



- ▶ Linear Programming (LP)
- ▶ LP in Production planning example
  - ▶ Static systems
  - ▶ Dynamical systems
- ▶ Model Predictive Control

**Mini Problem**

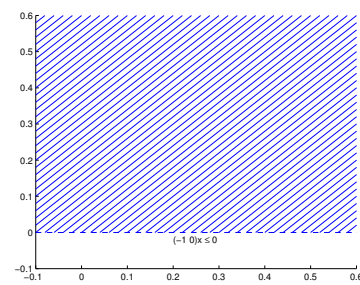
Minimize  $-x_1 - x_2$   
 subject to  $x_1 + 2x_2 \leq 1$   
 $2x_1 + x_2 \leq 1$   
 $x_1 \geq 0$   
 $x_2 \geq 0$

Equivalent matrix formulation:

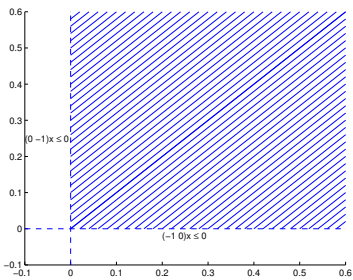
Minimize  $(-1 \ -1) x$   
 subject to  $\begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} x \preceq \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x \succeq 0$

where  $x = (x_1 \ x_2)^T$

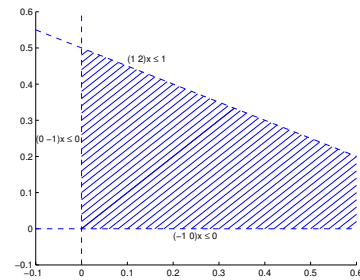
**Mini Problem graphical solution**



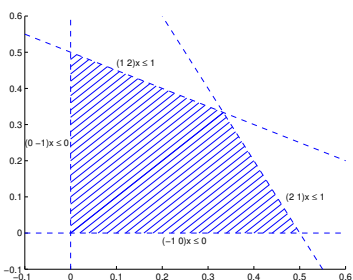
**Mini Problem graphical solution**



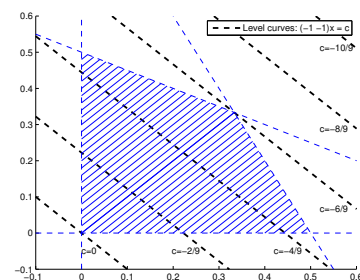
**Mini Problem graphical solution**



**Mini Problem graphical solution**



**Mini Problem graphical solution**



General formulation:

$$\begin{aligned} & \text{Minimize} && c^T x \\ & \text{subject to} && Ax \leq b \\ & && Hx = g \end{aligned}$$

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## Production planning example

Two products are produced:

- ▶ Garden furniture
- ▶ Sleds

Two main parts of production

- ▶ Sawing
- ▶ Assembling

## Production planning example cont'd

Weekly production:

$x_1$  : Garden furniture  
 $x_2$  : Sleds

Product prices:

$p_1$  : Garden furniture  
 $p_2$  : Sleds

The objective is to maximize weekly profit:

$$\max p_1 x_1 + p_2 x_2$$

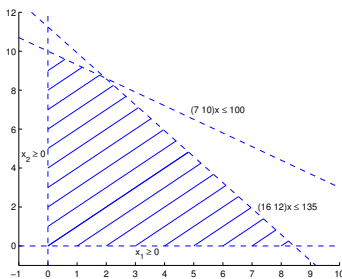
Subject to:

Sawing constraints:  $7x_1 + 10x_2 \leq 100$

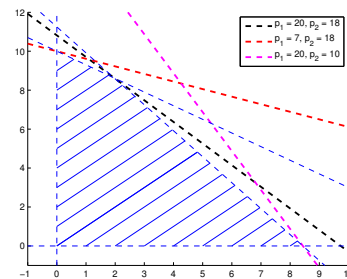
Assembling constraints:  $16x_1 + 12x_2 \leq 135$

## Production planning example cont'd

Sawing and assembling constraints:



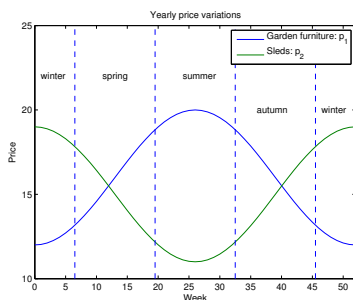
Level curves for optimal points obtained with different prices:



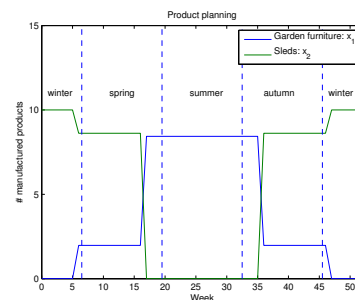
## Production planning example cont'd

## Production planning example cont'd

Seasonal variations in expected prices:



Optimal production for different seasons:



## Today's lecture

- ▶ Linear Programming (LP)
- ▶ **LP in Production planning example**
  - ▶ Static systems
  - ▶ Dynamical systems
- ▶ Model Predictive Control

### Mini problem

Assume that extra sawing personnel is working full-time, i.e.  $u_3(t) = 1$ ,  $t = 0, 1, \dots$

If the initial sawing capacity of the extra labor is 0, i.e.  $x_3(0) = 0$ , what is the sawing capacity after three weeks, i.e.  $x_3(3)$ ?

What is the stationary sawing capacity of the extra labor?

### Dynamic Production planning example cont'd

The weekly cost in hiring extra personnel is  $p_3$  and  $p_4$  respectively

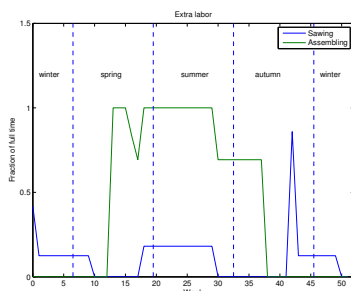
This gives the following production planning problem that optimizes one year ahead production:

$$\begin{aligned} \max \quad & p_1(t)x_1(t) + p_2(t)x_2(t) - p_3(t)u_3(t) - p_4(t)u_4(t) \\ \text{subject to} \quad & 7x_1(t) + 10x_2(t) \leq 100 + x_3(t) \\ & 16x_1(t) + 12x_2(t) \leq 135 + x_4(t) \\ & x_3(t+1) = 0.7x_3(t) + 30u_3(t) \\ & x_4(t+1) = 0.7x_4(t) + 40.5u_4(t) \\ & 0 \leq u_3(t) \leq 1 \\ & 0 \leq u_4(t) \leq 1 \\ & x_3(0) = x_3^0, x_4(0) = x_4^0 \end{aligned}$$

for  $t = 0, \dots, 52$  and  $x_3^0$  and  $x_4^0$  are the initial capacities for the extra personnel

### Dynamic Production planning example cont'd

Optimal extra labor:



## Dynamic Production planning example

Hire extra personnel to increase production:

Nominal learning (sawing):

$$x_3(t+1) = 0.7x_3(t) + 30u_3(t)$$

Nominal learning (assembling):

$$x_4(t+1) = 0.7x_4(t) + 40.5u_4(t)$$

where  $u_3 \in [0, 1]$ ,  $u_4 \in [0, 1]$  is fraction of full time employment

$x_3(t)$  and  $x_4(t)$  quantifies increased capacity:

Sawing:  $7x_1 + 10x_2 \leq 100 + x_3(t)$

Assembling:  $16x_1 + 12x_2 \leq 135 + x_4(t)$

### Mini problem - solution

Sawing capacity at time  $t = 3$ :

$$\begin{aligned} x_3(3) &= 0.7x_3(2) + 30u_3(2) = 0.7(0.7x_3(1) + 30u_3(1)) + 30u_3(2) \\ &= 0.7(0.7(0.7x_3(0) + 30u_3(0)) + 30u_3(1)) + 30u_3(2) \\ &= (0.7^3 + 0.7^2 + 0.7 + 1)30 = 65.7 \end{aligned}$$

Stationary capacity is given by:

$$x_3 = 0.7x_3 + 30$$

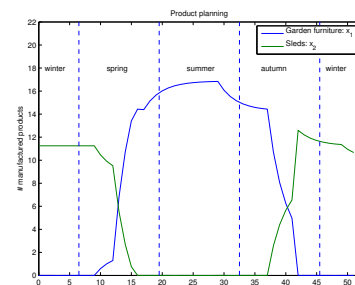
which gives

$$x_3 = \frac{30}{1 - 0.7} = \frac{30}{0.3} = 100$$

The total sawing capacity is doubled after learning period

### Dynamic Production planning example cont'd

Optimal production over 52 weeks with extra personnel and product prices as before and  $p_3 = p_4 = 100$ :



### Dynamic Production planning example - limitations

The following is not compensated for:

- ▶ Prices may not be equal to predicted prices
- ▶ Extra personnel might be fast or slow learners
- ▶ Decreased capacity due to employee illness
- ▶ ...

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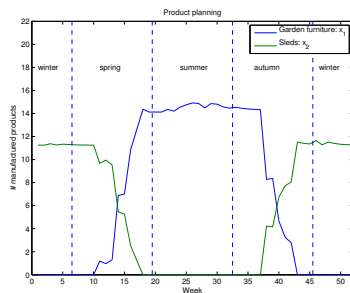
### MPC Loop

MPC Loop; In the end of each week:

1. Get data for extra employment capacity and product prices for the past week,  $(p_1(t), p_2(t), x_3(t), x_4(t))$
2. Solve the optimization problem with the gathered data as input
3. Hire extra personel the following week according to the obtained solution,  $(u_3(t), u_4(t))$
4. In the end of next week repeat the procedure, i.e. Go to 1

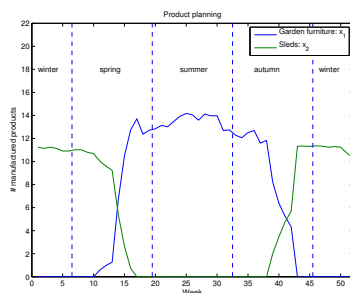
### MPC Example - Results

Weekly production when extra labor decided using MPC:



### MPC Example - Comparison

Production with extra labor as in dynamic production planning example (i.e. no feedback):



Profit over one year is 8.6% higher with MPC-feedback

Reoptimize every week to compensate for mis-match between reality and assumed model

Input to optimization problem:

- ▶ Current product prices,  $p_1(t), p_2(t)$
- ▶ Current capacity of extra workers,  $x_3(t), x_4(t)$

### MPC Example

Product planning example with model-reality mis-match:

Modeled employee learning:

$$\begin{aligned} x_3(t+1) &= 0.7x_3(t) + 30u_3(t) \\ x_4(t+1) &= 0.7x_4(t) + 40.5u_4(t) \end{aligned}$$

Actual employee learning:

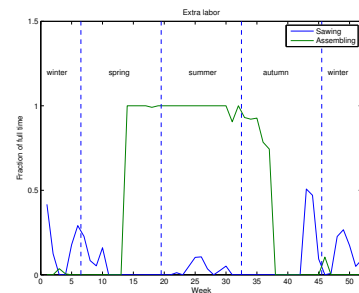
$$\begin{aligned} x_3(t+1) &= 0.75x_3(t) + 30u_3(t) + v_3(t) \\ x_4(t+1) &= 0.65x_4(t) + 40.5u_4(t) + v_4(t) \end{aligned}$$

where  $v_3(t)$  and  $v_4(t)$  are uniformly distributed random numbers in  $[-0.3x_3(t) \ 0]$  and  $[-0.3x_4(t) \ 0]$  respectively

The product prices  $p_1(t)$  and  $p_2(t)$  are additively affected by uniformly distributed random noise in  $[-1 \ 1]$

### MPC Example - Results

Extra personel (decided using MPC):



### MPC General Formulation

MPC introduced by an example. General formulation:

$$\text{Minimize } \sum_{t=0}^N \ell(x(t), u(t))$$

$$\text{subject to } \begin{aligned} x(t+1) &= f(x(t), u(t)) \quad , \quad x(0) = x_0 \\ x(t) &\in X \quad , \quad u(t) \in U \\ &\text{for } t = 0, \dots, N \end{aligned}$$

where  $x_0$  is a measurement of the current state

## MPC Loop - General

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At time  $t$ :

1. Get measurements for  $x(t)$ , set  $x_0 = x(t)$
2. Solve the optimization problem
3. Apply the optimization result  $u(0)$  to the system
4. After one sample, Go to 1 to repeat the procedure

## MPC Pros and Cons

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Pros:

- ▶ Good constraint handling
- ▶ Easily understandable tuning knobs (e.g. cost function)
- ▶ Usually gives good performance in practice
- ▶ Handles complex systems well

Cons:

- ▶ Calculation times
- ▶ System model needed
- ▶ Historically lack of theoretical understanding of the closed loop system

## MPC Application

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Pendulum - developed in our Department

MPC with quadratic cost and linear constraints

## Summary

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Model Predictive Control:

- ▶ Optimization based feedback of dynamical systems
- ▶ Explicit constraint handling
- ▶ Applicable to many types of problems
