Intelligent Solutions to Energy Management and Environmental Monitoring Part 2

Balázs Csanád Csáji

Joint work with: **András Kovács** & **József Váncza** *et al.*

SZTAKI: Institute for Computer Science and Control

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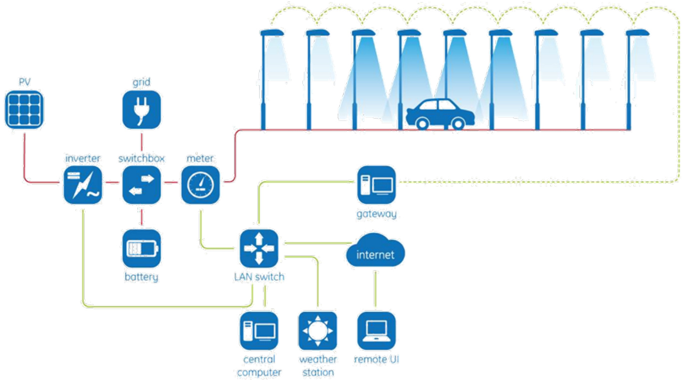
I. Energy Management

Forecasting the Energy Flow for Robust Control in E+Grid

Project: E+Grid

- Public lighting microgrid with partners: GE (General Electric), BME (Budapest University of Technology and Economics), MFA (Institute for Technical Physics and Materials Science)



Chance-Constrained Model Predictive Control

$$
\begin{aligned}
\underset{\pi \in \Pi}{\text{minimize}} \quad & \mathbb{E}\big[\, J_n^{\pi}(x_0) \,\big] \;=\; \mathbb{E}\Bigg[\, \sum_{k=0}^{n-1} \ell_k(x_k, u_{k+1}) \Bigg] \\
\text{subject to} \quad & x_0 = x_{t_0}^{*} \\
& u_k = \pi_k(x_{k-1}) \\
& x_k = f(x_{k-1}, u_k, \varepsilon_k) \\
& \mathbb{P}_{\varepsilon}\{ u \in \mathcal{U},\; x \in \mathcal{X} \} \geq 1 - \delta \\
& k = 1, \dots, n
\end{aligned}
$$

- where $x \doteq (x_0, \dots, x_n)^{\mathrm{T}}$, $u \doteq (u_0, \dots, u_n)^{\mathrm{T}}$, $\pi \doteq (\pi_1, \dots, \pi_n)$ are sequences of states, inputs and policies, respectively; $\mathcal{X}$, $\mathcal{U}$ are constraint sets; and $\{\ell_k\}$ are $\mathbb{R}$-valued immediate-cost functions.
- Furthermore, $\varepsilon \doteq (\varepsilon_1, \dots, \varepsilon_n)$ is a sequence of uncertainties, and (constant) δ is the allowed probability of constraint violation.

Modeling the Energy Balance

- To generate forecasts ("scenarios"), we model the energy balance, i.e., the difference of the energy production and the consumption.
- Let $\{\varepsilon_t\}$ be the quasi-periodic energy balance (time step: 1 hour), $\{v_t\}$ are side information, like clear sky data or historical averages.
- We can model the energy balance by NARX models, that is

$$\varepsilon_t \;=\; g(\varepsilon_{t-1}, \dots, \varepsilon_{t-p}, v_t) \,+\, n_t,$$

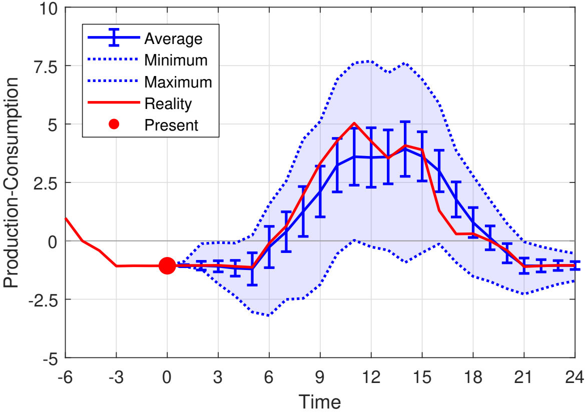
where n_t is the process noise at time t, and p is the order.
- Function g is realized by an SVR or an MLP (nonlinear) model.
- Another possible model is BJ (Box-Jenkins) that takes the form:

$$\varepsilon_t \;=\; F^{-1}(q)B(q)\, v_t + D^{-1}(q)C(q)\, n_t,$$

where B, C, D, F are finite polynomials in q^{-1} (backward shift).

Generating Trajectories

– The noise is estimated by its EDF and resampled by bootstrap.
– The figure shows generating trajectories by BJ (bootstraped noise).



Adaptive Forecast Aggregation

State Dependent Average Forecaster (SDAF)

$$\widehat{p}_t(s_t) = \frac{\sum_{i=1}^{n} \exp(-\eta\, K_{i,t-1}(s_t))\, \widehat{x}_{i,t}}{\sum_{i=1}^{n} \exp(-\eta\, K_{i,t-1}(s_t))}$$

$\widehat{x}_{i,t}$: forecast of expert i, $K_{i,t-1}$: similarity based loss; s_t : state

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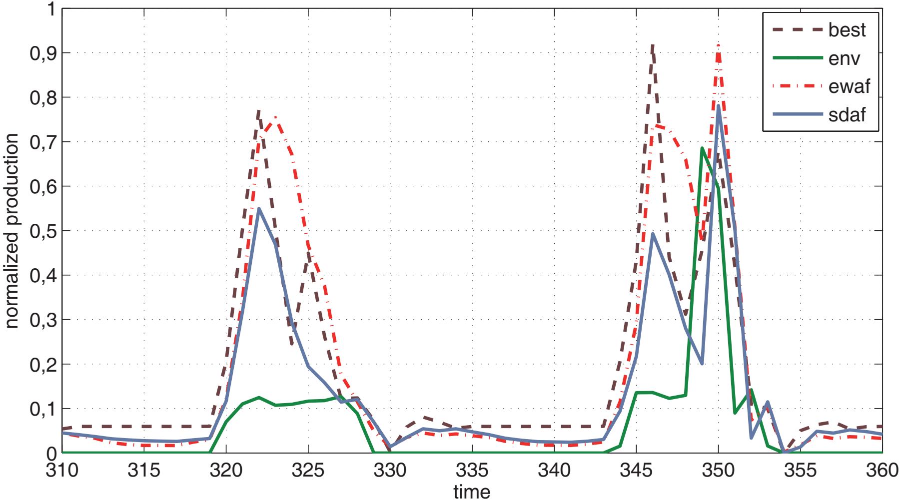
- A new forecasting approach was designed based on the framework of prediction with expert advice.
- SDAF utilizes side information through similarity kernels.
- It was used to aggregate forecasts of time-series models.
- Main advantage: better adaptation to changing environments.

Performance Evaluation

Time-Series Model		Production: Loss		Consumption: Loss	
Name	Side Info	Estimation	Validation	Estimation	Validation
FIR	+	16.92	13.94	27.15	30.18
AR	–	6.27	7.78	13.67	21.38
ARX	+	5.51	7.07	10.16	25.76
ARMA	–	5.68	7.81	16.53	22.09
BJ	+	5.15	7.06	9.17	18.31
STATE	+	5.21	6.96	9.28	26.28
HW	+	10.68	14.46	23.28	30.15
WAVE	+	4.21	9.29	6.95	20.07
MLP	–	5.24	9.83	13.64	25.04
MLPX	+	4.02	8.58	9.61	19.84
SVR	–	6.45	7.38	11.23	20.15
SVRX	+	6.37	7.18	5.37	16.43
Aggregation Method		Loss (Regret)		Loss (Regret)	
EWAF	–	4.93 (0.91)	6.89 (-0.07)	8.08 (2.71)	14.91 (-1.52)
SDAF	+	4.32 (0.30)	6.75 (-0.21)	5.43 (0.06)	14.59 (-1.84)

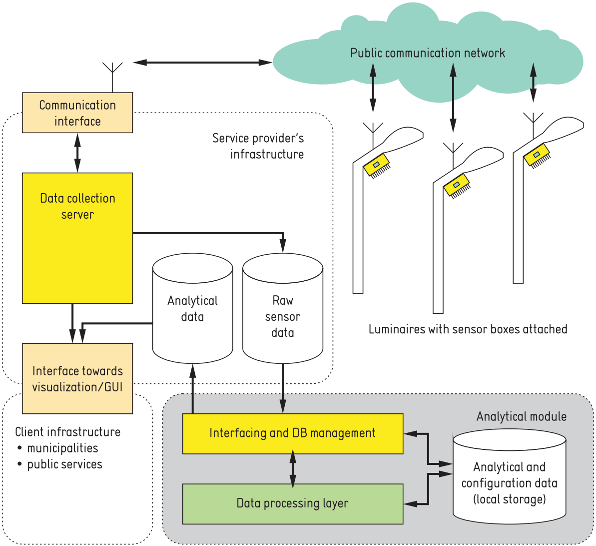
Predicting with Aggregated Forecasters



II. Environmental Monitoring

Statistical Inference in Wireless Sensor Networks for Smart Cities

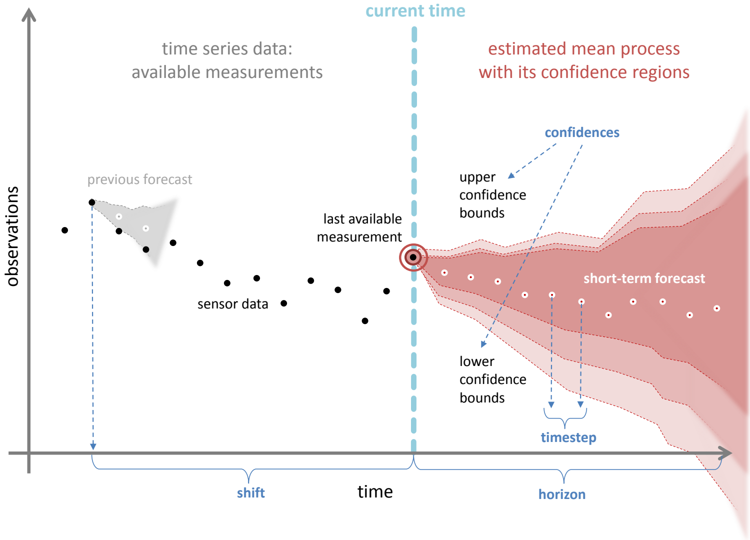
Overview of the Prototype System



Measured Stressors

	Default	Sampling interval	
Stressor	unit	minimum	maximum
particulate matter	g / m^3	10 min	60 min
environmental temperature	°C	1 min	5 min
ultraviolet irradiation (B)	index	10 min	30 min
ambient light	lux	10 min	30 min
air pressure	mbar	1 min	5 min
relative humidity	%	1 min	5 min
carbon monoxide	ppm	30 min	60 min
noise (histogram)	dBA	1 min	15 min
speed (x, y, z; histogram)	km / h	1 min	15 min
vibratory acceleration (x, y, z)	mG	1 min	10 min

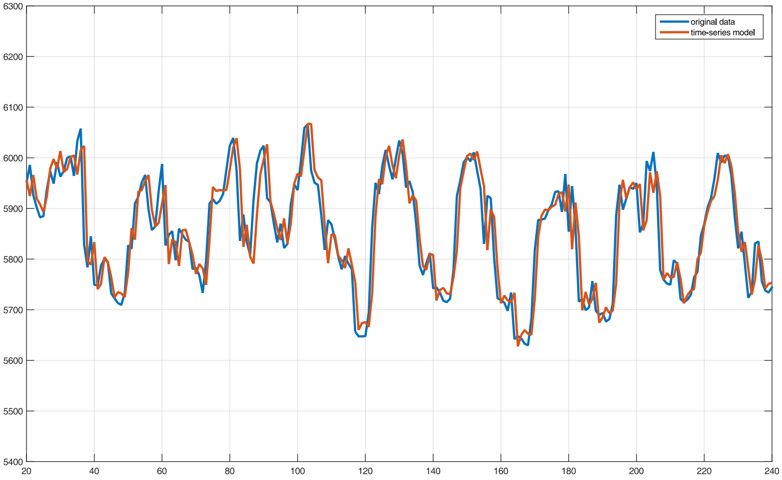
Aim: Extrapolation with Reliability Estimates



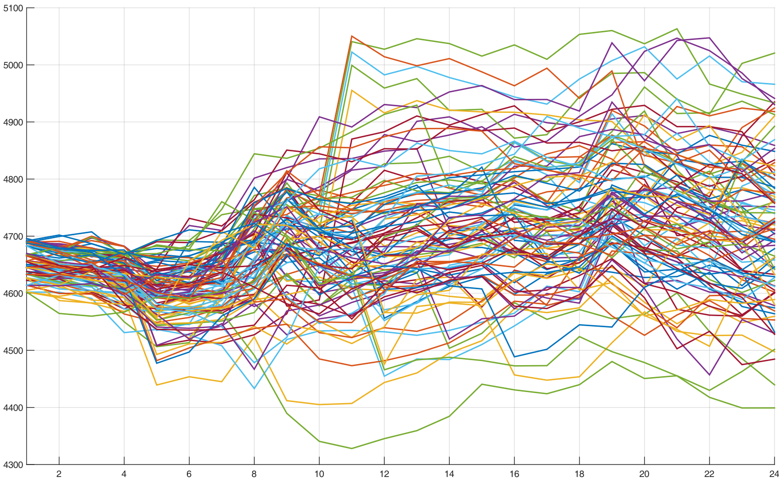
Extrapolation in Time and Space

- The main steps of pre-processing the measurements were
  - Filtering outliers (Hampel type filters were applied)
  - Discretization (to have a discrete-time process)
  - Standardization (centering and normalization)
  - Missing information (were estimated with a preliminary model)
  - Smoothing (removes high- and low- frequency disturbances)
  - Typical values (to help dealing with quasi-periodic signals)
- Then, ARX and SVR type time-series models were estimated.
- The process noise was estimated by the EDF of the residuals.
- With the process and noise models trajectories were generated.
- From these, the forecast and reliability estimates were calculated.
- The data was also extrapolated in space (not only in time) as smoothed maps with reliability estimates were constructed, as well.

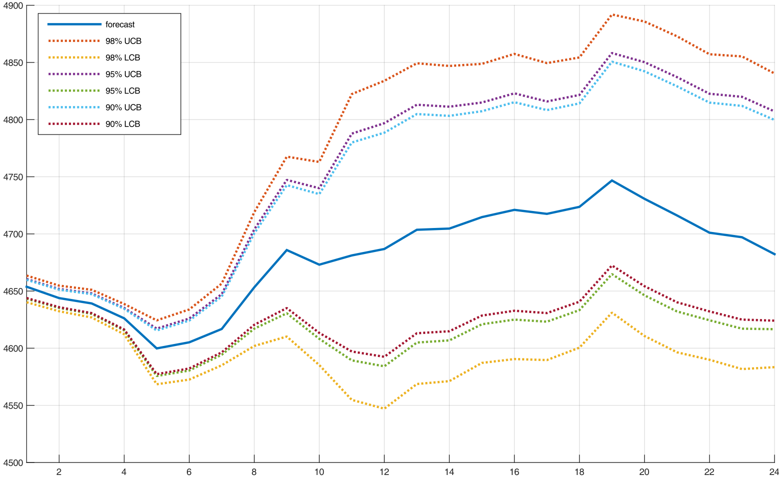
One-Step Predictions of Particle Dust with SVR



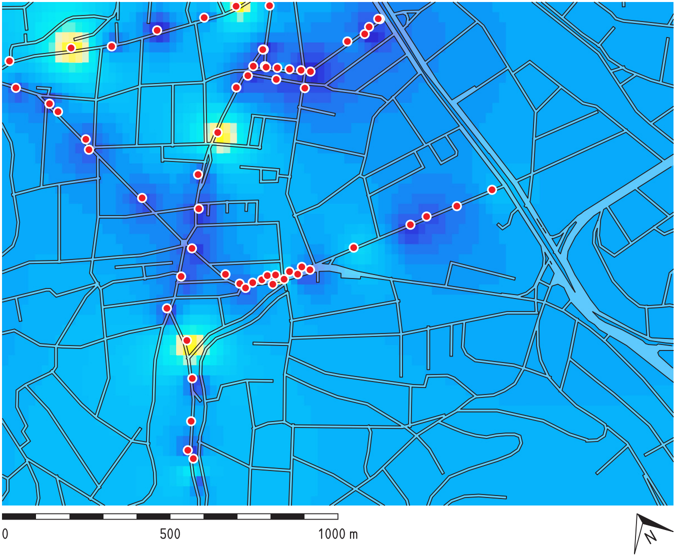
Monte Carlo Simulations of Dust Levels



Forecast and Prediction Regions for Dust Levels



Smoothed Map using Exponential Distance Metric



Recommended Literature

– Csáji, B. Cs.; Kis, K. B.; Kovács, A.: A Sampling-and-Discarding Approach to Stochastic Model Predictive Control for Renewable Energy Systems, 21st IFAC World Congress, July 11–17, 2020
– Csáji, B. Cs.; Kemény, Zs.; Pedone, G.; Kuti, A.; Váncza, J.: Wireless Multi-Sensor Networks for Smart Cities: A Prototype System with Statistical Data Analysis, IEEE Sensors Journal, IEEE Press, Vol. 17, Issue 23, 2017, pp. 7667–7676
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– Csáji, B. Cs.; Kovács, A.; Váncza, J.: Adaptive Aggregated Predictions for Renewable Energy Systems, 2014 IEEE ADPRL: Symposium on Adaptive Dynamic Programming and Reinforcement Learning, Orlando, Florida, December 9–12, 2014, pp. 132–139

Thank you for your attention!

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