



Parallel and distributed optimization methods for estimation and control in networks[☆]

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ABSTRACT

System performance for networks composed of interconnected subsystems can be increased if the traditionally separated subsystems are jointly optimized. Recently, parallel and distributed optimization methods have emerged as a powerful tool for solving estimation and control problems in large-scale networked systems. In this paper we review and analyze the optimization-theoretic concepts of parallel and distributed methods for solving coupled optimization problems and demonstrate how several estimation and control problems related to complex networked systems can be formulated in these settings. The paper presents a systematic framework for exploiting the potential of the decomposition structures as a way to obtain different parallel algorithms, each with a different tradeoff among convergence speed, message passing amount and distributed computation architecture. Several specific applications from estimation and process control are included to demonstrate the power of the approach.

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1. Introduction

In many application fields, the notion of networks has emerged as a central, unifying concept for solving different problems in systems and control theory such as analysis, process control and estimation. We live and operate in a networked world. We drive to work on networks of roads and communicate with each other using an elaborate set of devices such as phones or computers, that connect wirelessly and through the internet. Traditional networks include transportation networks (roads, rails) and networks of utilities (water, electricity, gas). But more recent examples of the increasing impact of networks include information technology networks (internet, mobile phones, acoustic networks, etc.), information networks (co-author networks, bibliographic networks), social networks (collaborations, organizations), and biological and genetic networks.

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These networks are often composed of multiple subsystems characterized by complex dynamics and mutual interactions such that local decisions have long-range effects throughout the entire network. Many problems associated to networked systems, such as state estimation and control, can be posed as *coupled optimization problems* (see e.g. [4,10,11,17,21,25,28,49]). Note that in these systems the interaction between subsystems gives rise to coupling in the cost or constraints, but with a specific algebraic structure, in particular sparse matrix representation that could be exploited in numerical algorithms. Therefore, in order to design an overall decision architecture for such complex networks we need to solve large coupled optimization problems but with specific structure. The major difficulty in these problems is that due to their size, communication restrictions, or requirements on robustness, often no central decisions can be taken; instead, the decisions have to be taken locally. In such a set-up, single units, or local agents, must solve local optimization subproblems and then they must negotiate their outcomes and requirements with their neighbors in order to achieve convergence to the global optimal solution. Basically, there are two general optimization approaches:

- (i) “Centralized” optimization algorithms: In this class the specific structure of the system is exploited, as it represents considerable sparsity in the optimization problem due to the local coupling between optimization variables (sometimes referred to as *separable optimization problems*). The sparsity of the prob-