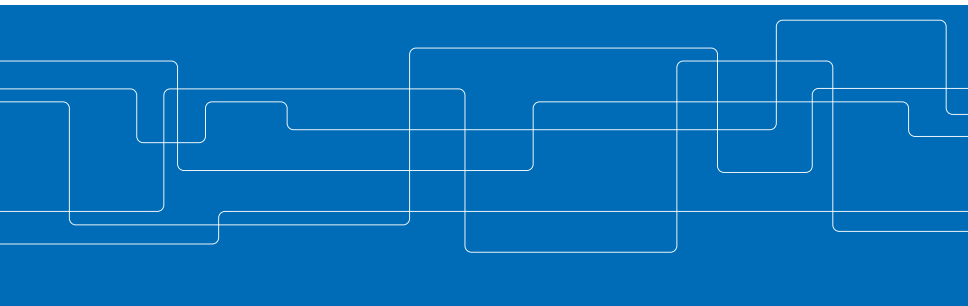




Optimal Order Strategies on the Day-Ahead Electricity Market

Martin Biel

20/9-2017





Outline

Background

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Contribution

Optimal Strategies

Outlook on Future Work



Outline

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Background - Motivation

- ▶ Simulation of hydro power operations → Decision-support



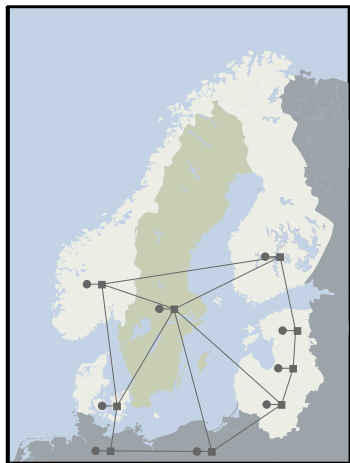
Background - Motivation

- ▶ Simulation of hydro power operations → Decision-support
 - ▶ Price forecasts
 - ▶ Irregular power production: solar and wind
 - ▶ Nuclear power phase-out



Background - Motivation

- ▶ Simulation of hydro power operations → Decision-support
 - ▶ Price forecasts
 - ▶ Irregular power production: solar and wind
 - ▶ Nuclear power phase-out
- ▶ Common: Trade-off between accuracy and computation time



2017

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2041



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Figure: Simulations of hydro power operations



Background - Aim

Provide reliable decision-support in real time



Background - Aim

Provide reliable decision-support in real time

- ▶ Accurate models
- ▶ Fast computations



Background - Aim

Provide reliable decision-support in real time

- ▶ Accurate models
 - ▶ Optimal model reductions
- ▶ Fast computations



Background - Aim

Provide reliable decision-support in real time

- ▶ Accurate models
 - ▶ Optimal model reductions
- ▶ Fast computations
 - ▶ Scalable algorithms that make efficient use of commodity hardware



Background - Approach

Stochastic programming for hydro power operations:

- ▶ Optimal orders on the day-ahead market
- ▶ Maintenance scheduling
- ▶ Long-term investments
- ▶ Wind/solar uncertainties



Background - Approach

Stochastic programming for hydro power operations:

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- ▶ Maintenance scheduling
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Improvements

- ▶ Multiple scenarios → More accurate models
- ▶ Parallel decomposition → Faster computations



Background - Approach

Stochastic programming for hydro power operations:

- ▶ **Optimal orders on the day-ahead market**
- ▶ Maintenance scheduling
- ▶ Long-term investments
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Problem Description - Scandinavian Electricity Market

Electricity markets in Scandinavia deregulated since 90s

- ▶ Norway 1991
- ▶ Sweden 1996
- ▶ Finland 1998
- ▶ Denmark 2000



Problem Description - Scandinavian Electricity Market

Electricity markets in Scandinavia deregulated since 90s

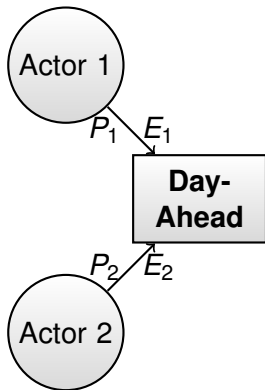
- ▶ Norway 1991
- ▶ Sweden 1996
- ▶ Finland 1998
- ▶ Denmark 2000

Energy volumes actively traded on a competitive market: Nord Pool

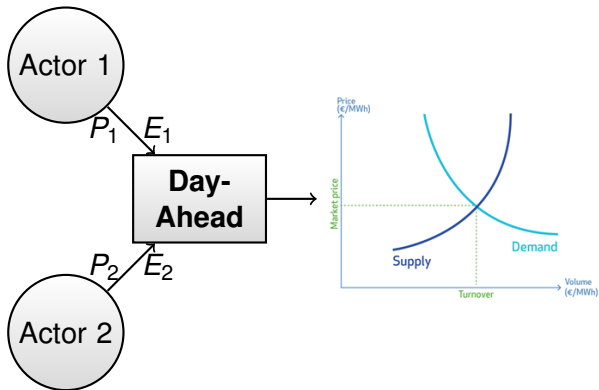
- ▶ Day-ahead market
- ▶ Intraday market



Problem Description - Electricity Market

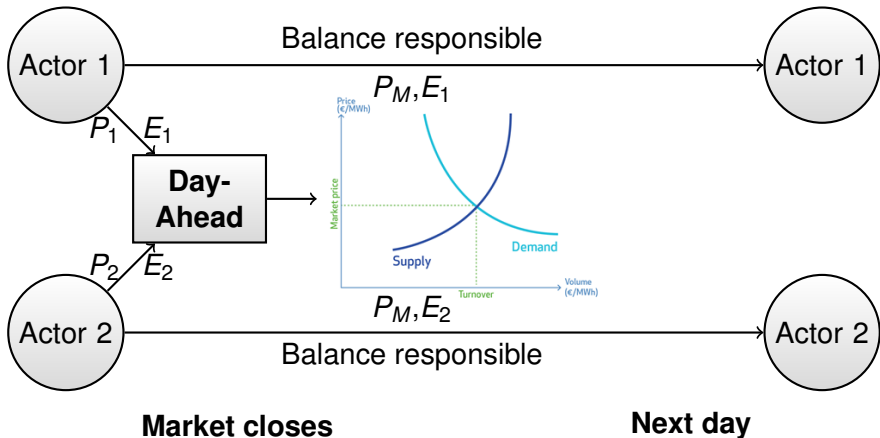


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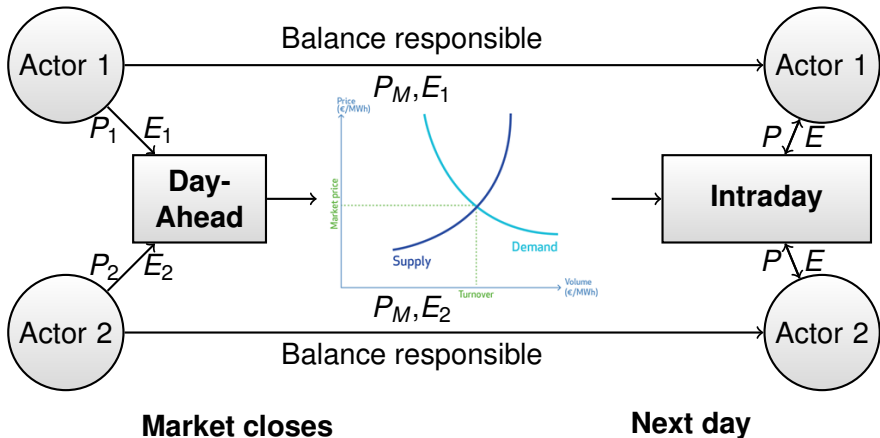


Market closes

Problem Description - Electricity Market



Problem Description - Electricity Market





Problem Description - The Day-Ahead Market

Order Types

- ▶ Single Hourly Order
 - ▶ Price independent
 - ▶ Price Dependent
- ▶ Block Order
 - ▶ Regular
 - ▶ Linked
- ▶ Exclusive Group
- ▶ Flexible Order



Problem Description - The Day-Ahead Market

Order Types

- ▶ **Single Hourly Order**
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 - ▶ Price Dependent
- ▶ **Block Order**
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- ▶ Exclusive Group
- ▶ Flexible Order

Problem Description - Single Order

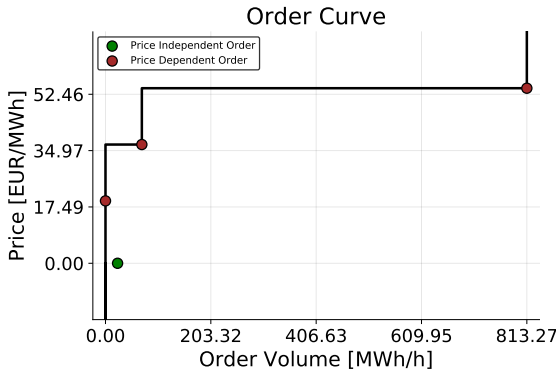


Figure: Single hourly order

Problem Description - Single Order

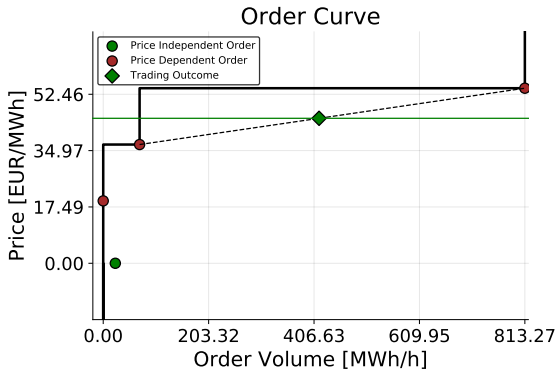


Figure: Interpolated energy volume for a given market price

Block Order



Figure: Block order between 00:00-15:00

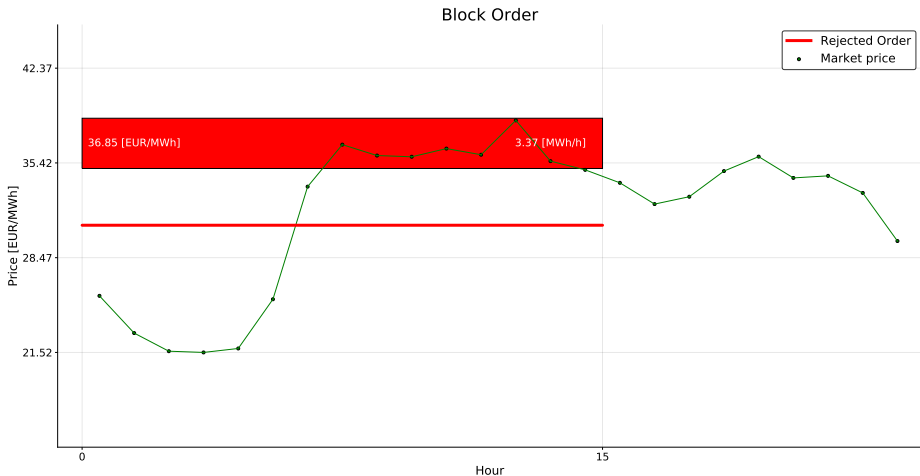


Figure: Rejected after market price settlement

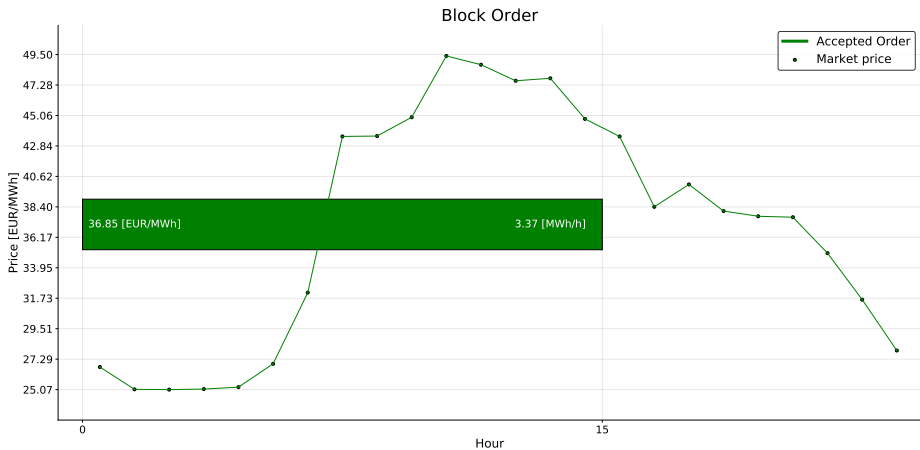


Figure: Accepted after market price settlement



Problem Description - Optimal Order Strategies

- ▶ Optimal orders given price forecasts
- ▶ Price taking hydro power producer
- ▶ Next day production governed by hydroelectric model



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Contribution - Model Framework

Data

- ▶ Physical data of Swedish hydro power stations
 - ▶ Topologies
 - ▶ Capacities
 - ▶ Flow times
- ▶ Financial data from Nord Pool
 - ▶ historic prices



Contribution - Model Framework

Data

- ▶ Physical data of Swedish hydro power stations
 - ▶ Topologies
 - ▶ Capacities
 - ▶ Flow times
- ▶ Financial data from Nord Pool
 - ▶ historic prices

Julia: JuMP + StructJuMP

- ▶ Domain-specific modeling language for mathematical optimization
- ▶ Optimization models can be processed programmatically

HydroModels.jl

Variables

```
# =====  
@variable(internalmodel, xt_d[i = model.bids, t = model.hours] >= 0)  
@variable(internalmodel, yt[t = model.hours] >= 0)  
@variable(internalmodel, H[t = model.hours] >= 0)
```

Define objective

```
# =====  
@objective(internalmodel, Max, net_profit + value_of_stored_water)
```

Constraints

```
# =====  
# Load balance  
@constraint(internalmodel, loadbalance[s = model.scenarios, t = model.hours],  
            yt[s, t] + sum(yb[s, b]  
                           for b = find(A->in(t, A), model.hours_per_block))  
            - H[s, t] == z_up[s, t] - z_do[s, t]  
            )
```

HydroModels.jl

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            )  
            +
```

Byarforsen	134	134	17	200	0	0	124	75	75 Ljusnan
Krokstrommen	135	135	100	200	0	830	130	30	30 Ljusnan
Langstrommen	136	136	48	180	0	278	131	25	40 Ljusnan
Storastrommen	137	137	24	180	0	556	142	35	35 Ljusnan
Ojeforsen	138	138	25	190	0	278	143	55	55 Ljusnan
Laforsen	139	139	57	190	0	830	149	280	280 Ljusnan

HydroModels.jl

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    +
```

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Laforsen	139	139	57	190	0	830	149	280	280 Ljusnan

=

```
data = HydroModelData("data/plantdata.csv", "data/spotpricedata.csv")
dayahead = DayAheadModel(data, 5, "Ljusnan")
plan!(dayahead)
```



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Contribution - Stochastic Day-Ahead Model

maximize Profit + Water Value – Balance Cost

subject to Day-Ahead Orders

 Physical Limitations

 Economic/Legal Limitations



Contribution - Stochastic Day-Ahead Model

Day-Ahead Orders - $\mathbf{x} \in \mathcal{X}$

- ▶ Indices $t \in T := \{1, \dots, 24\}$, $b \in B := \{b = (t_a, \dots, t_b) : t_j \in T\}$
- ▶ Price independent: $x_t^i \geq 0$
- ▶ Price dependent: $0 \leq x_{i,t}^d \leq x_{i,t+1}^d$
- ▶ Block: $x_{j,b}^b \geq 0$



Contribution - Stochastic Day-Ahead Model

Day-Ahead Orders - $\mathbf{x} \in \mathcal{X}$

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- ▶ Block: $x_{j,b}^b \geq 0$

Scenario Outcomes - $\mathbf{y} \in \mathcal{Y}(\mathbf{x}, \xi)$

$$y_t = x_t^i + \frac{\rho_t^\xi - p_i}{p_{i+1} - p_i} x_{i+1,t}^d + \frac{p_{i+1} - \rho_t^\xi}{p_{i+1} - p_i} x_{i,t}^d, \quad p_i \leq \rho_t^\xi \leq p_{i+1}$$

$$y_b = \sum_{j=1}^{\bar{j}(b)} x_{j,b}, \quad \bar{j}(b) = \max \left\{ i : p_i \leq \frac{1}{|b|} \sum_{t \in b} \rho_t^\xi \right\}$$



Contribution - Stochastic Day-Ahead Model

Next Day Production - $\mathbf{h} \in \mathcal{H}(\mathbf{y})$

- ▶ Indices $p \in P := \{\text{All power stations operable by the producer}\}$
- ▶ Water discharge/spillage: $0 \leq Q_{p,t} \leq \bar{Q}_p, S_{p,t} \geq 0$
- ▶ Reservoir content: $0 \leq M_{p,t} \leq \bar{M}_p$
- ▶ Energy production: $H_{p,t} \geq 0$
- ▶ Local inflow/outflow: V_p
- ▶ Power imbalances: $z_t^+, z_t^- \geq 0$



Contribution - Stochastic Day-Ahead Model

Next Day Production - $\mathbf{h} \in \mathcal{H}(\mathbf{y})$

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- ▶ Power imbalances: $z_t^+, z_t^- \geq 0$

Load Balance

$$L(\mathbf{y}, \mathbf{h}) : y_t + \sum_{b \in B: t \in b} y_b - \sum_p H_t = z_t^+ - z_t^-$$

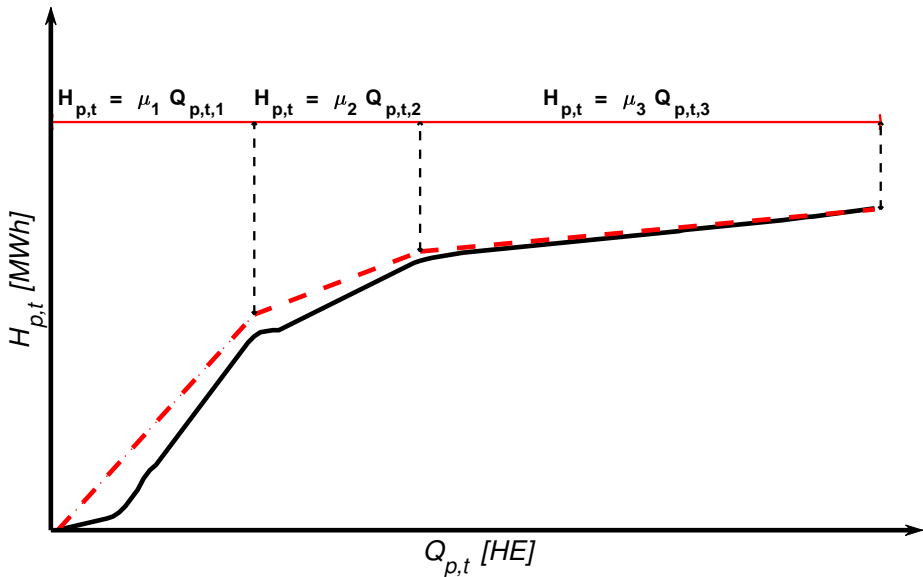
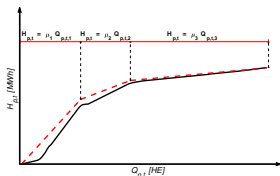


Figure: Piecewise linear production equivalent

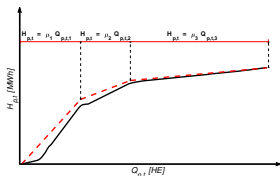
Hydro power production



$$\rightarrow H_{p,t} = \sum_s \mu_{p,s} Q_{p,t,s}$$

Figure: Piecewise linear production equivalent

Hydro power production



$$\rightarrow H_{p,t} = \sum_s \mu_{p,s} Q_{p,t,s}$$

Figure: Piecewise linear production equivalent

Hydrological balance

$$M_{p,t} = M_{p,t-1} - Q_{p,t} - S_{p,t} + \sum_{p_q \in Q_u} Q_{p_q,t-\tau_{p_q}} + \sum_{p_s \in S_u} S_{p_s,t-\tau_{p_s}} + V_p$$



Contribution - Stochastic Day-Ahead Model

Water value

$$W(\mathbf{h}) = \lambda_f \sum_p M_{p,24} \sum_{pq \in Q_{d,s}} \mu_{pq,s}$$



Contribution - Stochastic Day-Ahead Model

Water value

$$W(\mathbf{h}) = \lambda_f \sum_p M_{p,24} \sum_{pq \in Q_{d,s}} \mu_{pq,s}$$

Profit

$$\Pi(\mathbf{y}) = \sum_t \rho_t^\xi y_t + \sum_b |b| \bar{\rho}_b^\xi y_b - \sum_t (\lambda_t^+ z_t^+ - \lambda_t^- z_t^-)$$



Contribution - Stochastic Day-Ahead Model

Water value

$$W(\mathbf{h}) = \lambda_f \sum_p M_{p,24} \sum_{pq \in Q_{d,s}} \mu_{pq,s}$$

Profit

$$\Pi(\mathbf{y}) = \sum_t \rho_t^\xi y_t + \sum_b |b| \bar{\rho}_b^\xi y_b - \sum_t (\lambda_t^+ z_t^+ - \lambda_t^- z_t^-)$$

Objective

$$Q(\mathbf{y}, \mathbf{h}, \xi) = W(\mathbf{h}) + \Pi(\mathbf{y})$$



Contribution - Stochastic Day-Ahead Model

Complete Model

$$\min \mathbb{E}_{\xi} [Q(\mathbf{y}, \mathbf{h}, \xi)]$$

$$\text{s.t. } \mathbf{x} \in \mathcal{X}$$

$$\mathbf{y} \in \mathcal{Y}(\mathbf{x}, \xi)$$

$$\mathbf{h} \in \mathcal{H}(\mathbf{y})$$

$$L(\mathbf{y}, \mathbf{h}) = 0$$



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Contribution - Optimization Algorithms

Benders decomposition for stochastic programming



Contribution - Optimization Algorithms

Benders decomposition for stochastic programming

- ▶ L-Shaped [Van Slyke, Wets]



Contribution - Optimization Algorithms

Benders decomposition for stochastic programming

- ▶ L-Shaped [Van Slyke, Wets]
- ▶ Regularized Decomposition [Ruszczynski]



Contribution - Optimization Algorithms

Benders decomposition for stochastic programming

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- ▶ Regularized Decomposition [Ruszczynski]
- ▶ Trust-Region L-Shaped [Linderoth,Wright]



Contribution - Optimization Algorithms

Benders decomposition for stochastic programming

- ▶ L-Shaped [Van Slyke,Wets]
- ▶ Regularized Decomposition [Ruszczynski]
- ▶ Trust-Region L-Shaped [Linderoth,Wright]

LShaped.jl

```
ls = LShapedSolver(model, x0)
rls = RegularizedLShapedSolver(model, x0)
trls = TrustRegionLShapedSolver(model, x0)
```



Contribution - Parallel Optimization Algorithms

The algorithms are cutting-plane methods:

- ▶ Solve subproblems and generate cutting-planes
- ▶ Update and resolve a master problem

$$\begin{array}{ll} \min & c^T x + \mathbb{E}_{\xi} \left[\min_{y \in \mathcal{Y}(x)} Q(y, \xi) \right] \\ \text{s.t.} & x \in \mathcal{X} \end{array} \quad \rightarrow \quad \begin{array}{ll} \min & c^T x + \sum_{i=1}^n \theta_i \\ \text{s.t.} & x \in \mathcal{X} \\ & \partial Q_i x + \theta_i = q_i \end{array}$$



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Readily extendable to asynchronous variants

- ▶ Master problem is solved on a master node
- ▶ Subproblems are distributed among workers



Contribution - Parallel Optimization Algorithms

Idea to exploit structure and make use of commodity hardware



Contribution - Parallel Optimization Algorithms

Idea to exploit structure and make use of commodity hardware

- ▶ Linear subproblems have the same underlying matrix structure



Contribution - Parallel Optimization Algorithms

Idea to exploit structure and make use of commodity hardware

- ▶ Linear subproblems have the same underlying matrix structure
 - ▶ LU factorize once and store on GPU
 - ▶ Reuse for efficient linear solves during simplex iterations



Contribution - Summary

- ▶ HydroModels.jl
 - ▶ Possible to extend to other models of hydro power operations
- ▶ Day-Ahead Model
 - ▶ Optimization formulation
 - ▶ Visualization tools
- ▶ LShaped.jl
 - ▶ 3 fully implemented serial L-Shaped variants
 - ▶ 1 parallel implementation (work in progress)



Contribution - Summary

- ▶ HydroModels.jl
 - ▶ Possible to extend to other models of hydro power operations
 - ▶ Modular
- ▶ Day-Ahead Model
 - ▶ Optimization formulation
 - ▶ Visualization tools
- ▶ LShaped.jl
 - ▶ 3 fully implemented serial L-Shaped variants
 - ▶ 1 parallel implementation (work in progress)
 - ▶ Modular



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Example 1: Ljusnan

Example 2: All rivers

Outlook on Future Work



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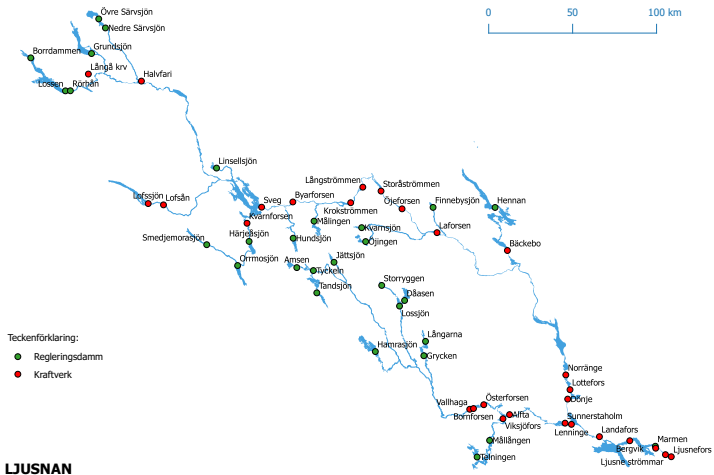


Figure: Courtesy of VRF (<http://www.vattenreglering.se/>)



Example 1: Ljusnan

- ▶ 21 power stations
- ▶ 5 price curves from historic data



Example 1: Ljusnan

- ▶ 21 power stations
- ▶ 5 price curves from historic data

Day-Ahead model with:

- ▶ 9305 linear constraints
- ▶ 18274 variables

Example 1: Single Order

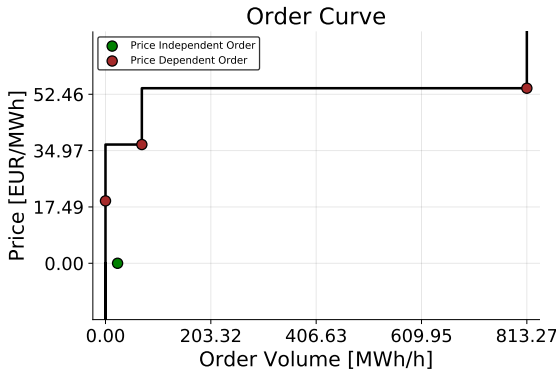


Figure: Single order during the first hour



Figure: All single orders in optimal strategy

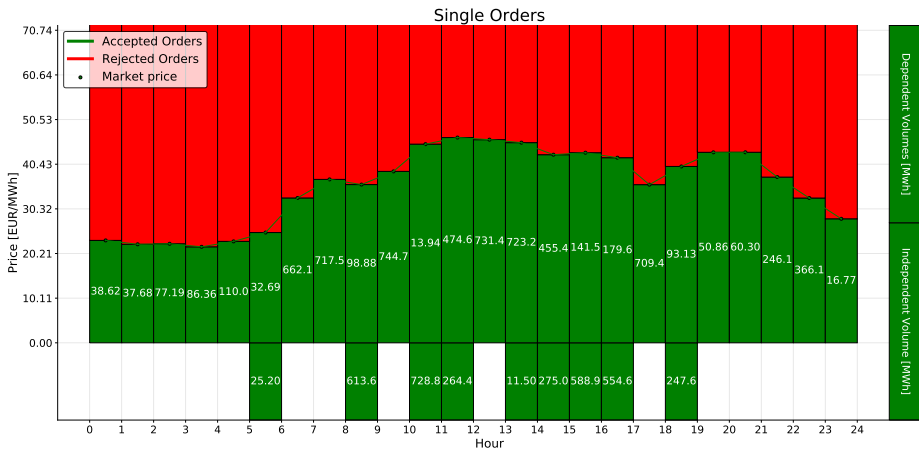


Figure: Single order outcome of optimal strategy, for a given price curve

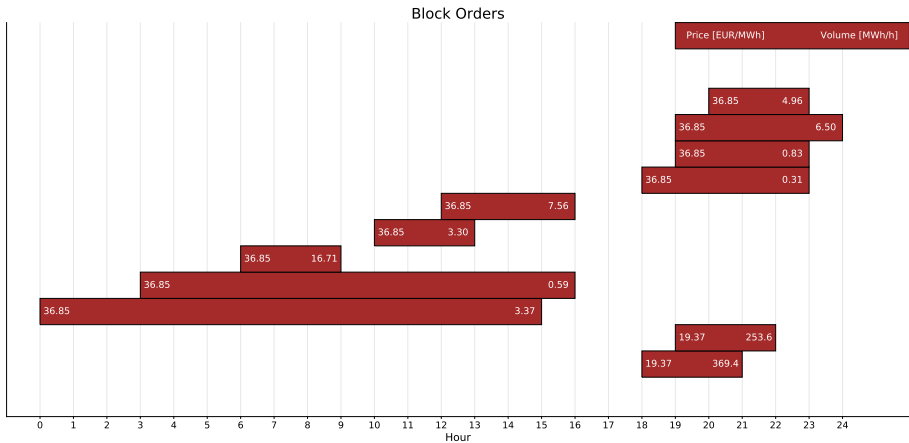


Figure: All block orders in optimal strategy

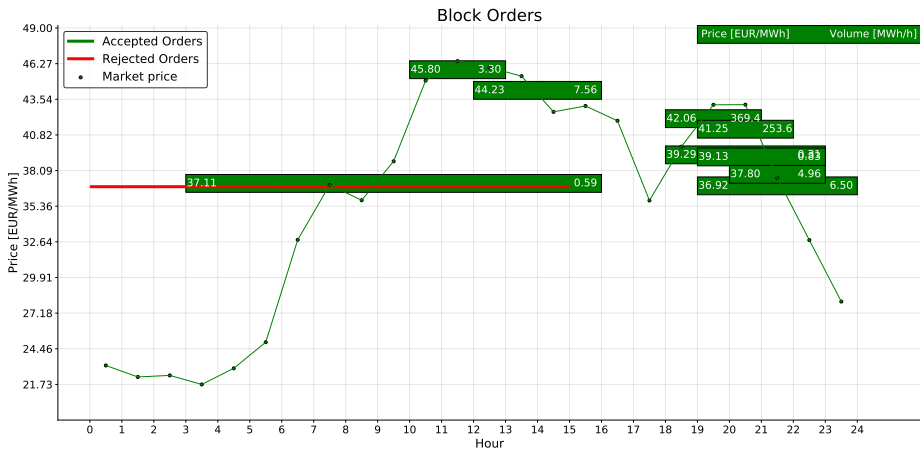


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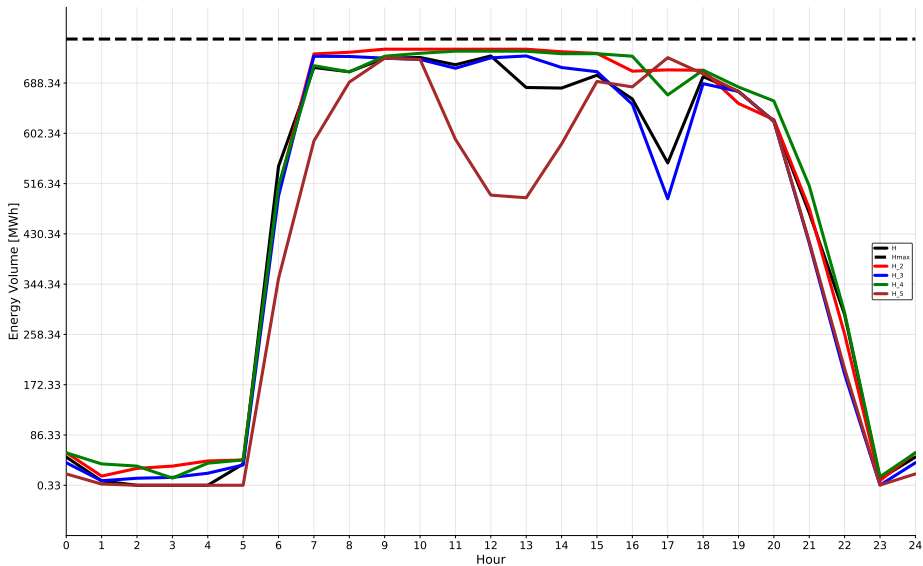


Figure: Energy production in all scenarios



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Example 1: Ljusnan

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Example 2: All rivers

- ▶ 257 power stations
- ▶ 20 price curves from historic data



Example 2: All rivers

- ▶ 257 power stations
- ▶ 20 price curves from historic data

Day-Ahead model with:

- ▶ 376700 linear constraints
- ▶ 748043 variables

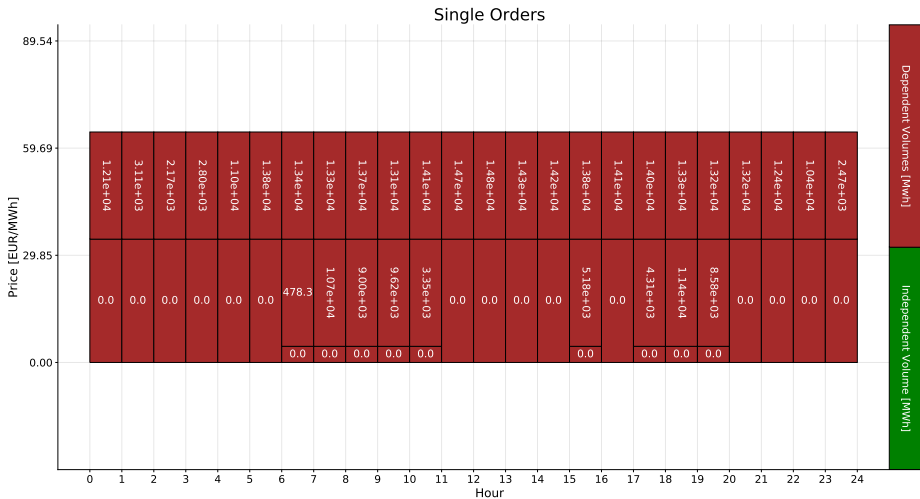


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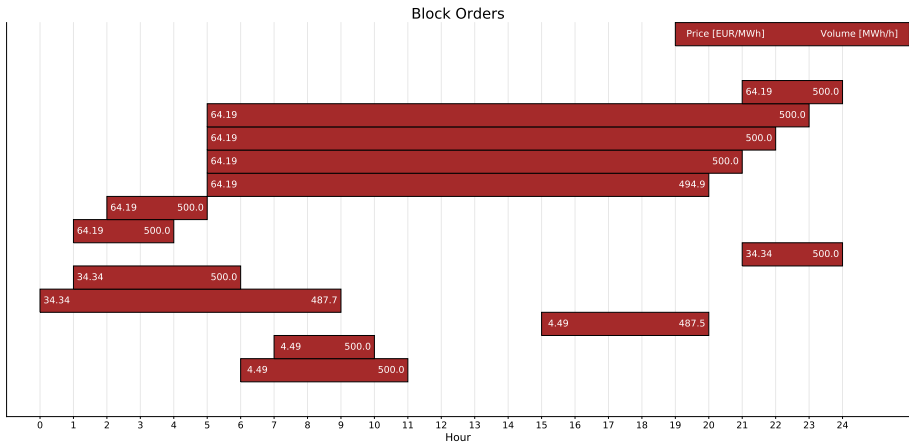


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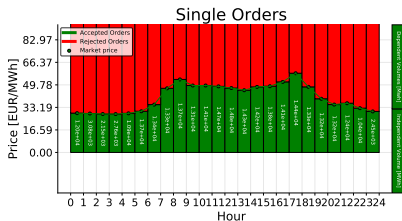
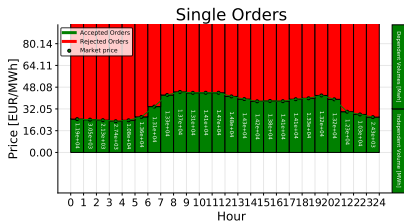
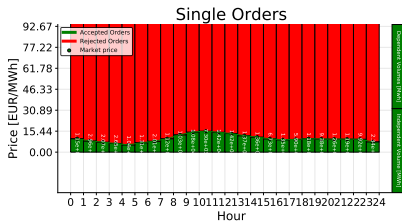
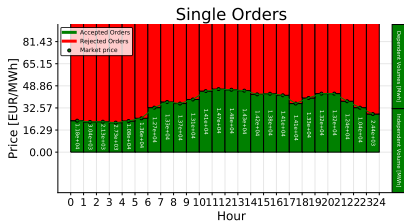


Figure: Single order outcomes of optimal strategy, for 4 different price curves

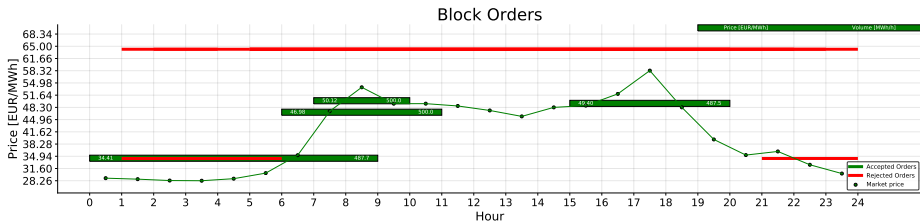
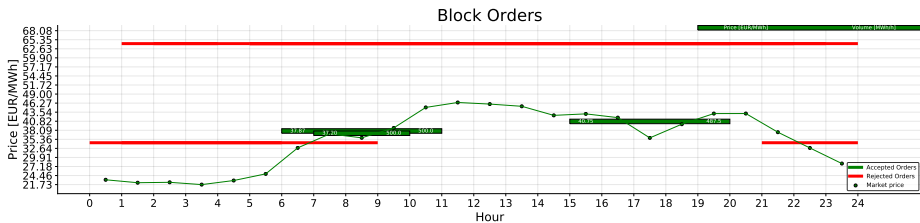


Figure: Block order outcomes of optimal strategy, for two given price curves

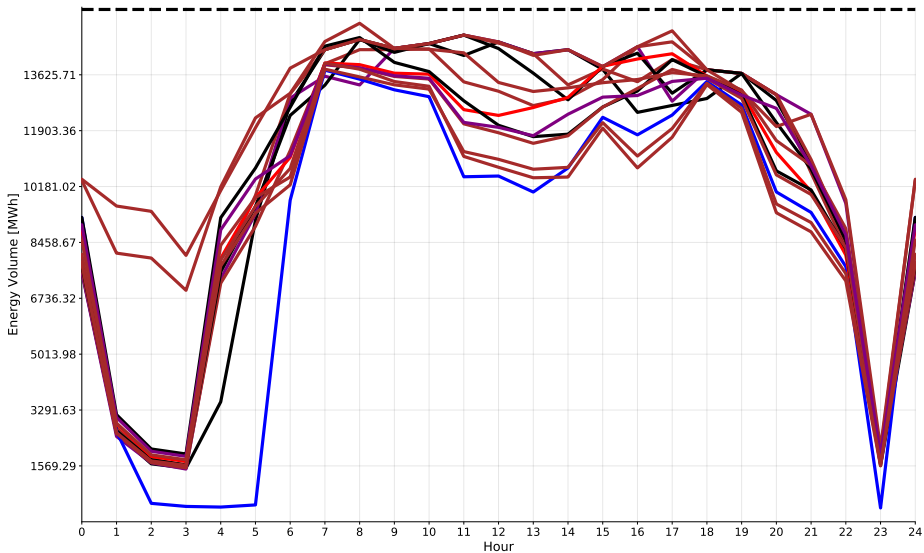


Figure: Energy production in all scenarios



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Optimization Algorithms



Future Work

Model framework

- ▶ Implement more models of hydro power operations

Day-Ahead Model

Optimization Algorithms



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Day-Ahead Model

- ▶ Generate price curves from statistic model
- ▶ Allow varying order prices

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Model framework

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Day-Ahead Model

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Optimization Algorithms

- ▶ Finish parallel variants
- ▶ Evaluate on day-ahead model