Advanced automation and control

Prof. Davide M. Raimondo - Prof. Antonella. Ferrara

Dipartimento di Ingegneria Industriale e dell'Informazione

Università degli Studi di Pavia

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Course schedule

Lectures

- Monday (14-16), room EF3
- Wednesday (14-16), room E1
- Thursday (16-18), room A1

Laboratories

- 10-Oct-2016 (14-16), room D8
- Eventual other laboratories will be announced

Two modules (running in parallel)

- one part on optimization and graphs (Raimondo)
- one part on nonlinear systems (Ferrara)

Course schedule

October 2016

Sun	Mon	Tue	Wed	Thu	Fri	Sat
25	26 Raimondo	27	28 Raimondo	29 Raimondo	30	Oct 1
2	3 Raimondo	4	5 Raimondo	6 Raimondo	7	8
9	10 Raimondo (Laboratory)	11	12 Raimondo	13 Raimondo	14	15
16	17 Ferrara	18	19 Ferrara	20 Ferrara	21	22
23	24 Ferrara	25	26 Ferrara	27 Raimondo	28	29
30	31 holiday	Nov 1 holiday	2 Raimondo	3 Raimondo	4	5

The rest of the schedule will be added on the course website as the course progresses

Course schedule

Website: http://sisdin.unipv.it/labsisdin/teaching/courses/ails/files/ails.php

- course schedule, slides, etc.

Office hours: by appointment

Dipartimento di Ingegneria Industriale e dell'Informazione
Davide M. Raimondo: floor C (davide.raimondo@unipv.it)
Antonella Ferrara: floor F (antonella.ferrara@unipv.it)

Textbook and exams

Textbooks

- W. L. Winston & M. Venkataramanan “Introduction to Mathematical Programming: Applications and Algorithms”, 4th ed., Duxbury Press, 2002. ISBN: 0-534-35964-7
- C. Vercellis “Ottimizzazione: Teoria, metodi, applicazioni”, McGraw-Hill, 2008. ISBN: 9788838664427
- H. K. Khalil “Nonlinear Systems”, 3rd ed., Pearson, 2001. ISBN: 9780130673893

Exams: Closed-books closed-notes written exam on all course topics
Date/time/room on the website of the Faculty of Engineering
No graphic or programmable calculators are allowed

Registration to exams: Through the university website. *Usually, registrations end 7 days before the exam date*

Why optimization?

Useful in many contexts

- Control
- Identification
- Management
  - Optimal placement/sizing
  - Resources allocation
  - Routing/redistribution problems
  - ….

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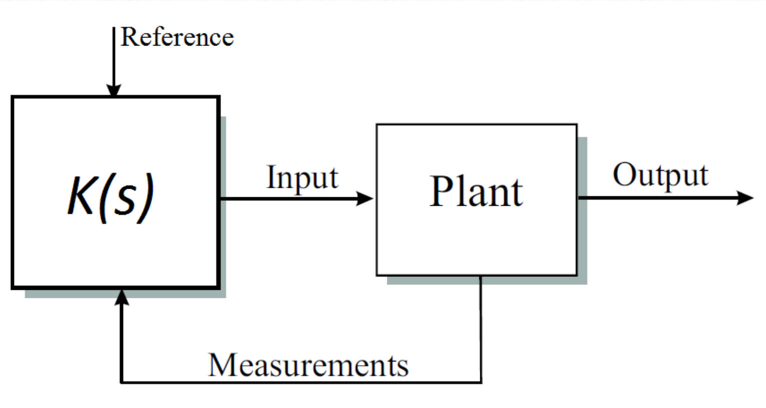
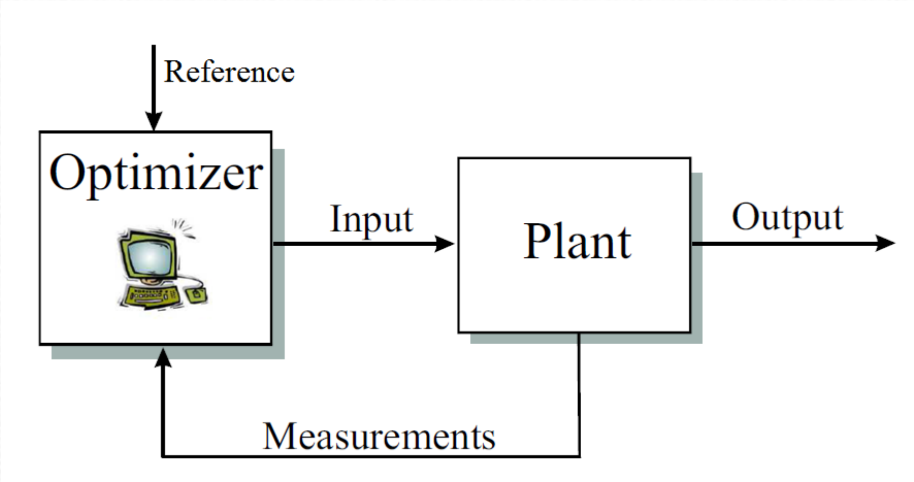
Control

Classic control



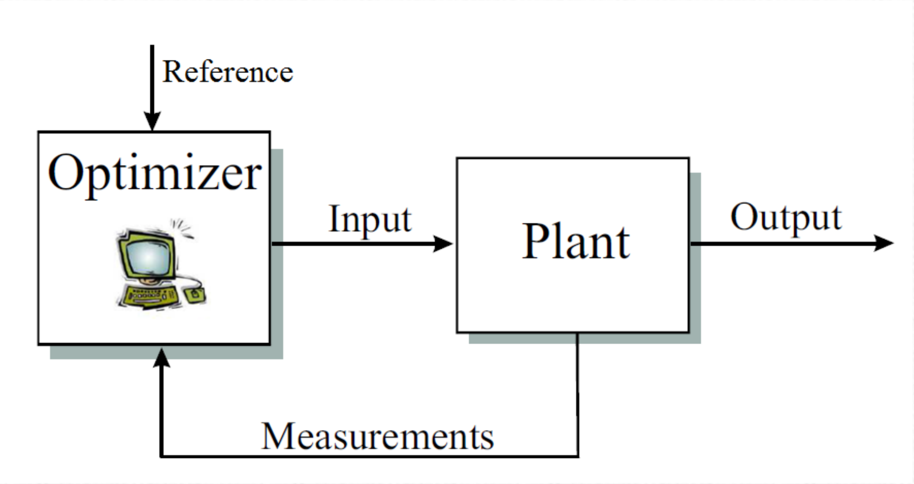
Optimization-based control

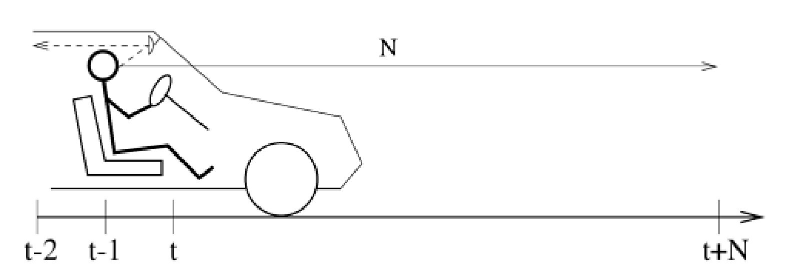


The classic controller is replaced by an **optimization** algorithm that runs on-line

Optimization-based control

Optimization-based control





The optimization uses **predictions** based on a **model** to optimize performance (e.g. minimize costs, maximize return of investment, etc.)

Optimization-based control

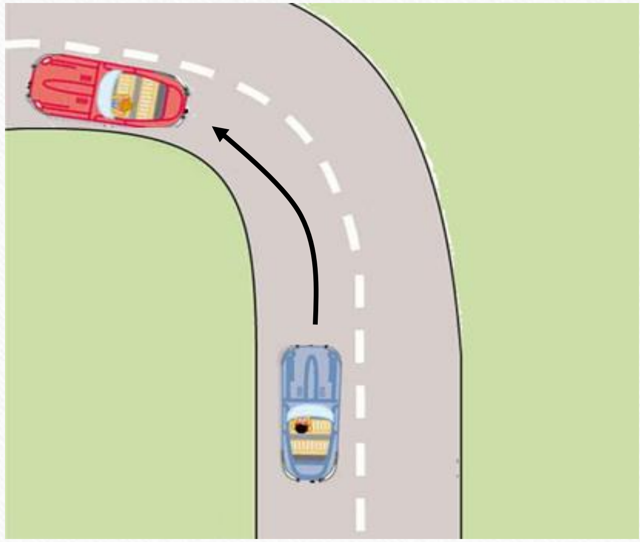
Driving a car

minimize (distance from desired path)

subject to constrains on:

- car dynamics
- distance from leading car
- speed limitations
- …

Further details in the course of
Industrial Control (Prof. Lalo Magni)



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Identification

Given an input-output data set (u, y), consider the following system

$\sum_{j=1}^{n} X_{ij}\beta_j = y_i \ (i = 1, \cdots, m)$

with m linear equations in n $(m > n)$ unknown parameters β_j, $(j = 1, \cdots, n)$.

Let $X_{i1} = 1$, for all $i = 1, \cdots, m$. For each i, X_{ij} is a predefined function of the input u_i (i.e. $u_i, u_i^2, \cdots$).

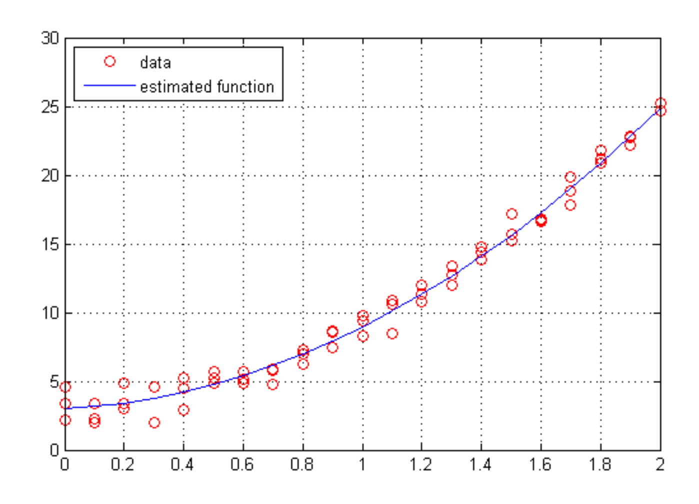
$$\text{Define } \boldsymbol{X} = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mn} \end{bmatrix}, \quad \boldsymbol{\beta} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix}, \quad \boldsymbol{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}$$

Than, the problem above can be rewritten as $\boldsymbol{X\beta} = \boldsymbol{y}$.

Since the data is affected by noise the equality does not hold in general.

We aim to find the set of parameters which provides the least square error $\hat{\boldsymbol{\beta}} = \text{argmin}_{\boldsymbol{\beta}} ||\boldsymbol{X\beta} - \boldsymbol{y}||^2$

If prior knowledge is available, the problem above may be subject to constraints (e.g. $\boldsymbol{\beta} > 0$).



$$y_i = \beta_1 u_i^2 + \beta_2 u_i + \beta_3$$

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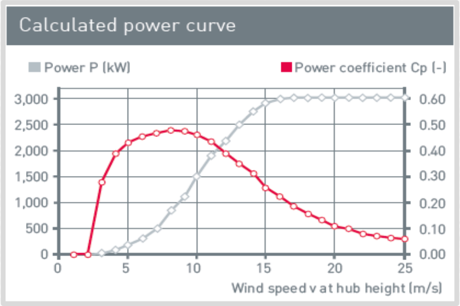
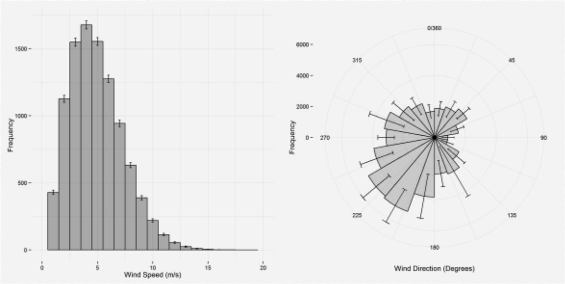
Optimal placement/sizing

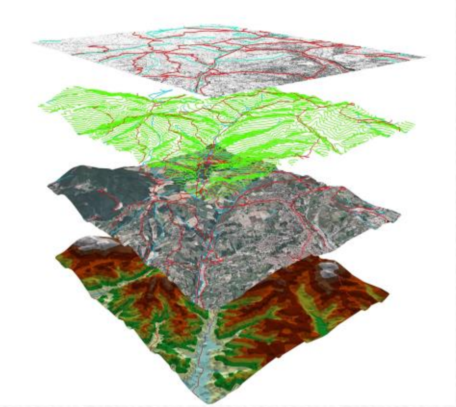
Choose the **number** and the **location** of a set of **wind turbines** in order to maximize the return of investment of a wind farm. Several elements need to be taken into account



Power Curve



Wind distribution

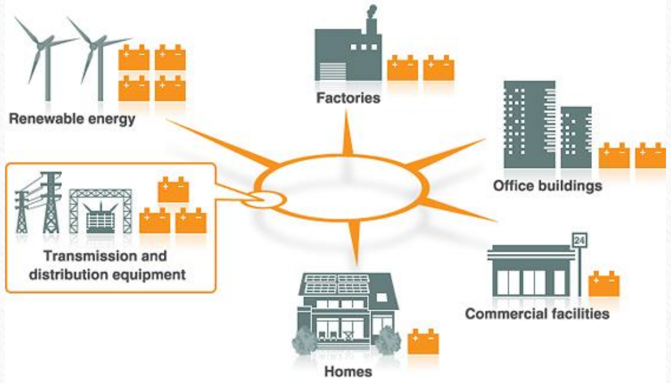


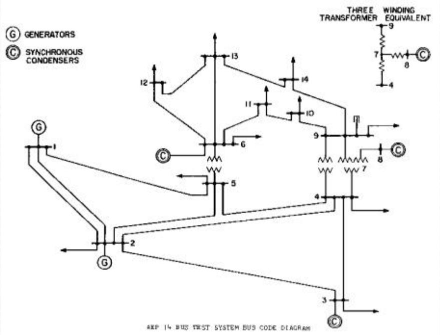
Geographic information

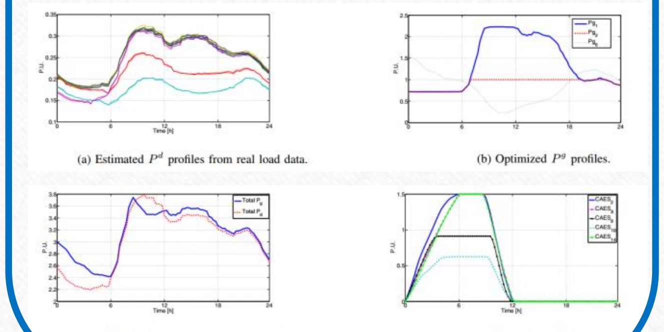
Wake effect

Optimal placement/sizing

Energy Storage Systems (ESS) can help to cope with intermittent availability of renewable sources. However, fixed, maintenance, and operating costs are a critical aspect that must be considered in the optimal positioning and sizing of these devices







(a) Estimated P^d profiles from real load data.

(b) Optimized P^g profiles.

(c) Total Power Demand and Generation.

(d) CAES dynamics

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Resources allocation

Demand Driven Employee Scheduling for the Swiss Market

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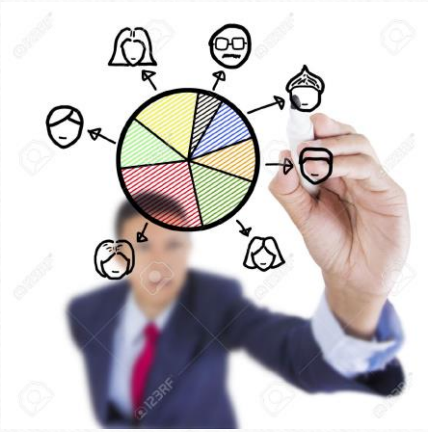
June 24, 2013

1 Introduction

Standard practice for Swiss retail chains is to schedule employees so that the total number of workers present in the store is approximately constant during open hours. The number of shoppers, however, fluctuates throughout the day, which results in periods of under- and/or over-staffing that in turn reduces the effectiveness of the workforce. This paper reports on a new scheduling system that has been developed specifically for the Swiss market by Apex Optimization GmbH. The tool seeks to match expected customer demand to the number of sales staff by optimizing the shifts of the work force. The system has been successfully used by 38 small to mid-sized retail stores of the Migros chain of Switzerland over the past year, and the results of this initial implementation are reported here.

Schedules are computed on a weekly basis, one or more weeks in advance. Each week, the employees and/or store managers specify a wide range of store and employee-specific constraints through a web-based interface. The system then formulates a mixed-integer optimization problem in order to select a shift schedule that minimizes over- and under-staffing against a predicted customer demand profile, which has been estimated from past sales records.



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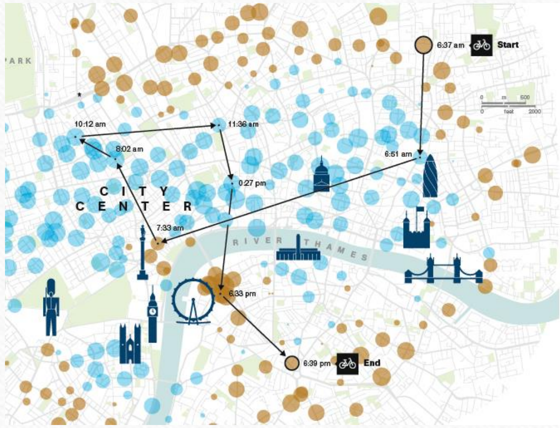
Routing/redistribution problems

EURO Journal on Transportation and Logistics
August 2013, Volume 2, Issue 3, pp 187–229

Static repositioning in a bike-sharing system: models and solution approaches

Authors | Authors and affiliations

Tal Raviv, Michal Tzur, Iris A. Forma



Abstract

Bike-sharing systems allow people to rent a bicycle at one of many automatic rental stations scattered around the city, use them for a short journey and return them at any station in the city. A crucial factor for the success of a bike-sharing system is its ability to meet the fluctuating demand for bicycles and for vacant lockers at each station. This is achieved by means of a *repositioning* operation, which consists of removing bicycles from some stations and transferring them to other stations, using a dedicated fleet of trucks. Operating such a fleet in a large bike-sharing system is an intricate problem consisting of decisions regarding the routes that the vehicles should follow and the number of bicycles that should be removed or placed at each station on each visit of the vehicles. In this paper, we present our modeling approach to the problem that generalizes existing routing models in the literature. This is done by introducing a unique convex objective function as well as time-related considerations. We present two mixed integer linear program formulations, discuss the assumptions associated with each, strengthen them by several valid inequalities and dominance rules, and compare their performances through an extensive numerical study. The results indicate that one of the formulations is very effective in obtaining high quality solutions to real life instances of the problem consisting of up to 104 stations and two vehicles. Finally, we draw insights on the characteristics of good solutions.

Routing/redistribution problems

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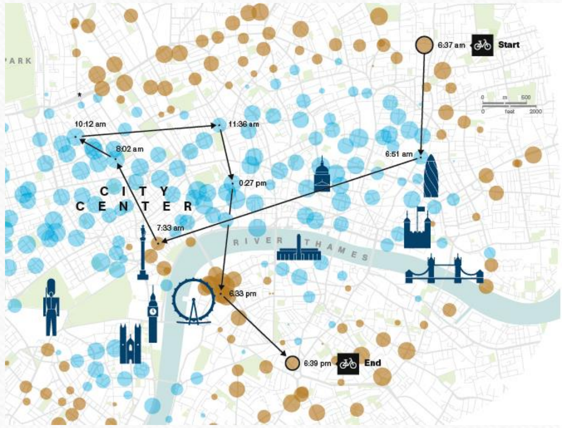

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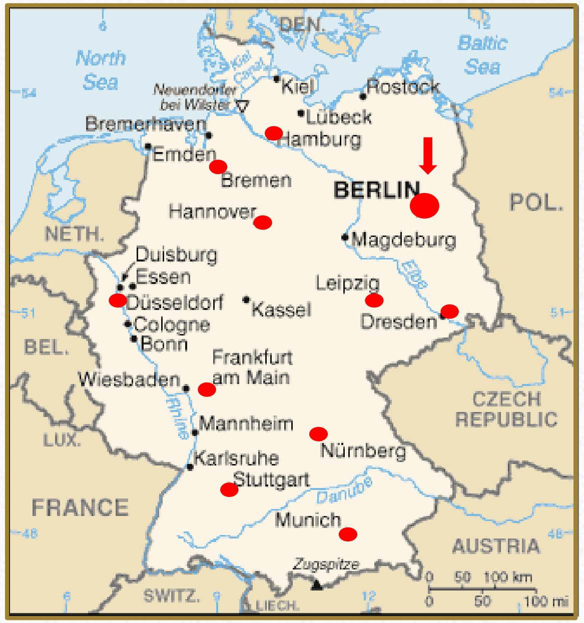
Routing/redistribution problems

The Travelling Salesman Problem

Given a list of cities and the distances between each pair of cities…



What is the shortest route that visits each city once and only once?

Routing/redistribution problems

The Travelling Salesman Problem

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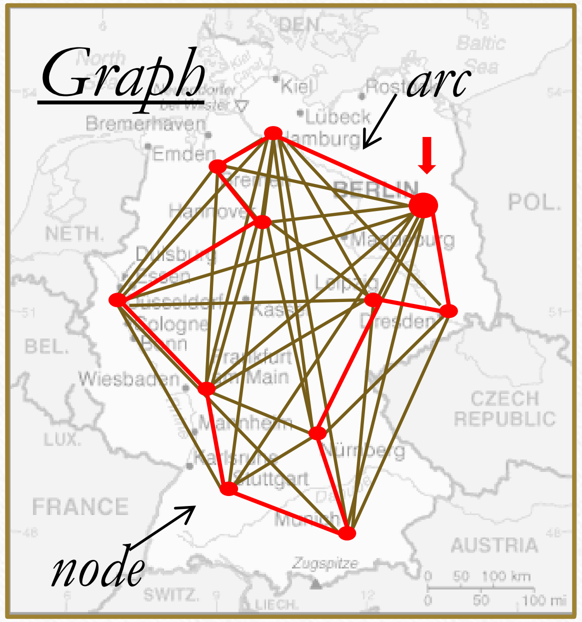

The objective function is the minimization of the cost of the path:

$$\boxed{min \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ij}}$$

Optimization

Mathematical formalization

+

Optimized algorithms

Is it worth?

Optimization