Delft University of Technology

Delft Center for Systems and Control

Technical report 06-001

Challenges for process system engineering in infrastructure operation and control*

Z. Lukszo, M.P.C. Weijnen, R.R. Negenborn, B. De Schutter, and M. Ilić

If you want to cite this report, please use the following reference instead:
Z. Lukszo, M.P.C. Weijnen, R.R. Negenborn, B. De Schutter, and M. Ilić, "Challenges for process system engineering in infrastructure operation and control," in *16th European Symposium on Computer Aided Process Engineering and 9th International Symposium on Process Systems Engineering* (Garmisch-Partenkirchen, Germany, July 2006) (W. Marquardt and C. Pantelides, eds.), vol. 21 of *Computer-Aided Chemical Engineering*, Amsterdam, The Netherlands: Elsevier, ISBN 978-0-444-52969-5, pp. 95–100, 2006.

Delft Center for Systems and Control
Delft University of Technology
Mekelweg 2, 2628 CD Delft
The Netherlands
phone: +31-15-278.24.73 (secretary)
URL: https://www.dcsc.tudelft.nl

Challenges for process system engineering in infrastructure operation and control

Z. Lukszo[a], M.P.C. Weijnen[a], R.R. Negenborn[b], B. De Schutter[b], M. Ilić[c]

[a] *Faculty of Technology, Policy and Management, Delft University of Technology, NL*
[b] *Delft Center for Systems and Control, Delft University of Technology, NL*
[c] *Electrical and Computer Engineering and Engineering and Public Policy, Carnegie Mellon University, USA*

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 sociotechnical systems operated by a multitude of actors in a setting of decentralized decision making. This paper briefly presents main classes of optimization models applied in PSE system operation, explores their applicability in infrastructure system operation and stresses the importance of multi-level optimization and multi-agent model predictive control.

Keywords: infrastructures, optimization, multi-agent systems, 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. Recent events such as large-scale power blackouts have contributed to a renewed awareness of the critical role of infrastructures in our economies. Malfunctioning and service outages entail substantial social costs and hamper economic productivity. Instead of installing additional capacity, more intelligent control of the existing capacity seems a more affordable and promising strategy to ensure efficient and reliable operation of critical infrastructures which, moreover, stimulates the creation of innovative value-added services such as dynamic congestion pricing.

However, the multitude and variety of nodes and links in these 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 are networked systems and the PSE field has enabled tremendous advances in their optimization, it is inter sting 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. This is the focus of this paper.

2 Infrastructure definition

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.

Similar to the hierarchical decomposition of, e.g., the operation of an industrial plant in planning, scheduling, and processing functions, 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. 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. In the practical situation of many infrastructure industries in liberalized markets, however, such central co-ordination or supervision no longer exists. Especially in these situations it is a challenging task to develop a method for decentralized optimization that can be implemented, e.g., by a regulatory authority, to influence local decision making by individual actors in respect of societal interests.

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 autonomous decisions on which route to follow to avoid road congestion or companies involved in the generation, transmission and distribution of electricity)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 system — considered as a multi-agent system — has its own overall objective, while the agents have their own individual objectives.

3 Decentralized Decision Systems

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 him 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. The individual decision-making step usually takes the form of single-criterion optimization as often applied in PSE. Optimization is one of the most frequently used tools in PSE decision-making to determine, e.g., operational and maintenance schedules, the sizing of equipment, pricing mechanisms, allocation of capacity or resources among several units, etc. For a detailed review of optimization methods, see, e.g., Edgar (2001).

3.1 (Multi-criteria) Optimization problem

Each optimization problem contains two elements: at least one *objective function*, or criterion, to be optimized, and *constraints*. The type of the ultimate optimization function(s) together with the specified constraints determines the type of optimization problem. The individual goals of each agent often represent a variety of criteria that, more often than not, turn out to be conflicting: an improvement in any one of them may be accompanied by a worsening in others. For the sake of simplicity it is assumed here that there is only one decision maker (i.e., one agent), which is actually searching for a satisfactory compromise rather than for a hypothetical numerical optimum. In principle, a multi-objective optimization problem can be formulated as follows:

$$\min_{\mathbf{x}\in X} J(\mathbf{x}) = \min_{\mathbf{x}\in X}(J_1(\mathbf{x}), J_2(\mathbf{x}), \ldots, J_k(\mathbf{x}))^T$$

where:

$J_i : \Re^n \to \Re$ is an individual objective, $i = 1, 2, \ldots, k$,
$X = \{\mathbf{x} \in \Re^n : g_j(\mathbf{x}) \geq 0,\ j = 1, \ldots, m\}$ is the feasible area determined by constraints.

Four classes of solution methods for multi-objective optimization problems can be distinguished, see Verwater-Lukszo (1996):

- Methods based on some measure of optimality,
- Interactive methods,
- Methods searching for Pareto-optimal solutions,
- Lexicographic methods.

Methods based on a measure of optimality make an attempt to measure alternatives in one way or another, by weighting each objective and then optimizing their weighted sum, or by replacing multi-objective optimization by optimizing only one criterion with the greatest preference. Therefore, methods of this category translate a multi-criteria problem into a single criterion. The second group of methods uses the information obtained from the decision maker in an iterative process to assign appropriate priority levels, e.g., weights, to all individual objectives. Pareto methods of the third group use the notion of Pareto optimality to achieve a balance between objectives. Here the optimal solution appears to be the natural extension of optimizing a single criterion, in the sense that in multi-objective optimization any further improvement in any one objective requires a worsening of at least one other objective. Finally, the lexicographic methods assume that the individual objectives may be ranked by their importance, so that a sequential optimization of the ordered set of single criteria is possible. In this way a multi-objective problem is translated into a multi-level optimization problem. This brings us to another important optimization approach applicable for decision problems in the world of infrastructure system operation: multi-level optimization.

3.2 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 $F(\mathbf{x}, \mathbf{y})$ and $f(\mathbf{x}, \mathbf{y})$ taking into account a set of interdependent constraints. Solving multi-level problems may pose formidable mathematical and computational challenges. In recent years, however, remarkable progress was made in developing efficient algorithms for this class of decision problems (see Bard, 1998). Interesting applications from the world of energy infrastructure operation concern the supplier-household interaction resulting from an introduction of micro CHP, see Houwing (2006). Another example concerned with dynamic road pricing aimed at better use of road capacity is described by Lukszo (2006); the upper level describes the overall road performance and the lower level the user-specific objective function.

The simplest problem representation of a hierarchical optimization problem is the bi-level programming problem concerning the linear version of hierarchical optimization, alternatively known as the linear Stackelberg game:

$$\min_{\mathbf{x}\in X} F(\mathbf{x}, \mathbf{y}) = \mathbf{c}_1\mathbf{x} + \mathbf{d}_1\mathbf{y} \qquad \mathbf{x} = [x_1, \ldots, x_n]^T$$
$$\mathbf{y} = [y_1, \ldots, y_m]^T$$

$$\text{subject to: } \mathbf{A}_1\mathbf{x} + \mathbf{B}_1\mathbf{y} \leq \mathbf{b}_1$$
$$\min_{\mathbf{y}\in Y} f(\mathbf{x}, \mathbf{y}) = \mathbf{c}_2\mathbf{x} + \mathbf{d}_2\mathbf{y}$$
$$\text{subject to: } \mathbf{A}_2\mathbf{x} + \mathbf{B}_2\mathbf{y} \leq \mathbf{b}_2$$

It should be stressed, that even in the linear case the bi-level programming problem is a non-convex optimization problem which is NP-hard. Generally, infrastructure systems pose 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, which are even more challenging to solve.

3.3 Optimal Control

Optimal control is another important, though hard to apply, technique to be used in infrastructure system operation. When modeling a system by a set of differential equations, an interesting type of *dynamic* optimization problem can be formulated, also referred to, e.g., by Leonard (1992) as an optimal control problem. An optimal control problem is formulated and solved by an agent to find those inputs to the system that minimize the objective function over the running time of the system.

A general optimal control problem is formulated as:

$$
\begin{aligned}
&\min_{\mathbf{u}(t)} J = \int_{t_0}^{t_F} f(\mathbf{x}(t),\mathbf{u}(t),t)dt + \Phi(\tau_0,\tau_F) \\
&\text{subject to: } d\mathbf{x}(t)/dt = g(\mathbf{x}(t),\mathbf{u}(t),t) \\
&\qquad \phi_i(\mathbf{u}(t)) \geq 0 \qquad i = 1,2,\ldots,p \\
&\qquad \kappa_j(\mathbf{x}(t)) \geq 0 \qquad j = 1,2,\ldots,q \\
&\qquad \nu_k(\tau_0,\tau_F) \geq 0 \qquad k = 1,2,\ldots,r
\end{aligned}
$$

where:

$$
\begin{aligned}
&\mathbf{x}(t) = [x_1(t),x_2(t),\ldots,x_n(t)]^T \text{ is the state vector} \\
&\mathbf{u}(t) = [u_1(t),u_2(t),\ldots,u_m(t)]^T \text{ is the control vector} \\
&\tau_0 = [t_0,x_1(t_0),x_2(t_0),\ldots,x_n(t_0)]^T \\
&\tau_F = [t_F,x_1(t_F),x_2(t_F),\ldots,x_n(t_F)]^T \\
&\Phi(\tau_0,\tau_F) \text{ is the initial cost/final value function.}
\end{aligned}
$$

The following features can make an optimal control problem extra hard to solve:

- Besides a final value function the criterion may contain an initial cost function.
- Final time can be a free variable, which in many cases may have to be chosen optimally;
- Not only final states, but also initial states can be free variables, which must be chosen optimally.
- The optimization problem usually involves constraints on state variables, which are notoriously difficult to handle.
- Constraints may be imposed (lower/upper bounds, linear and non-linear constraints) on initial and final states variables.
- Integral constraints may be imposed on control variables; these constraints may also involve initial and final states, and possible final time.

Optimal control methods can be solved by variational methods or, alternatively, by discretization converting the original problem into a large-scale static LP or NLP optimization problem. Variational methods use the optimality conditions given by the Maximum Principle of Pontryagin resulting in a so-called two-point boundary value problem, which is often hard to solve. If discretization methods are applied to an optimal control problem, then standard *static* NLP solvers may be used, e.g., the conjugate gradient method, or the sequential quadratic programming algorithm SQP, see Edgar (2001). In the following section we consider a particular control scheme that approximates the dynamic control problem with static control problems.

3.4 Model Predictive Control

A particular approach to solve optimal control problems as introduced in Section 3.3 is Model Predictive Control (MPC), see, e.g., Maciejowski (2002), Morari (1999). This method from the PSE area has become an important technology for 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.

3.4.1 Multi-Agent Model Predictive Control

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 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. 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, see Camponogara (2002):

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.

In particular determining how agents have to communicate with one another to ensure that the overall system performs as desired is a huge challenge that still requires a substantial amount of research. Negenborn describes many possible approaches (2006).

4 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.

Acknowledgments

This research was supported by the BSIK project "Next Generation Infrastructures (NGI)", and the VIDI project "Multi-Agent Control of Large-Scale Hybrid Systems" (DWV.6188) of the Dutch Technology Foundation STW.

References

Camponogara, E., D. Jia, B.H. Krogh and S. Talukdar, *Distributed model predictive control*, IEEE Control Systems Magazine, 1:44.52, February 2002.

Edgar, T.F, D.M. Himmelblau, L.S. Lasdon, *Optimization of Chemical Processes*, McGraw Hill, Boston, 2001

Grossmann, I.E. and A.W. Westerberg, *Research challenges in process systems engineering*, AICHE J., 46 (9), 2000.

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

Kirk, D.E., *Optimal Control Theory: An introduction*, Prentice Hall, Englewood Cliffs, N.J., 1970.

Leonard, D. and N. van Long, *Optimal Control Theory and Static Optimization in Economics*, Cambridge Univ. Press, 1992.

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

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

Morari, M. and J.H. Lee, *Model predictive control: Past, present and future*, Computers and Chemical Engineering, 23, 1999.

Negenborn, R.R., B. De Schutter and J. Hellendoorn, *Multi-agent control of transportation networks*, IEEE Int. Conf. Networks, Sensing, and Control, Ft. Lauderdale, Florida, April 2006.

Verwater-Lukszo, Z., *A Practical Approach to Recipe Improvement and Optimization in the Batch Processing Industry*, PhD Thesis, Eindhoven University of Technology, 1996.