (Houwing et al., 2006). If distributed generation by households takes off, dynamic pricing schemes will be needed to influence decisions of households with respect to, e.g., the micro-CHP power level and the amount of discharged heat, in order to maintain the system balance at the distribution network level:

(Upper level)

Min {objective of the electricity supplier with respect to operational costs}

subject to constraints on frequency stability and voltage,

subject to:

(Lower level)

Min {operational costs of household}

subject to 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 2:

(Upper level)

Min {objective of the road authority, e.g., congestion}

subject to constraints on tolls,

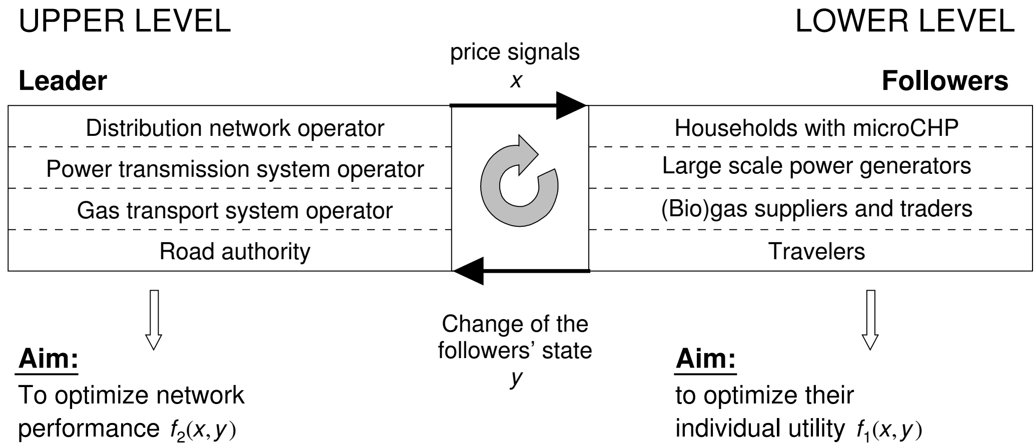

Figure 2: Schematic representation of some bi-level decision problems found in energy and transport infrastructures

subject to:

> *(Lower level)*
>
> Max {utility function of travelers}
>
> subject to 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, i.e., the travel behavioral part (Joksimovic, 2007; Staňková, 2009).

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 the most challenging to solve. Although some remarkable progress was made in developing efficient algorithms for this class of decision problems (Bard, 1998; Migdalas et al., 1998), solving the problems as encountered in dynamic road pricing and dynamic pricing of distributed power generation using conventional mathematical optimization techniques still seems to be inefficient for complex networks. Therefore, it is useful to consider heuristic methods to solve such complex problems in the operation of multi-agent multi-level infrastructure systems. Applying multi-level optimization to decentralized decision making in infrastructure system operation is a promising approach to cope with a layered decision structure. Inspiring examples are found already in industrial applications of multi-level optimization (Rodriges et al., 2000; Ryu et al., 2004; Heijnen et al., 2005).

4.2 Single-level multi-agent control

In the previous section we have considered multi-level control, which is concerned with the interplay between higher levels and lower levels, where the higher levels typically have more system-wide objectives, while the lower levels have more local, individual agents' objectives. In this section we consider multi-agent control within one level. The type of control within a single level is concerned with the communication and cooperation between agents that have similar goals. The agents within one level cooperate with each other in order to obtain the best level-wide solution.

As an example of single-level multi-agent control we can consider a group of power distribution network managers that each control a regional part of the national power grid. These regional network managers have to coordinate among each other the flows of power between their regional networks in order to make optimal decisions. Since one network manager does not have authority over another and does not consider the same geographical area (as is the case with multi-level control), these actors/agents work at the same level.

4.2.1 Model predictive control

A well-suited approach for this single-level multi-agent control is based on Model Predictive Control (MPC), a particular approach coming from the PSE area to solve an optimal control problem (Camacho, 1995; Maciejowski, 2002; Morari and Lee, 1999). MPC has become an important approach for finding control policies for complex, dynamic systems. It 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 (Hegyi et al., 2005), power networks (Hines, 2007; Negenborn, 2007), combined gas and electricity networks (Arnold et al., 2009), railway networks (van den Boom and De Schutter, 2007), and water networks (Negenborn et al., 2009b).

MPC is a model-based control approach. A prediction model and on-line optimization are used to optimize performance over a prediction horizon subject to operational and other constraints. The resulting optimal control input sequence is applied to the system in a receding horizon fashion, i.e., at each controller sample step the optimization problem is solved to find the sequence of N actions that are expected to optimize system performance over the prediction horizon. Only the action for the first step is implemented, after which the system transits to a new state and the controller determines new actions, given the new state of the system.

Advantages of MPC are the fact that the framework handles operational input and state constraints explicitly in a systematic way, and that a control agent employing MPC can operate without intervention for long periods of time, 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 as a feedback control strategy, which makes it more robust against disturbances and model errors.

When using MPC to control a system, e.g., from the domain of PSE or infrastructures, the originally dynamic optimal control problem is approximated with a series of optimization problems. The MPC optimization problems are formulated over a limited time horizon of N steps using a model of the system and a model of the desired behavior. Essentially, the system model is used to make predictions of the behavior of the system under various actions and together with the model of the desired behavior the agent can determine those actions that give the best predicted performance.

4.2.2 Multi-agent model predictive control

In the PSE area MPC has typically been used for local control, in the sense that several devices in the plant are equipped with an MPC controller that only considers that particular equipment. Using manual tuning of the parameters of the controllers, the controllers are adjusted to work reasonably well in the presence of each other, although not explicitly *with* each other in the sense of actively exchanging information.

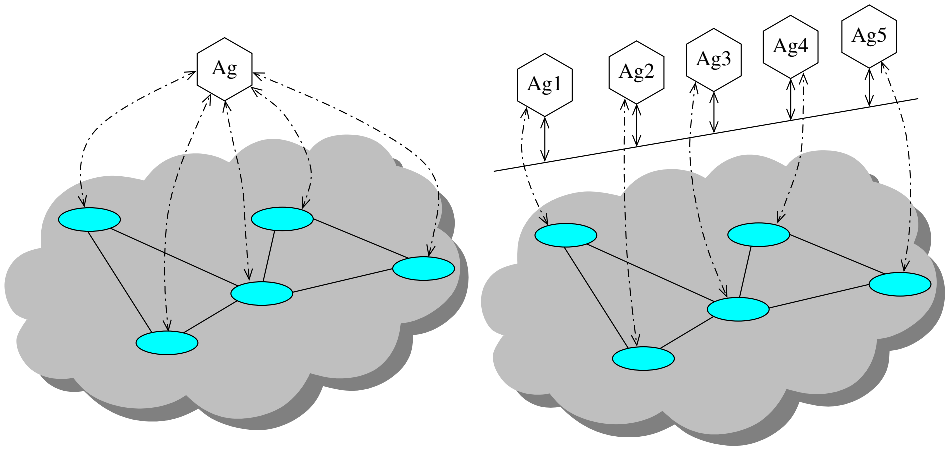

Figure 3: Single-agent versus multi-agent control of a complex network at a single level

When applying MPC to infrastructure operations, the main challenge stems from the large scale of the control problem. Typically infrastructures are hard to control by a single agent. Reasons for this could be of a technical nature, e.g., due to communication delays and computational requirements, but also originate from practical issues like distributed ownership, unavailability of information from one subsystem to another, and restricted control access. The associated dynamic control problem should be broken up into a number of smaller problems, see Figure 3.

Let for subsystem i at control step k the local objective function over the prediction horizon of N be given by

$$\tilde{J}_{i,\text{local}}(k) = \sum_{p=0}^{N-1} J_{i,\text{local}}(x_i(k+p+1), u_i(k+p))$$

and the dynamics of subnetwork i by a model that describes the evolution of the subsystem in the following form for $p = 0, \ldots, N-1$, and $j = j_{1,i}, \ldots, j_{m,i}$,

$$\begin{aligned} &x_i(k+1+p) = f_i(x_i(k+p), u_i(k+p), w_{j_{1,i}i,\text{in}}(k+p), \ldots, w_{j_{m,i}i,\text{in}}(k+p)) \\ &w_{ji,\text{out}}(k+p+1) = g_{ji,\text{out}}(x_i(k+p+1)), \end{aligned}$$

where for subnetwork i, at time step $k+p$, f_i is the state transition function, x_i are the local states, u_i are the local inputs, $j_{1,i}, \ldots, j_{m,i}$ are the indices of the neighboring subnetworks of i, $w_{ji,\text{in}}$ and $w_{ji,\text{out}}$ are interconnecting inputs and interconnecting outputs, respectively, and $g_{ji,\text{out}}$ is the function that indicates how subnetwork j depends on subnetwork i. The subnetworks depend on each other through interconnecting constraints, defined for $p = 1, \ldots, N$ as

$$w_{ji,\text{in}}(k+p) = w_{ij,\text{out}}(k+p)$$

for all neighboring subnetwork couples (i, j), meaning that the influence of subnetwork i on subnetwork j has to be equal to the influence exerted by subnetwork j on subnetwork i to obtain the overall system description. If the interconnecting constraints were not present, then a set of subproblems would have been obtained that can be solved independently of each other in a completely decentralized way. However, for practically relevant applications this is usually not the case. Depending on the way these interconnecting constraints are dealt with, the performance of the resulting multi-agent scheme differs.

One way to deal with the interconnecting constraints is to neglect them at the time of operation. For each subsystem an MPC controller is installed, which is manually fine tuned to give reasonable performance in the presence of the other MPC controllers. However, as infrastructures, like power and road traffic networks, are more and more pushed to their capacity limits, the variety in operating points increases and manual tuning of controllers will lead to deteriorating performance, or even become intractable. Thus, the consequences of the interconnecting constraints can no longer be dealt with through manual tuning. Instead, the controllers should automatically and autonomously coordinate their best settings with each other, in order to improve the overall system's flexibility and robustness. This shows the need for infrastructure control that makes this working together explicit and automatic, something from which the PSE area may benefit. So, instead of manually adjusting the individual controllers, the agents should employ communication and collaboration. A typical multi-agent MPC scheme therefore involves for each agent the following steps (Camponoraga et al., 2002; Negenborn, 2007):

1. Obtain information from other agents and measure the current *sub*system state.

2. Formulate and solve the static optimization problem of finding the actions over a prediction horizon of length N from the current decision step k until time step $k+N$. Since physically the subnetwork is influenced by other subnetworks through the interconnecting constraints, solving the local problem involves serial or parallel iterations between agents to obtain agreement on the mutual influences. In each of the iterations the agents inform each other about how they would like their influence to be. Through the iterations, the agents thus obtain implicit information about the objectives of the others. So each agent solves a series of optimization problems structured as:

$$\min_{u_i(k),\ldots,u_i(k+N-1)} \tilde{J}_{i,\mathrm{local}}(k) + \sum_{p=0}^{N-1} \sum_{j \in A_i} J_{\mathrm{inter},ji}(w_{ji,\mathrm{in}}(k+p), w_{ij,\mathrm{out}}(k+p))$$

   subject to subnetwork dynamics for time $k+p$, for $p = 1,\ldots,N$, and other constraints on local states and inputs for time $k+p$, for $p = 1,\ldots,N$.

   Here, $A_i = \{j_1,\ldots,j_n\}$ is the set of neighboring subnetworks of subnetwork i, and $J_{\mathrm{inter},ji}$ is an interconnecting objective function term between subnetworks i and j that is updated every time an agent receives new information from the other agent. The interconnecting objective function is used to encourage agents to obtain agreement on the variables that interconnect the dynamics of their subnetworks.

3. Implement the actions found for the first predicted time step.

4. Move on to the next decision step $k+1$, and repeat the procedure.

Determining how agents have to communicate to ensure that the overall system performs as desired is a huge 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). Depending on the updating scheme used for the interconnecting objective function terms and properties of the overall control problem, the resulting scheme does or does not converge to a global optimal solution in a distributed way. E.g., for convex overall optimization problems, involving linear interconnected subsystems, with a convex objective function, and closed and bounded domains on the states and inputs, serial and parallel schemes that converge to the overall optimal problem in distributed way can be derived (Negenborn et al., 2008). However, difficulties arise already when the domain of the inputs is defined to be a bounded discrete domain. In that case, the agents may not be able to come to a unique agreement on the solution, but may instead come up with a periodic sequence of solutions (Negenborn, 2007). To fully understand the nature of the underlying problems, many interesting open problems remain to be considered.

5 Multi-level optimization with lower-level multi-agent MPC control

So far, we have discussed multi-level optimization and control within a level as independent techniques. However, in practice, each level in a multi-level control structure may in principle consist of several control agents with distinctive, although related, control objectives. These control agents should jointly perform their decision making. Hence, in these cases a combination and integration of the optimization and control techniques discussed in the previous sections is necessary. In order to obtain coordination within a level, multi-agent single-layer MPC control is required. In order to obtain coordination between levels, i.e., between the groups of control agents acting at different levels, multi-level control is required.

An example of a situation in which this combination of multi-level and multi-agent MPC would be required, is found in the energy sector. Recall from Section 4.1 the multi-level problem defined for a network operator on the one hand and a household on the other. The main task of the network operator is to ensure that the energy demand of the household in the lower level is satisfied. Hence, the network operator has as objectives minimizing the costs, while maintaining frequency and voltage magnitude requirements, and satisfying the energy demand of the household. The household has its own objectives, consisting mainly of minimizing the costs for the energy that it requires. It can hereby buy energy, possibly generate its own energy, and even sell its energy (van Dam et al., 2008).

In future power networks several households may be interconnected and have the possibility to exchange electricity among each other. Some households may have small-scale power generators, while others may have energy storage units. To more efficiently use available energy, households that have their own generation, e.g., generated by a windmill or solar panel, may use the energy storage and consumption capabilities of other households. The households then jointly have the objective to minimize their costs for energy consumption. Each household will have a control agent employing MPC in order to determine how the energy consumption of the household has to be optimized. To determine which energy flows should take place between the households in order to optimize the energy consumption of the group of households as a whole, multi-agent MPC could be used. Hence, when a network operator provides and obtains energy from clusters of households, the combination of multi-level and multi-agent MPC is required, see Figure 4. A smart metering system with control abilities can be used to support this. For example, such a system can shut down a number of customers to balance the grid, to perform demand side management, as well as to respond automatically to dynamic prices.

6 Conclusions

In this paper we have considered challenges in the area of infrastructure system operation and control and we have discussed how control approaches originating in process systems engineering might be used to address these challenges. The relevance of optimization models as decision-support tools is very high for many players in the world of infrastructures. In all systems that exhibit interactions and interdependencies between subsystems, where multiple functionality plays a role, where capacity

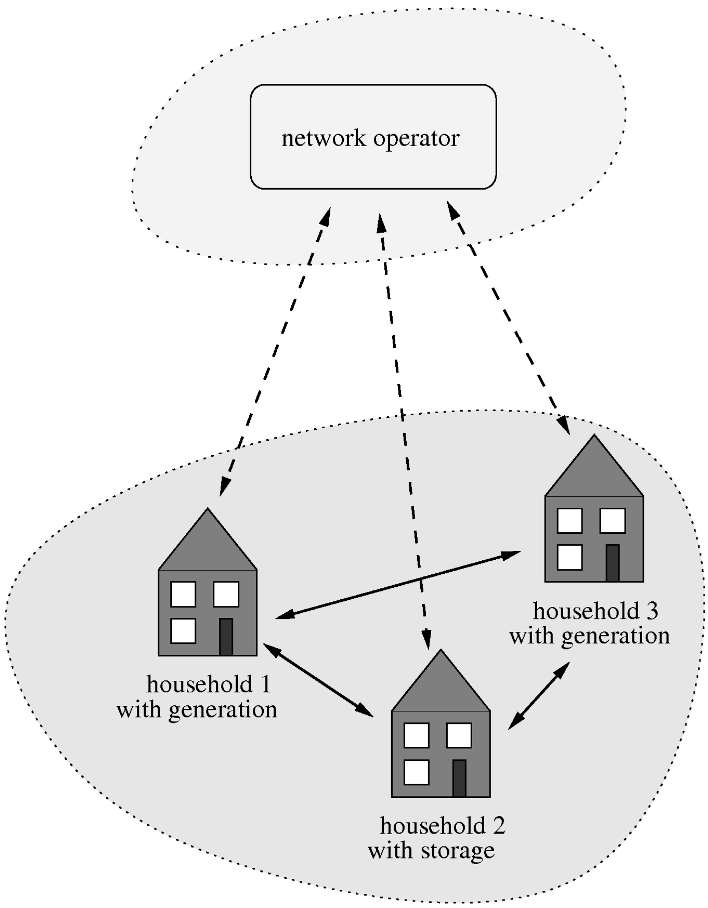

Figure 4: Illustration of a situation in which multilevel control and multi-agent MPC within a single level is necessary. The households at the lower level use multi-agent MPC to coordinate how much energy should flow between the households. Multilevel control is used between the higher and lower levels.

allocation in a complex and dynamic environment is an issue, feasible concepts of decentralized optimization are called for. As a particular challenge we have 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 reach decisions that are both acceptable locally and that ensure an overall system performance in respect of social and economic public interests. We have also argued that for efficient control of many infrastructure networks a combination of multi-level and multi-agent MPC is required.

Acknowledgments

This research was supported by the BSIK research programme “Next Generation Infrastructures” sponsored by the Dutch government, the VIDI project “Multi-Agent Control of Large-Scale Hybrid Systems” (DWV.6188) of the Dutch Technology Foundation STW, the European STREP project “Hierarchical and distributed model predictive control of large-scale systems (HD-MPC)”, and the Delft Research Center Next Generation Infrastructures.

References

Aldea, A., R. Bañares-Alcántara, The scope of application of multi-agent systems in the process industry, *Expert Systems with Applications*, 26(1), 2004.

Arnold, M., R.R. Negenborn, G. Andersson, B. De Schutter, Multi-area predictive control for combined electricity and natural gas systems, *European Control Conference 2009*, Budapest, Hungary, 2009.

Bard, J.F., *Practical Bilevel Optimization*, Kluwer Academic Publisher, 1998.

Behdani B., Z. Lukszo, R. Srinivasan, A. Adhitya, Agent-based modeling to support operations management in a multi-plant enterprise, *IEEE International Conference on Networks, Sensing, and Control*, Okayma, Japan, 2009.

Camacho, E.F., C. Bordons, *Model Predictive Control in the Process Industry*, Springer-Verlag, 1995.

Camponogara, E., D. Jia, B. Krogh, S. Talukdar, Distributed model predictive control, *IEEE Control Systems Magazine*, 52(1), pp. 44-52, 2002.

Cardell J.B, M. Ilic, The control and operation of distributed generation in a competitive electric market, *Electric Power Systems Restructuring*, Kluwer Academic Publishers, pp. 453-518, 1998.

Hegyi, A., B. De Schutter, J. Hellendoorn, Optimal coordination of variable speed limits to suppress shock waves, *IEEE Transactions on Intelligent Transportation Systems,* 6(1), pp. 102-112, 2005.

Heijnen, P., I. Bouwmans, Z. Verwater-Lukszo, Improving short-term planning by incorporating scheduling consequences, *Computer Aided Chemical Engineering*, 20(2), pp. 997-1002, 2005.

Hines, P., A decentralized approach to reducing the social costs of cascading failures, Ph.D. dissertation, Carnegie Mellon University, 2007.

Houwing, M., P. Heijnen, I. Bouwmans, Deciding on micro CHP, *IEEE International Conference on Networks, Sensing, and Control*, Ft. Lauderdale, Florida, April 2006.

Joksimovic, D., Dynamic bi-level optimal toll design approach for dynamic traffic networks, PhD Thesis, Delft University of Technology, Delft, The Netherlands, 2007.

Julka, N., I. Karimi, R. Srinivasan, Agent-based supply chain management-2, *Computers & Chemical Engineering,* 26(12), pp. 1771-1781, 2002.

Lukszo, Z., D. Joksimovic, Optimization of the operation of infrastructures, *IEEE International Conference on Networks, Sensing, and Control*, Ft. Lauderdale, Florida, April 2006.

Maciejowski, J.M., *Predictive Control with Constraints*, Prentice Hall, England, 2002.

Migdalas A., P. Pardalos, P. Varbrand, (Editors), *Multilevel Optimization: Algorithms and Applications*, Kluwer Academic Publisher, 1998.

Morari, M., J.H. Lee, Model predictive control: past, present and future, *Computers & Chemical Engineering*, 23, pp. 667-682, 1999.

Negenborn, R.R., Multi-Agent Model Predictive Control with Applications to Power Networks, PhD Thesis, Delft University of Technology, Delft, The Netherlands, 2007.

Negenborn, R.R., B. De Schutter, J. Hellendoorn, Multi-agent model predictive control for transportation networks: Serial versus parallel schemes, *Engineering Applications of Artificial Intelligence*, 21(3), pp. 353-366, 2008.

Negenborn, R.R., S. Leirens, B. De Schutter, J. Hellendoorn, Supervisory nonlinear MPC for emergency voltage control using pattern search, *Control Engineering Practice*, 17(7), pp. 841-848, 2009a.

Negenborn, R.R., P.J. van Overloop, T. Keviczky, B. De Schutter, Distributed model predictive control for irrigation canals, *Networks and Heterogeneous Media*, 4(2), pp. 359-380, 2009b.

Rodrigues M., L. Latre, L. Rodrigues, Short-term planning and scheduling in multipurpose batch chemical plants: a multi-level approach, *Computers and Chemical Engineering 24*, pp. 2247-2258, 2000.

Ryu, J.H., V. Dua, E.N. Pistikopoulos, A bilevel programming framework for enterprise-wide process networks under uncertainty, *Computers & Chemical Engineering*, 28(6-7), pp. 1121-1129, 2004.

Staňková, K., On Stackelberg and Inverse Stackelberg Games & Their Applications in the Optimal Toll Design Problem, the Energy Markets Liberalization Problem, and in the Theory of Incentives, PhD Thesis, Delft University of Technology, Delft, The Netherlands, 2009.

van Dam K.H., M. Houwing, Z. Lukszo, I. Bouwmans, Agent-based control of distributed electricity generation with micro combined heat and power – Cross-sectoral learning for process and infrastructure engineers, *Computers & Chemical Engineering*, 32, pp. 205-217, 2008.

van den Boom, T.J.J., B. De Schutter, On a model predictive control algorithm for dynamic railway network management, *2nd International Seminar on Railway Operations Modelling and Analysis (RailHannover2007)* (I.A. Hansen, A. Radtke, J. Pachl, E. Wendler, eds.), Hannover, Germany, 2007.

van Katwijk, R., Multi-agent look-ahead traffic adaptive control, PhD Thesis, Delft University of Technology, 2008.

Weiss, G., *Multiagent Systems*, MIT Press, 1999.