



Very-Short Term Forecasting of Electricity Price Signals Using a Pareto Composition of Kernel Machines in Smart Power Systems

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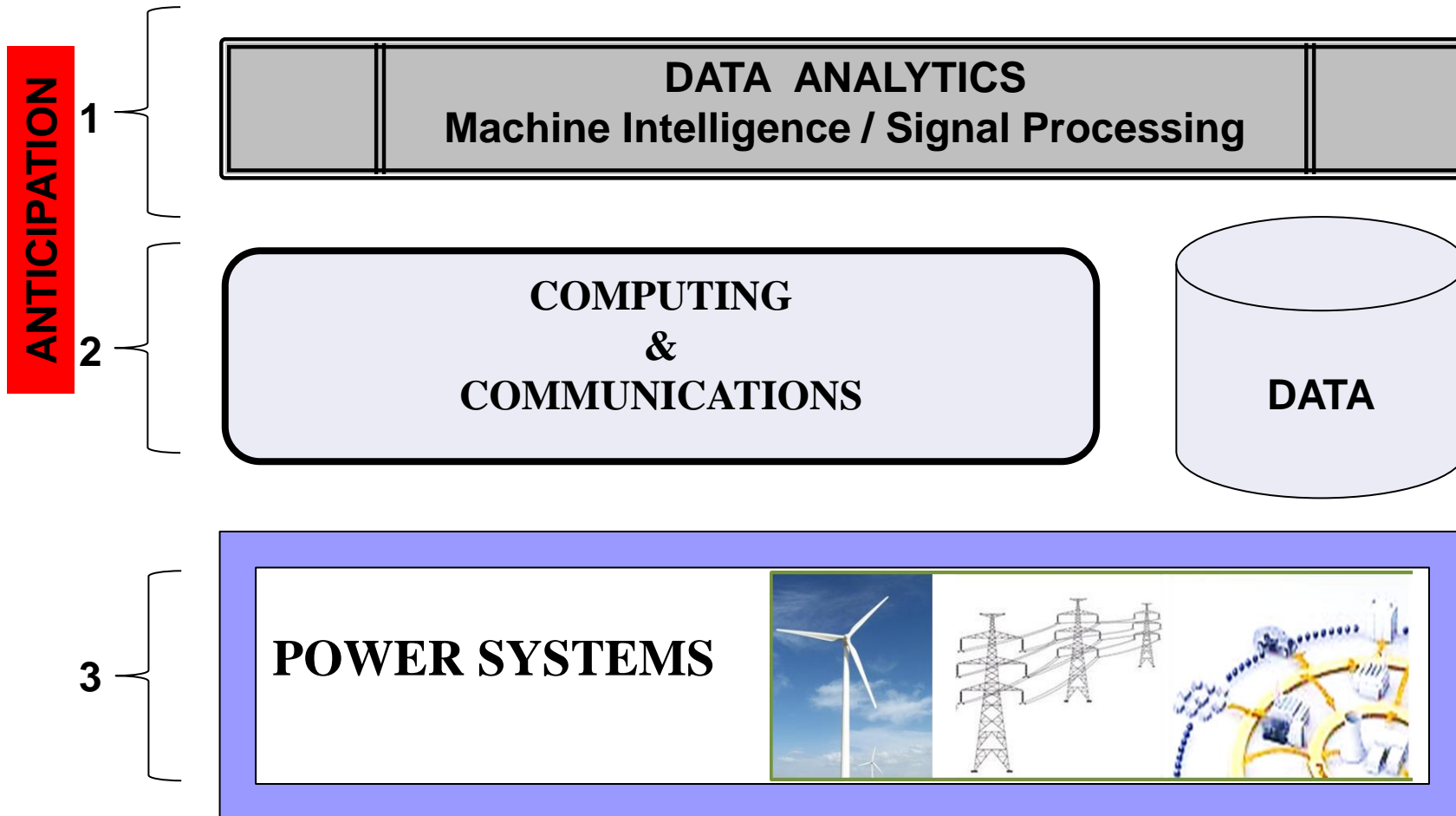
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Outline

- Intelligent Energy Systems
- CIMEG-Energy Internet
- Methodology
 - Kernel Machines
 - Pareto Formulation
- Results
- Summary / Questions

Smart Power Systems

Main Components

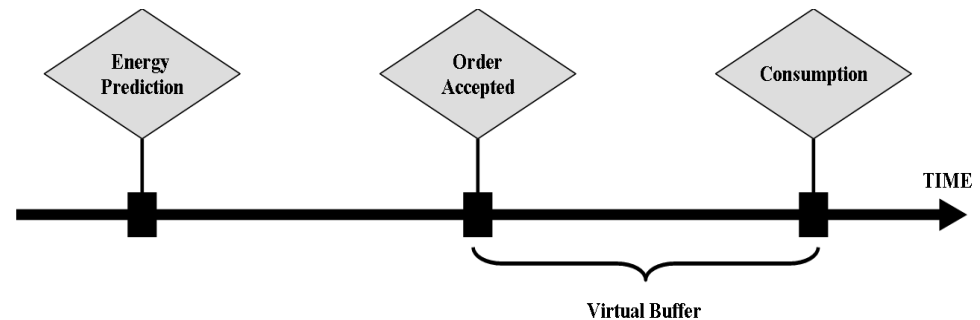


Consortium for Intelligent Management of Electric Grid (CIMEG)

ENERGY INTERNET

- Intelligent agents:
 - Anticipate Load
- Intelligent meters
 - Negotiate with suppliers
 - Place orders
- Suppliers and generators
 - Maximize gain
 - Keep power demand below optimal generation levels

Virtual Buffer (Storage)



Picture taken from: Alamaniotis, Miltiadis, Rong Gao, and Lefteri H. Tsoukalas. "Towards an energy internet: A game-theoretic approach to price-directed energy utilization." *Energy-Efficient Computing and Networking*. Springer Berlin Heidelberg, 2011. 3-11.

- CIMEG:
 - *Uses Elasticity models which can affect demand*
 - *Generates appropriate pricing signals*
 - *Allows consumers to update demand*

Problem in Energy Internet

- Strategy of updating demand
 - Respond with demand
 - How to modify demand?
 - What to expect from supplier?
- Need to know the electricity price signal
 - Prices of a very short term ahead of time horizon
- Price Signal
 - High fluctuation and variability
 - Dynamic

Motivation

- Very Short Term Price Forecasting
 - Prices in the next few hours
 - Strategy of Demand Updates
 - Decisions based on price forecasts
- Automated method
 - Captures price dynamics
 - Develop a framework fusing different prognoses under a single umbrella

Relevance Vector Machines (RVM)

- Kernel Functions

- Dual Formula: $k(x_1, x_2) = \varphi(x_1)^T \varphi(x_2)$

- Parametric Models

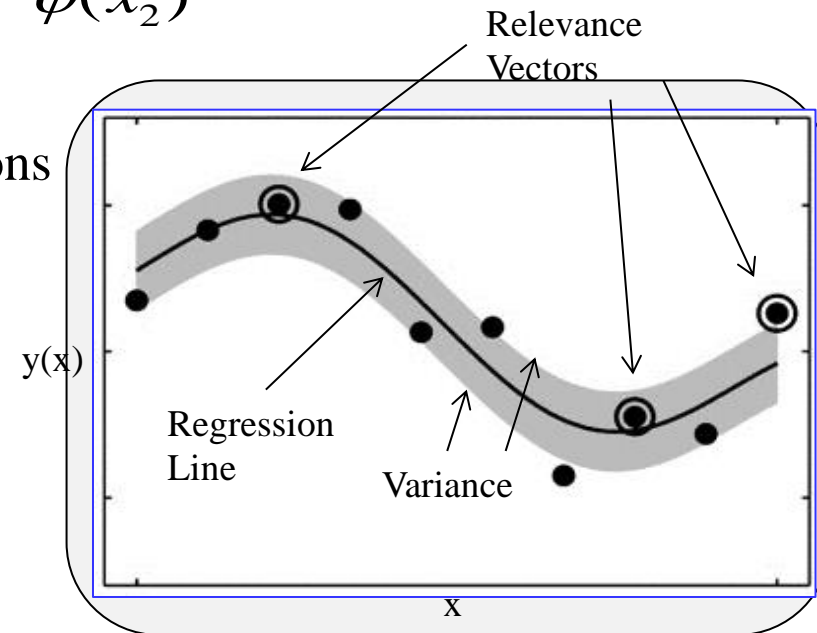
- Linear Combination of Kernel Functions

- RVM Regression

$$y(x) = \sum_{n=1}^N w_n k(x, x_n) + b$$

- Training points for which w is not zero are called relevance vectors

- Weights are evaluated via a Maximum Likelihood Schema



Gaussian Process for Machine Learning

Figure may be found at:
www.rainsoft.de/projects/gauspro.html

- In machine learning:

- Gaussian Processes are identified as the *probabilistic extension* of kernel methods
- Prior distribution over functions:
- Predictive distribution: $p(y) = N(y | 0, K)$

$$m(x_{N+1}) = k^T K_*^{-1} t$$

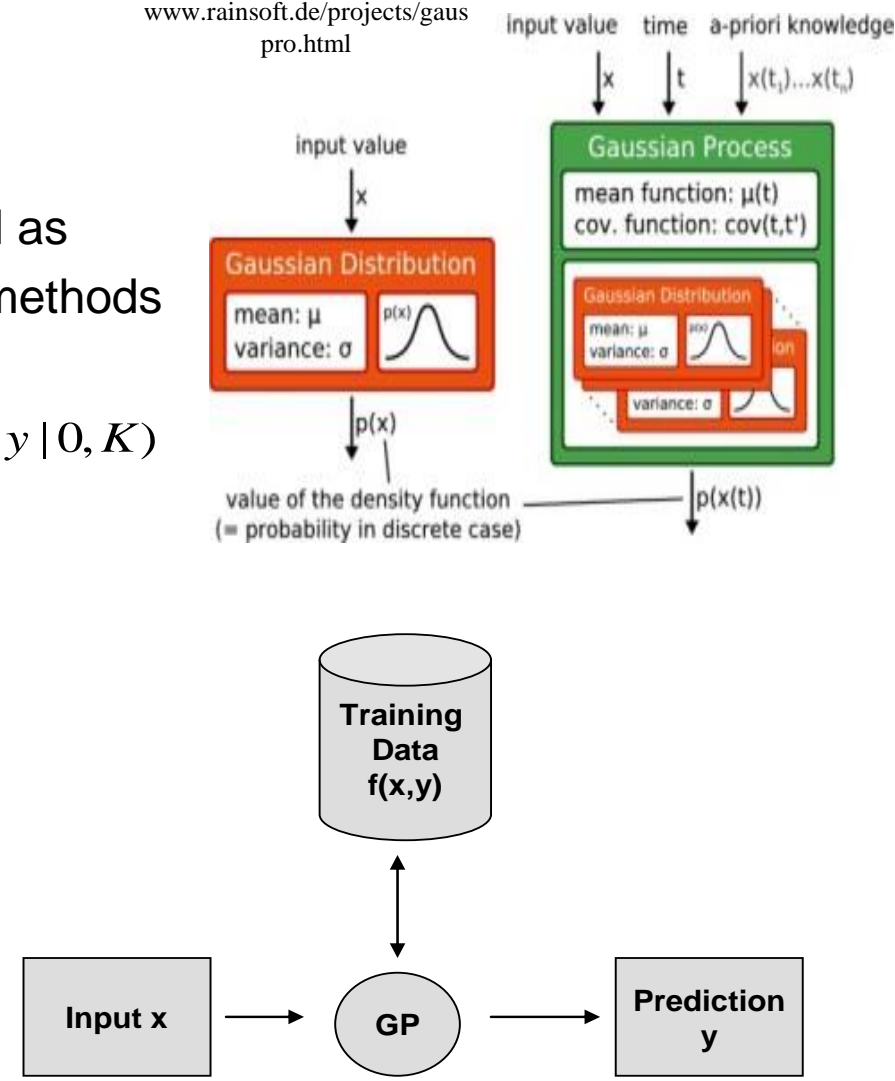
$$\sigma^2(x_{N+1}) = k_* - k^T K_*^{-1} k$$

- with K being the Gram Matrix:

$$k(x_1, x_2) = \varphi(x_1)^T \varphi(x_2)$$

- Kernels: Dual representation:

$$K_*(x_i, x_j) = k(x_i, x_j) + \sigma_n^2 \delta_{ij}$$



Pareto Optimality

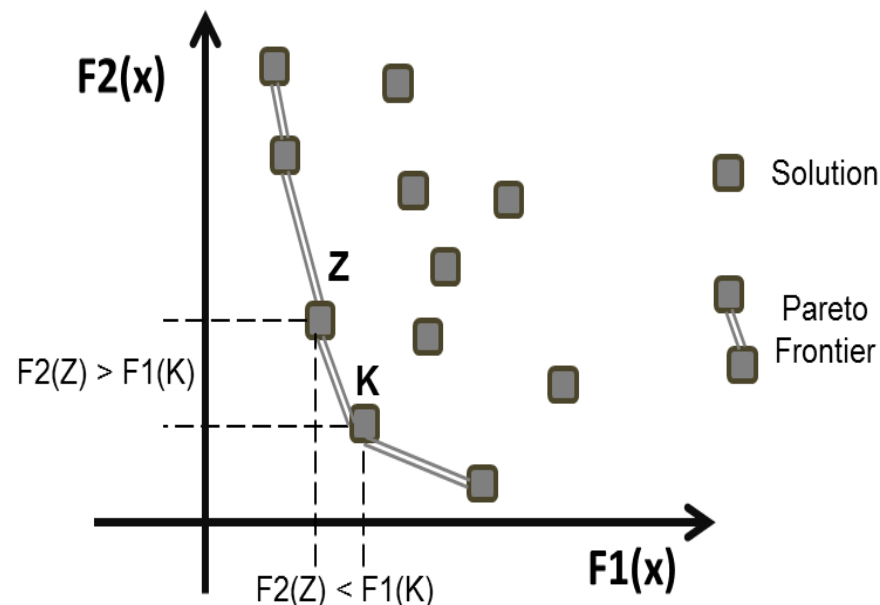
Multiobjective Optimization Problems

$$\min_{\mathbf{x}} \mathbf{C}(\mathbf{x}) = [C_1(\mathbf{x}), C_2(\mathbf{x}), \dots, C_N(\mathbf{x})]$$

$$s.t. \quad f_i(\mathbf{x}) \leq 0, \quad i = 1, \dots, k$$

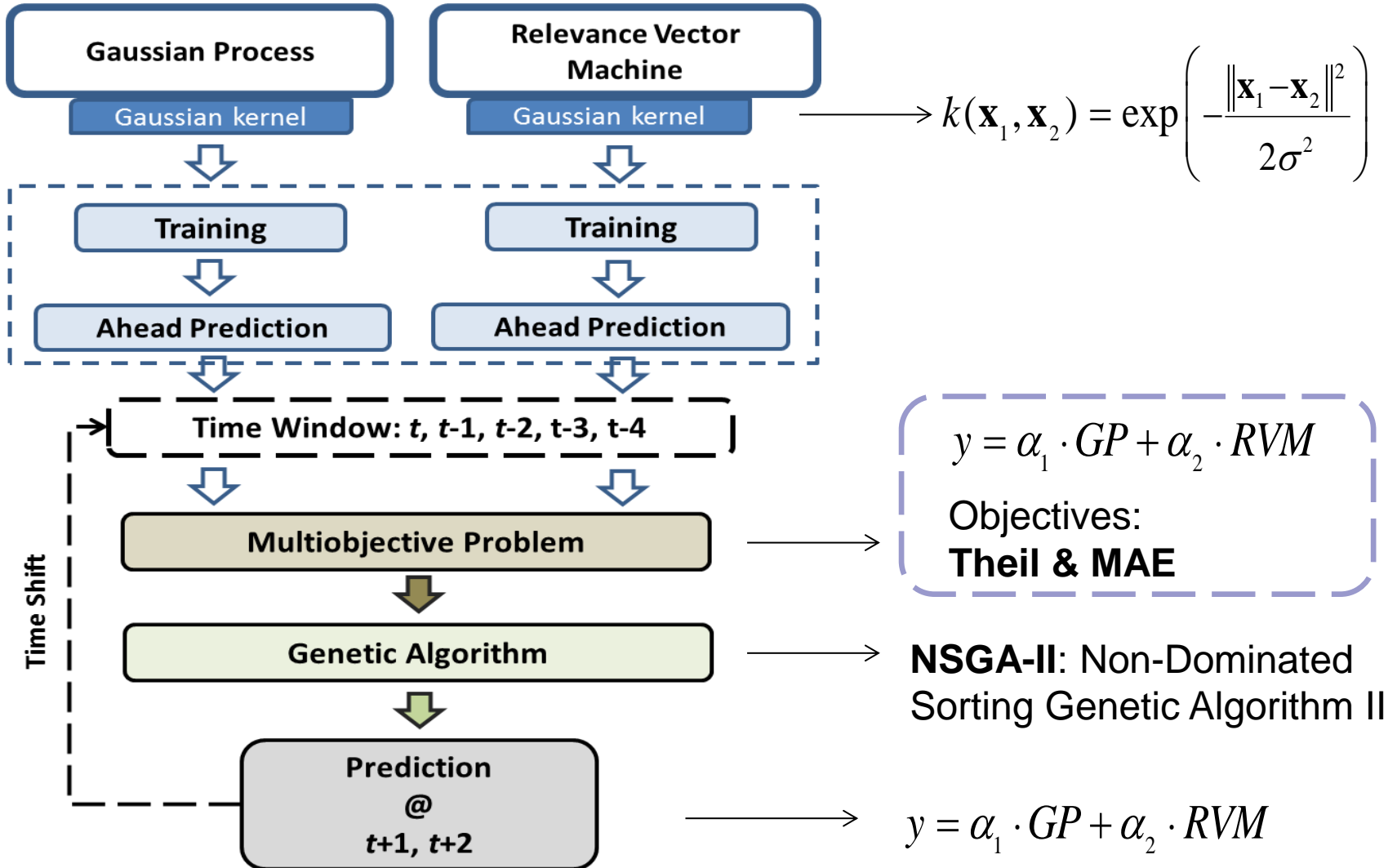
$$g_j(\mathbf{x}) = 0, \quad j = 1, \dots, m$$

A point, $\mathbf{x}^ \in \mathbf{X}$, is Pareto Optimal iff there does not exist another point, $\mathbf{x} \in \mathbf{X}$, such that $\mathbf{C}(\mathbf{x}) \leq \mathbf{C}(\mathbf{x}^*)$, and $C_i(\mathbf{x}) < C_i(\mathbf{x}^*)$ for at least one function.*



- A Pareto frontier illustration where each box represents a feasible solution.
- Boxes Z and K are part of Pareto Frontier

Methodology



Methodology Testing

- Signals of 12 different days
 - Hourly prices
 - Year 2001
 - New England Area
- Predictions every two hours
 - Learning of the five most recent prices
- Benchmark
 - Autoregressive Moving Average (6,6)
 - Akaike Information Criterion (AIC)

Results

68% MAE
59% Theil

0% MAE
0% Theil

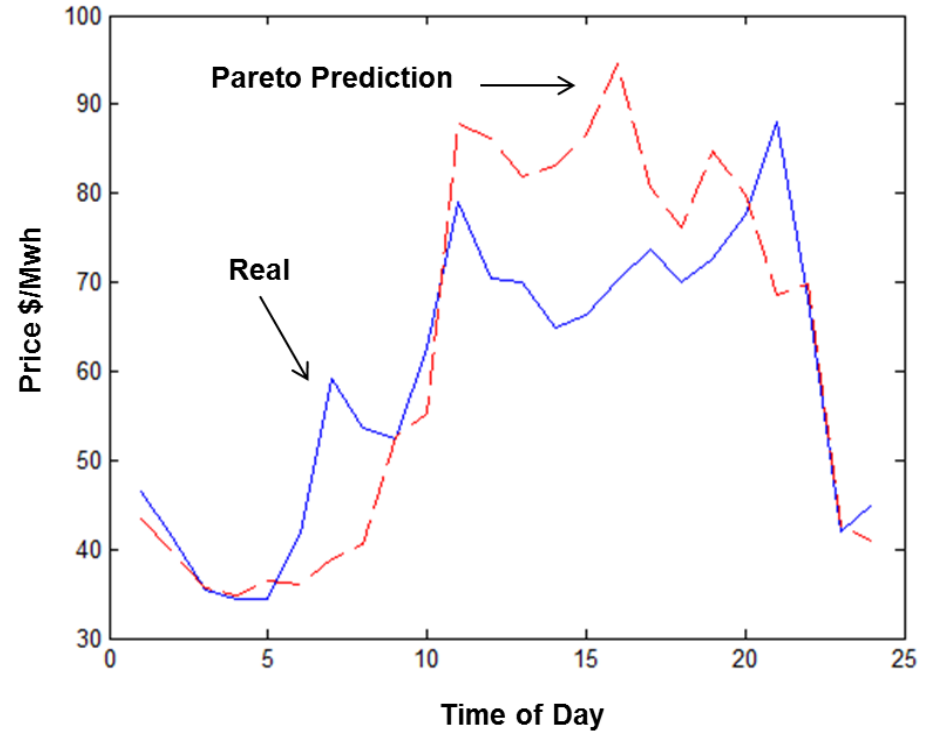
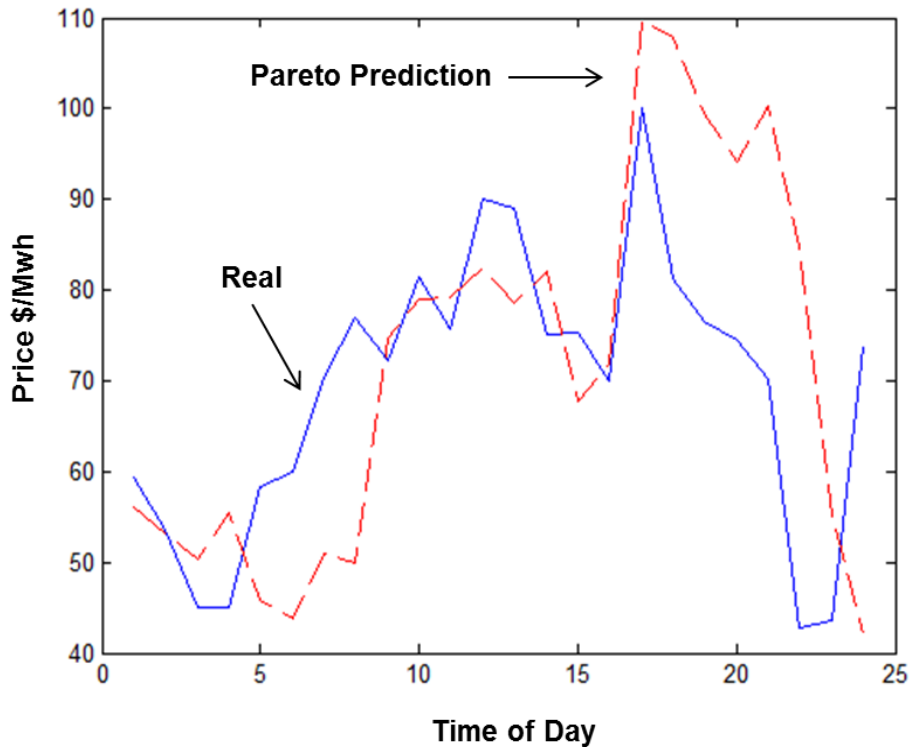
16% MAE
25% Theil

16% MAE
16% Theil

Day of 2001	Measure	Forecaster			
		Pareto	ARMA	GP	RVM
January 8	Theil	0.0035	0.0129	0.0063	0.0049
	MAE	15.8586	30.2036	29.1646	21.4047
February 10	Theil	0.0133	0.0196	0.0107	0.0111
	MAE	14.6037	20.3070	17.8090	18.7168
March 15	Theil	0.0240	0.0188	0.0048	0.0033
	MAE	12.0693	20.260	10.5353	6.5426
April 9	Theil	0.0058	0.0217	0.0125	0.0119
	MAE	9.6789	22.5575	14.6272	11.1888
May 21	Theil	0.0050	0.0129	0.0097	0.0079
	MAE	10.0982	29.625	17.0409	12.2382
June 15	Theil	0.0033	0.0212	0.0083	0.0057
	MAE	6.7777	22.74	14.4733	8.1808
July 28	Theil	0.0018	0.0325	0.0040	0.0063
	MAE	2.1970	14.10	2.6915	4.6468
August 8	Theil	0.0024	0.0150	0.0056	0.0036
	MAE	8.6252	32.5762	19.1358	10.5478
September 19	Theil	0.0040	0.0240	0.0066	0.0038
	MAE	5.3471	25.0196	9.4242	4.7013
October 11	Theil	0.0068	0.0352	0.0060	0.0125
	MAE	3.2056	13.8017	2.7463	8.0050
November 14	Theil	0.0039	0.0271	0.0038	0.0072
	MAE	3.5177	10.1411	3.2308	5.8209
December 20	Theil	0.0058	0.0367	0.0116	0.0208
	MAE	2.9191	19.2865	4.6741	10.1673

Examples - Signals

January 8, 2001



August 8, 2001

Future Work

- Testing of model
 - Larger price datasets
- Extending model
 - Various kernels
 - Validation and testing
- Modify multiobjective problems
 - Higher dimension (e.g. use of MAPE)

Conclusions

■ Energy Internet

- Negotiation among entities
- Forecasting is fundamental

■ Price Forecasting Method

- Kernel machines: GP, RVM
- Pareto Optimality: MAE, Theil

■ Results of Pareto Forecasting Method

- Testing on real world prices
- Most accurate than ARMA, GP, RVM

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Thanks for your Attention

Questions?

Comments?