SPACE WEATHER PREDICTION USIN

SRI develpments in space weath forecasting

Vitaliy Yatsenko

Space Research Institute of NASU-NSAU
Kiev, Ukraine
vyatsenko@gmail.com

Light-TPS

Outline

- Introduction (Space Plasma Department, Deparment of Remote Sensing and Advanced Instrumentations, PHD students: D. Vlasov, S. Ivanov)
- EU projects: EFFECTS (FP7), PROGRESS (HORISON 2020)
- Dynamical-information approach to NARMAX and bilinear systems identification
- Optimization approach to structure and parameter identification
- Estimation of Lyapunov exponents and Lyapunov dimension

Introduction

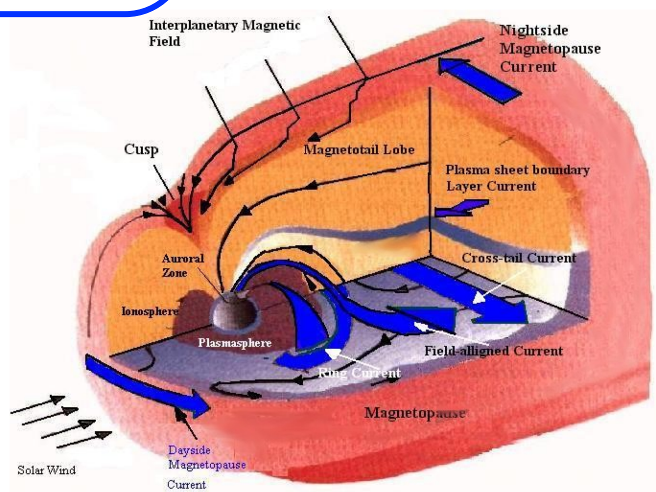
1. This report starts with the physical basis and a brief description of the system identification approach. Following that, several examples illustrate practical issues in temporal and spatiotemporal prediction, NARMAX and bilinear modeling.

2. An approach based on combination of nonlinear dynamical models and Lyapunov dimension are used to analyze measurements of the geomagnetic indexes and solar wind parameters.

Dynamical-information forecasting of geomagnetic indexes

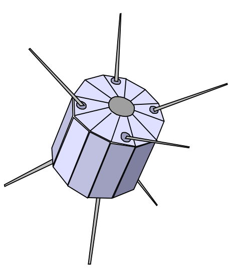
Magnetosphere is considered as a nonlinear complex dynamical system

Kp,AE,Dst indexes



Dst is sought for as an output of a nonlinear dynamical "black-box"

Solar wind parameters



Data are from OMNI2 database:
http://nssdc.gsfc.nasa.gov/omniweb/
and Kyoto WDC for Geomagnetism:
http://swdcdb.kugi.kyoto-u.ac.jp/

Dynamical-information approach

- Dynamical-information approach is based on the “black-box“ models and ***Lyapunov exponents*** to describe magnetospheric dynamics.
- Reconstruction of the dynamical model is based upon the application of **multiobjective learning algorithms** to identification of model’s structure and parameters.
- *A* forecasting algorithm based on ***Lyapunov exponents*** is also proposed.

Objectives/Problems

1. Structure and parameter identification of NARMAX and bilinear models
2. Combination of NARMAX model and Lyapunov exponents
3. Combination of NARMAX model and Lyapunov dimension
4. Guaranteed prediction
5. Robust prediction.

Problem Description

Forecast of the evolution of geomagnetic indices

Our research concerns improvement and new development of models based on data driven modelling, such as BILINEAR and NARMAX (M. Balikchin S. Walker). Existing models for Dst and Kp will be analysed and verified with the aim of finding weaknesses and to suggest improvements. Solar wind and geomagnetic indices shall also be analysed in order to develop models for the identification of features, such as (but not limited to) shocks, sudden commencements, and substorms. Such categorisation will aid the model development and verification, and can also serve as alternative approach to models providing numerical input-output mapping. In addition to the development of Dst and Kp models new models will be developed to forecast AE.

Problem Description

- Recursive, robust bilinear dynamical model (RRBDM). It has minimal complexity and the same prediction limit as NARMAX. RRBDM provides forecasts of the Dst and Kp indices based on new robust algorithms and is driven by real time solar wind parameters measured at L1 with a time shift to account for the propagation of the solar wind to the terrestrial magnetopause and the real time Dst and Kp indices.

Problem Description

- The second, the Guaranteed NARMAX Model (GNM) also provides predictions of the Dst index. Its main advantage is that it delivers an increased prediction reliability in comparison to earlier SRI models.
- Guaranteed prediction of geomagnetic indexes

Problem (cont'd)

- A prediction methodology depends on the main Lyapunov exponent: a) if the main Lyapunov exponent positive we my use Lyapunov dimension for geomagnetic indexes prediction. b) if not, we my use NARMAX and the limit of predictability that based on Lyapunov exponents and their variations during coronal mass ejection

Papers and Conferences

1.V. Yatsenko, O. Cheremnykh. Preiction of geospace radiation environment an solar wind parameters: modeling, identification, and risk analysis.-Ukrainian Conference on Space Research.-Book Abstract, Odessa, Ukraine August, 22-27, 2016.-P.15.
2.V. Yatsenko. Space weather prediction using robust dynamical models: identification, optimization, and risk analysis.- 13th European Space Weather Week., November 14-17 2016, Oostende, Belgium,
3.V. Yatsenko. Space Weather Influence on Power Systems: Prediction, Risk Analysis, and Modeling. Geophysical Research Abstracts Vol. 18, EGU General Assembly, 2016.-P-6145.
4.V. Yatsenko. The influence of the free space environment on the superlight-weight thermal protection system: conception, methods, and risk analysis.- Automatic Welding, Paton Publishing House.-2016.-P.9 (in print).
5.V. Yatsenko, O. Cheremnykh. Kp index forecasting with robust dynamic models. - Journal "Automation and Information", Kiev, Ukraine, 2016.-12 P. (in print)

Horison 2020
Project "Progress"

SPACE WEATHER PREDICTION USING ROUBAST DYNAMICAL MODELS: IDENTIFICATION, OPTIMIZATION, AND RISK ANALYSIS

SRI
Ukraine

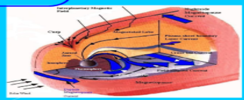
Vitaliy Yatsenko

The first, system science approach provides accurate forecasts of electron fluxes but is limited to regions in which continuous data are available, i.e. GEO. The second, based on physical principles, provides good coverage throughout the whole inner magnetosphere but with significantly lower accuracy. The third, based on new tools for modeling and system identification to prediction of risk using optimization methods. The combination of three approaches, as used in the SNB3GEO electron flux model (which combines the data driven NARMAX and physical VERB models), can overcome many of the short comings of the two individual models, generating improved short term forecasts for the whose RB region. Long term RB forecast require the estimation of solar wind parameters at L1 based on remote solar observations.

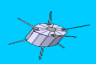
Dynamical-information forecasting of geomagnetic indexes

Magnetosphere is considered as a nonlinear complex dynamical system

Kp,AE,Dst indexes



Dst is sought for as an output of a nonlinear dynamical "black-box"



Data are from OMNI2 database: http://nssdc.gsfc.nasa.gov/omniweb/ and Kyoto WDC for Geomagnetism: http://swdcdb.kugi.kyoto-u.ac.jp/

Mathematical models

The Guaranteed NARMAX Model (GNM) provides predictions of the Dst index. Its main advantage is that it delivers an increased prediction reliability in comparison to earlier SRI models.

Guaranteed prediction of geomagnetic indexes

Algorithms and software

- Agorithms and software for optimal structure and parameters identification of mathematical models of ionizing radiation have been considered.
- Forecasting mathematical models of ionizing radiation by numerical methods has been tested

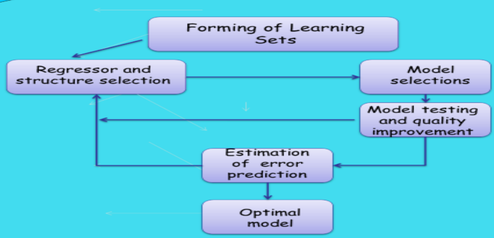


Fig. 1

Risk analysis

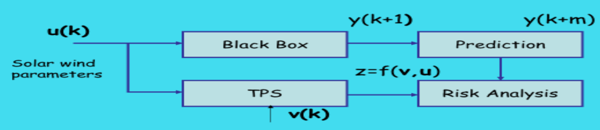


Fig. 2 Prediction and Risk Analysis

Optimization problem with constraints on risk

Let z=f(v,u) be a loss function of a device depending upon the control vector v and a random vector u. The control vector v belongs to a feasible set V, satisfying imposed requirements. We assume that the random vector u has a probability density p(u). We can define a function

$$\Phi_\beta(v,\beta) = (\alpha-\beta)^{-1}\int_{f(v,u)>\alpha} (f(v,u)) - \alpha)p(u)du.$$

Optimization model

$$\min \mu(v)$$

$$v \in V, \Phi_\beta(x) \le C_\beta, \Phi_\gamma(x) \le C_\gamma.$$

Hybrid energy storage system based on supercapacitors

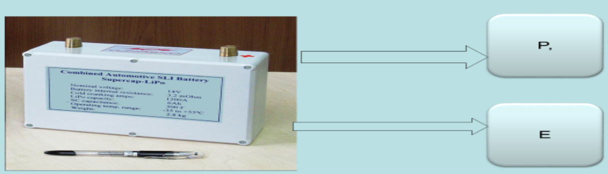


Fig. 3

Voltage decreases of supercapacitors before and after γ-irradiation

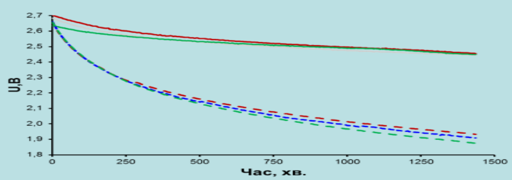


Fig. 4

Output of the diode laser after irradiation by gamma radiation

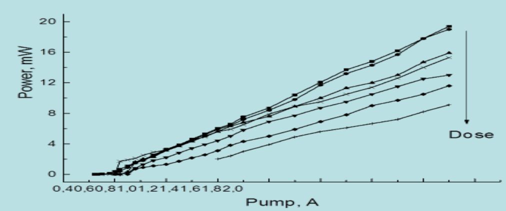


Fig. 5

Structure and parameter identification of NARMAX and bilinear models

$$y(t) = \sum_{i=1}^{\infty} \int_0^{\infty} \ldots \int_0^{\infty} h_i(\tau_1, \ldots, \tau_i) \prod_{j=1}^{i} u(t - \tau_j) d\tau_j$$

y(k) = F[y(k - 1),…,y(k - n), u(k - 1),
…, u(k - n), ξ(k - 1),…,ξ(k - n)+ξ(k)]

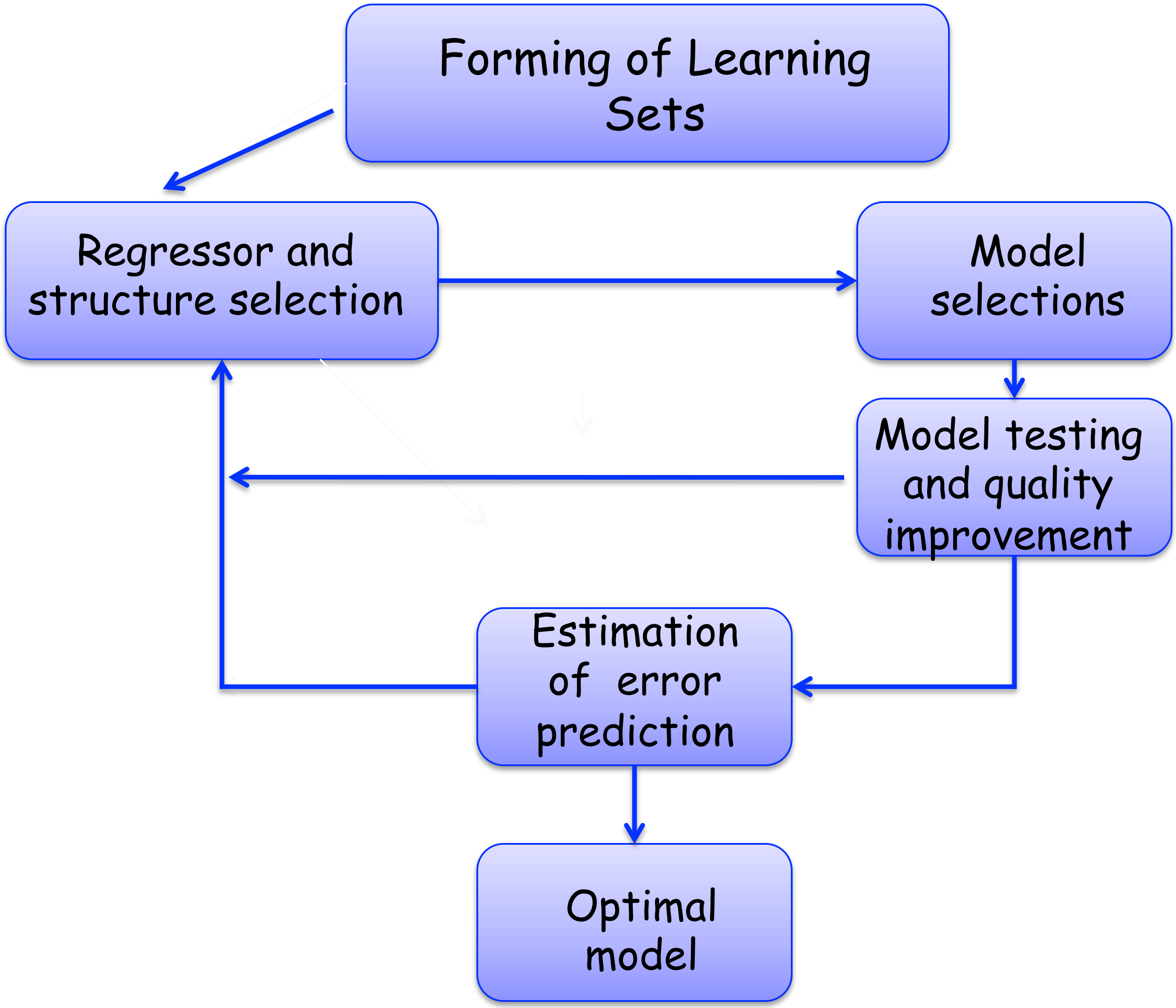
$$J = \sqrt{((\hat{y}(k) - y(k))^2) / (\sum (y(k) - \bar{y}(k))^2)}$$

Bilinear models

Methods of identifying bilinear systems from recorded input-output data have been proposed. The identified bilinear model is then used to forecast the evolution of the Dst index . For the investigation of robust forecasting, we perform a simulation study to demonstrate the applicability and the forecasting performance.

$$\dot{x}(t) = A_0 x + \sum_{i=1}^{m} B_i x(t) u_i(t),$$

$$y(t) = Dx(t),$$


Forming of Learning Sets
Regressor and structure selection
Model selections
Model testing and quality improvement
Estimation of error prediction
Optimal model

Optimization Problem

$$y(k) = \psi(k-1)^T \boldsymbol{\theta} + \xi(k) \qquad (1)$$

$$\min \quad J(\boldsymbol{\theta})$$
$$\text{subject to} \quad \Theta \in D \qquad (2)$$

Optimization Problem

$$(P_M)\left|\begin{array}{l}\text{minimize } v(x) = \prod_{i=1}^{m} f_i(x) \\ \text{subject to} \quad g_j(x) \leq 0, \ \ j = 1, 2, \ldots, p,\end{array}\right.$$

$$f_i : \mathbb{R}^n \rightarrow \mathbb{R} \ (i = 1, 2, \ldots, m) :$$

$$g_j : \mathbb{R}^n \rightarrow \mathbb{R} \ (j = 1, 2, \ldots, p)$$

$$\Omega := \{x \in \mathbb{R}^n : g_j(x) \leq 0, \ j = 1, 2, \ldots, p\}$$

Numerical Algorithms

For structure and parameter identification we use the following numerical methods:

1. Nonlinear parametric model identification using genetic algorithms
2. Nonlinear optimization with constraints

Numerical results

$$y(k) = a_1 y(k-1) + a_2 y(k-2) + a_3 y(k-3) + a_4 y(k-4) + a_5 y(k-5) + a_6 u(k-1) + \\ + a_7 u(k-2) + a_8 u(k-3) + a_9 u(k-4) + a_{10} u(k-5) + a_{11} u(k-6) + \\ + a_{12} u(k-4) u(k-5) + a_{13} y(k-1) u(k-4) + a_{14} u(k-5) u(k-3),$$

$$y(k) = a_1 y(k-1) + a_2 y(k-2) + a_3 y(k-3) + a_4 y(k-4) + a_5 y(k-5) + \\ + a_6 u(k) + a_7 u(k-1) + a_8 u(k-2) + a_9 u(k-3) + a_{10} u(k-4) + \\ + a_{11} u(k-5) + a_{12} u(k-6) + a_{13} y(k-5) \cdot u(k-5) + a_{14} y(k-3) \cdot u(k-5) + \\ + a_{15} u^2 (k-6),$$

$$y(k) = a_1 y(k-1) + a_2 y(k-2) + a_3 y(k-3) + a_4 y(k-4) + a_5 y(k-5) + a_6 u(k-1) + \\ + a_7 u(k-2) + a_8 u(k-5) + a_9 y(k-2) u(k-1) + a_{10} u(k-4)\, u(k-6) + \\ + a_{11} y(k-3)\, u(k-1) + a_{12} u(k-1) u(k-7) + a_{13} y(k-3) u(k-2) + a_{14} u(k-2) u(k-5) + \\ + a_{15} u(k-7) u(k-12).$$

Numerical results

$$y_i = 1.36\, y_{i-1} - 4.99\, u_{i-1} - 0.18\, y_{i-2}\, u_{i-1} - 0.57\, y_{i-4} -$$

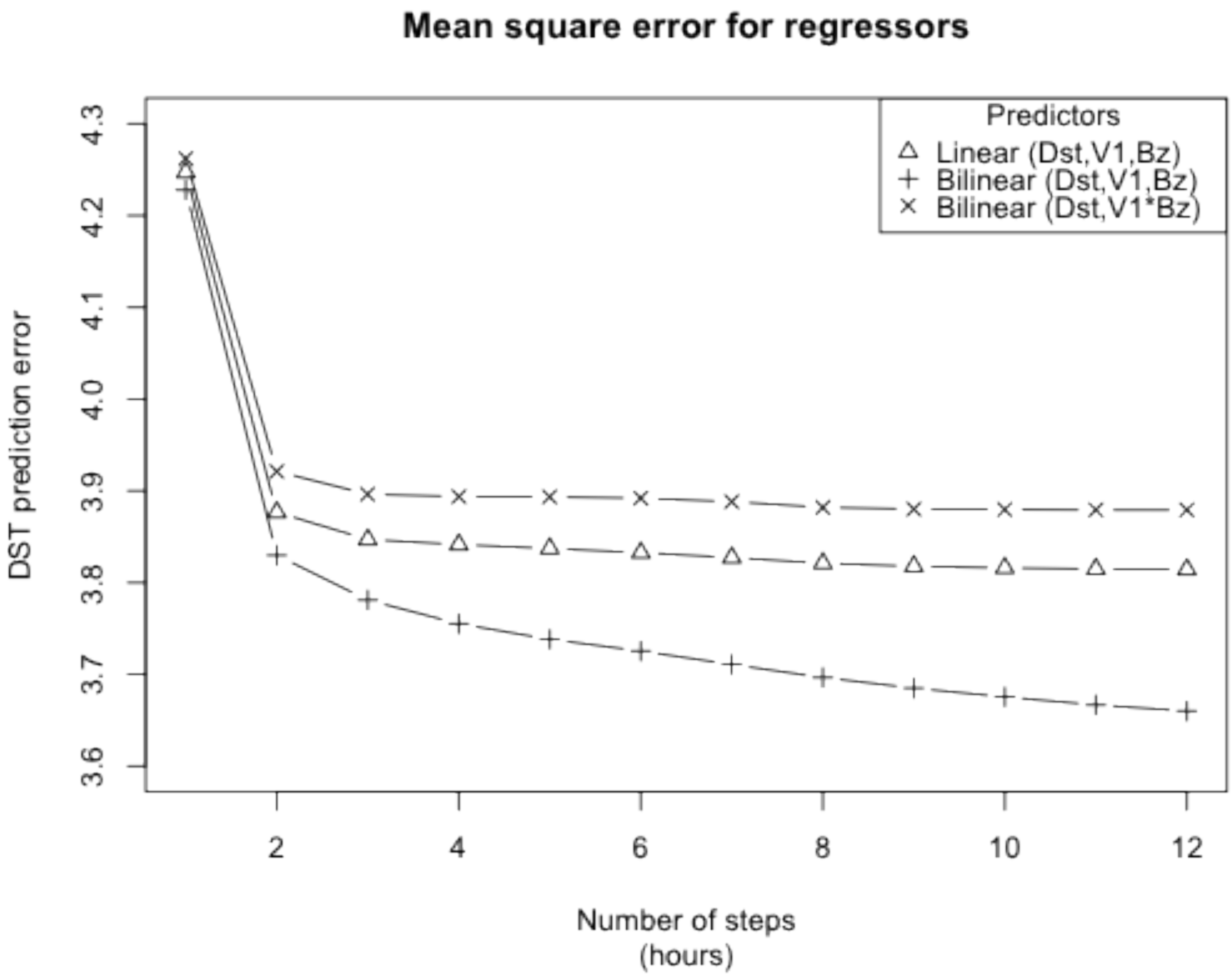
$$-1.43\, u_{i-4}\, u_{i-6} - 0.75\, y_{i-2} + 0.53\, y_{i-3} + 0.1\, y_{i-3}\, u_{i-1} +$$

$$+0.36\, y_{i-5} + 0.92\, u_{i-6}\, u_{i-7} + 2.71\, u_{i-2} + 0.08\, y_{i-3}\, u_{i-2} +$$

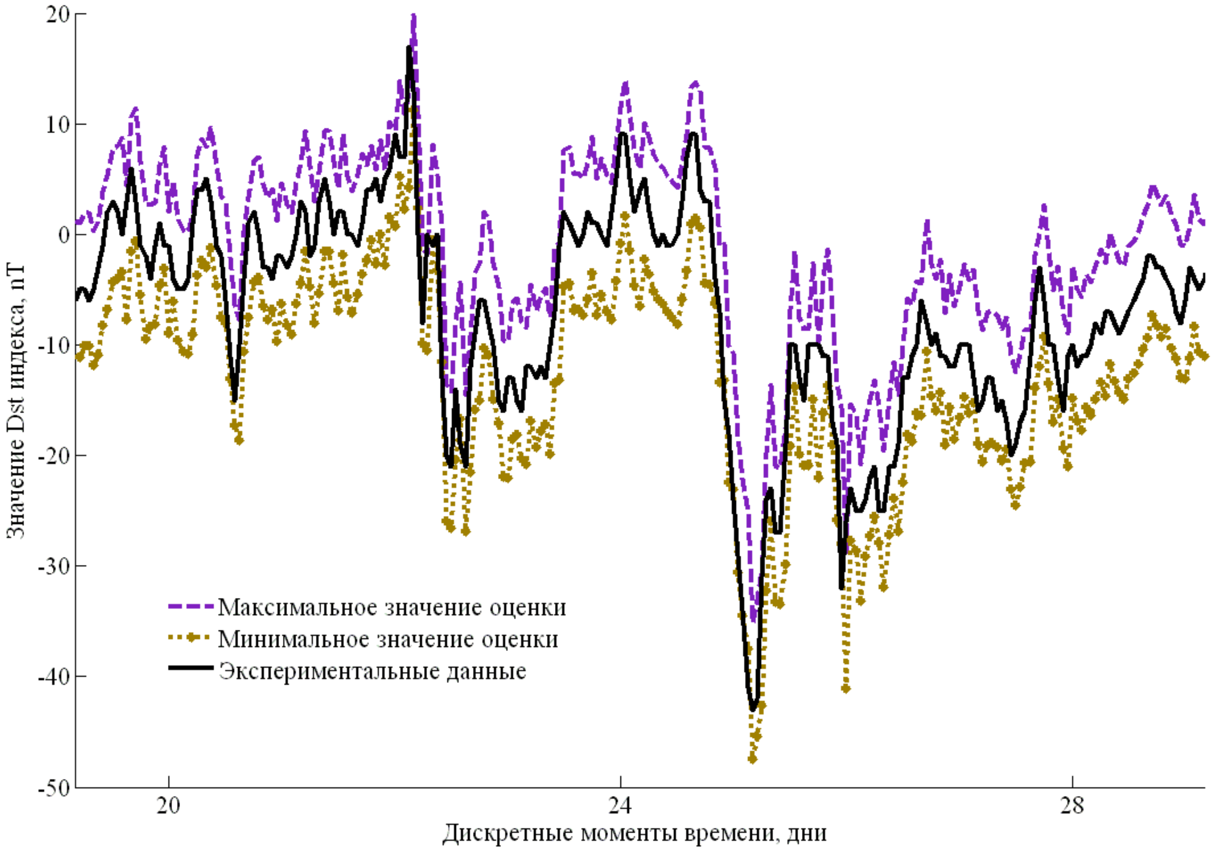
$$+0.78\, u_{i-2}\, u_{i-5} - 0.91\, u_{i-5} + 0.25\, u_{i-7}\, u_{i-12}$$

$$\Xi = \sqrt{((\hat{y}(k) - y(k))^2)/(\sum (y(k) - \bar{y}(k))^2)}$$

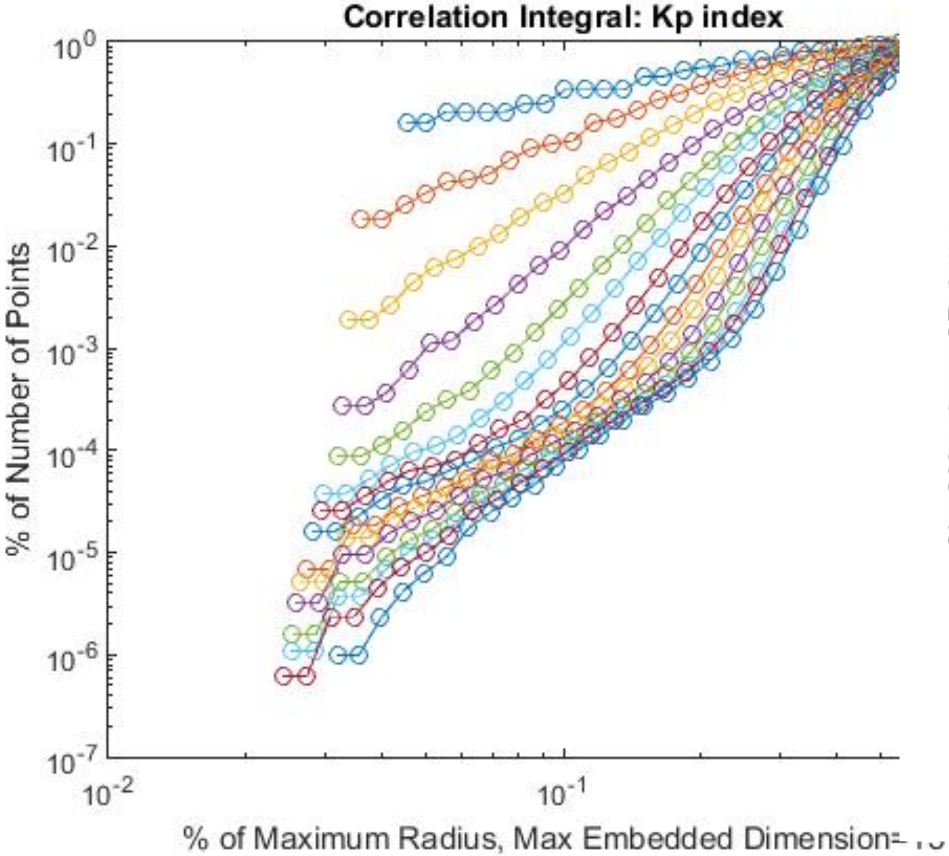
Numerical results

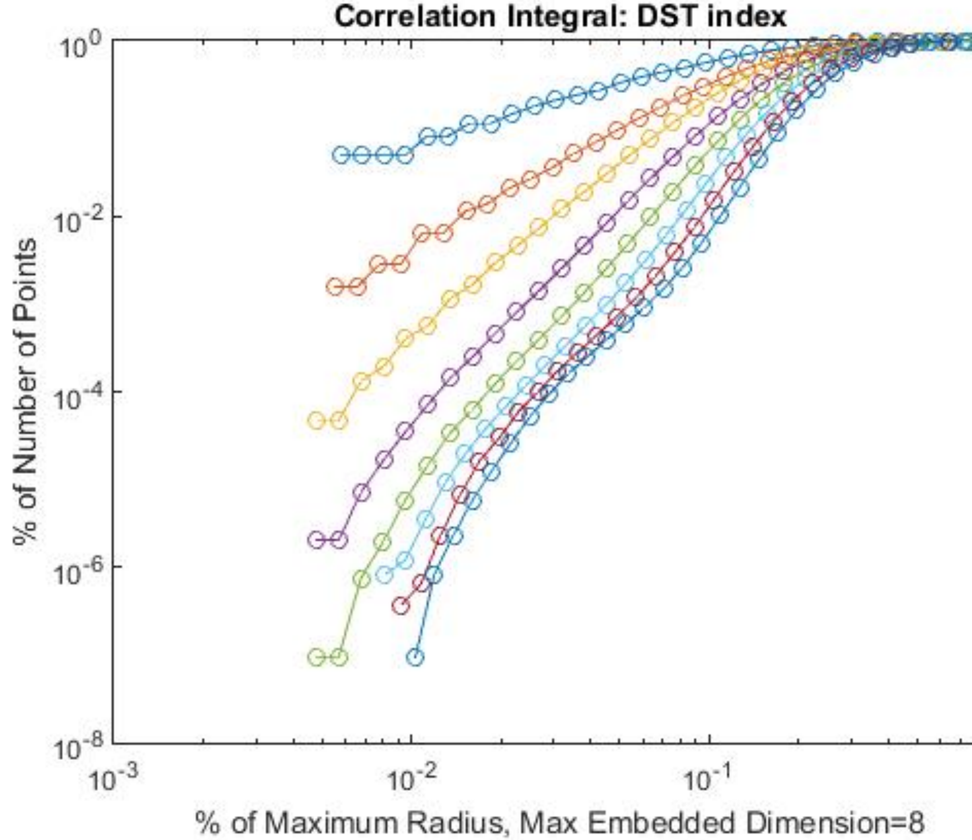


Results (Guaranteed prediction)



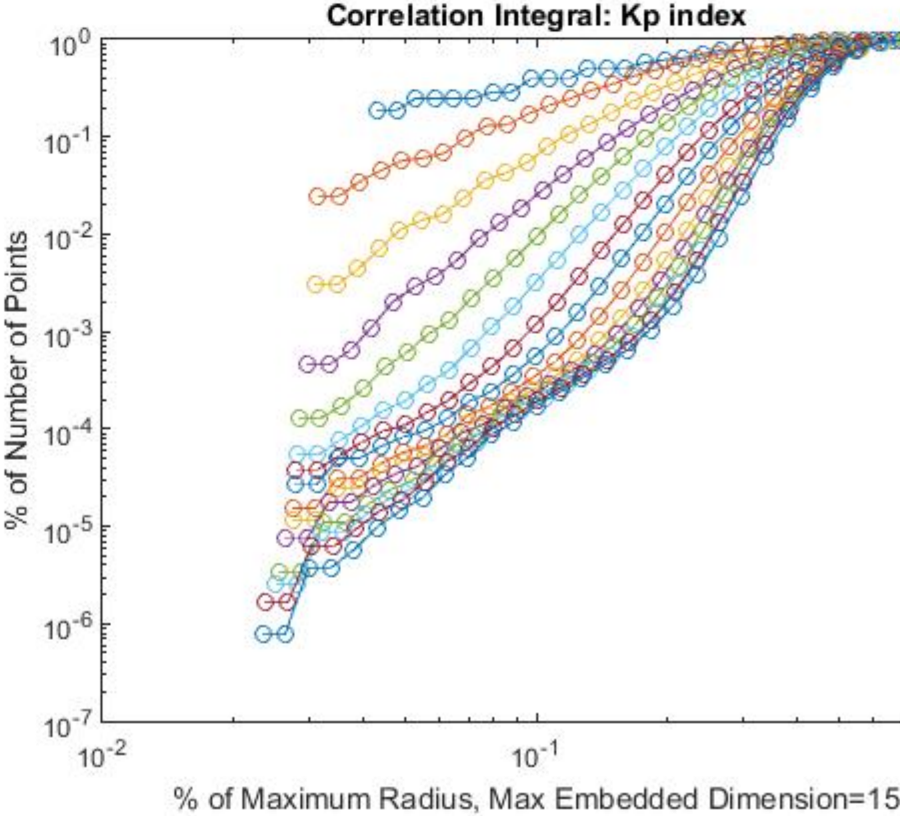
Correlation integrals of Kp & DST indices

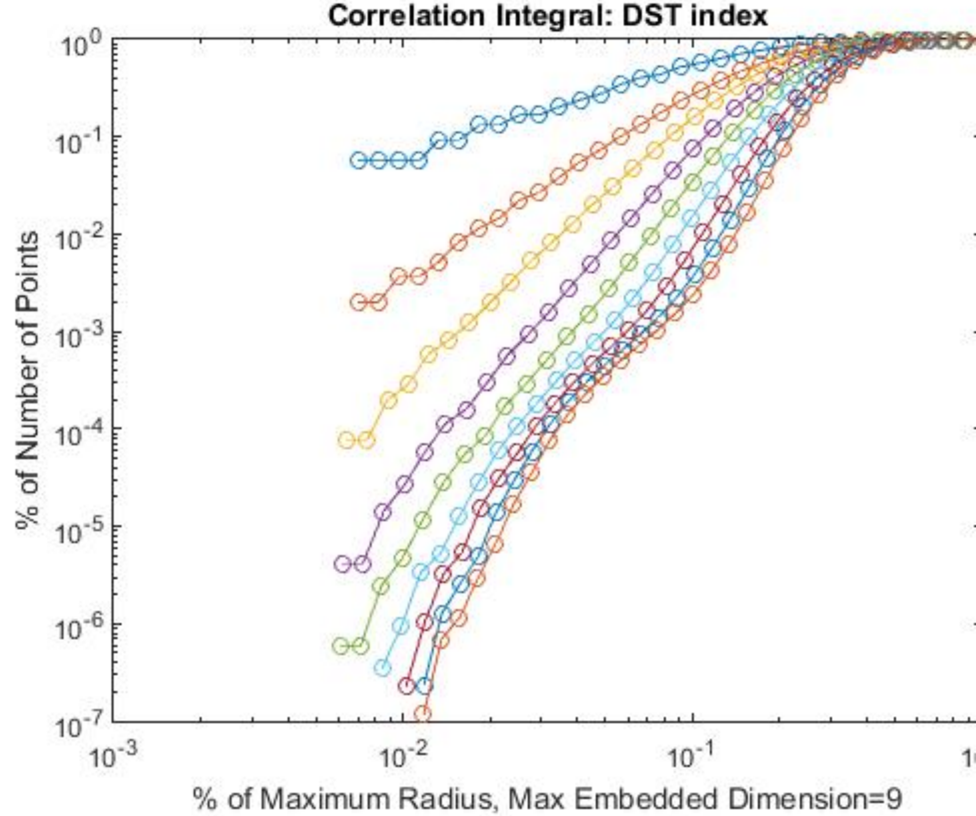




Data for: 06.2015 -04.2016.
Kp(avg) ~ 20;
DST(avg) ~ -18;

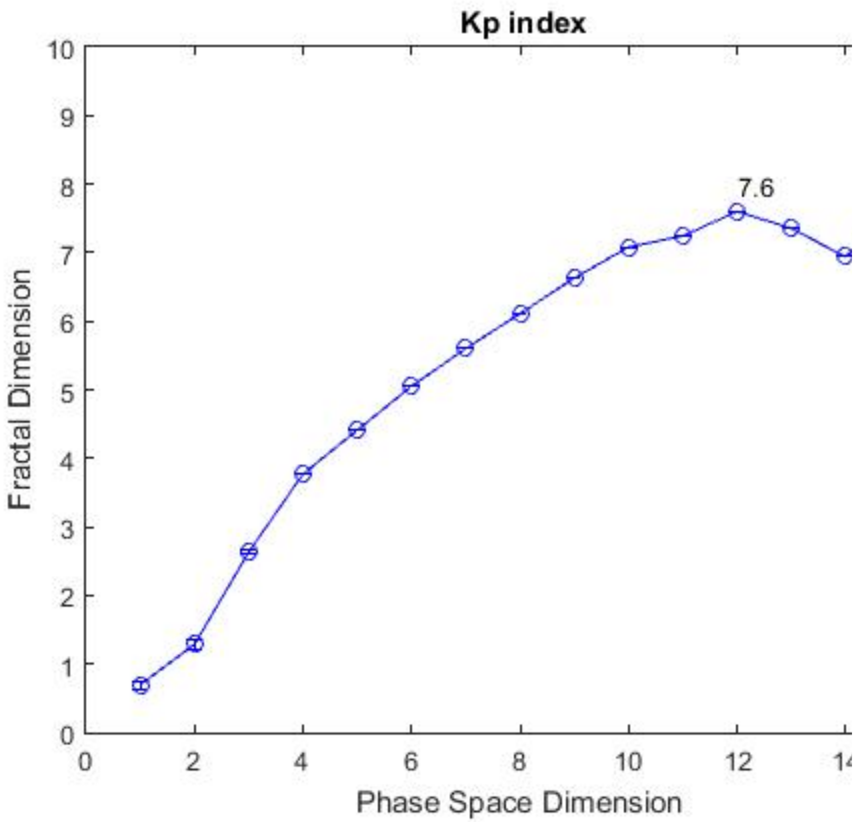
Correlation integrals of Kp & DST indices

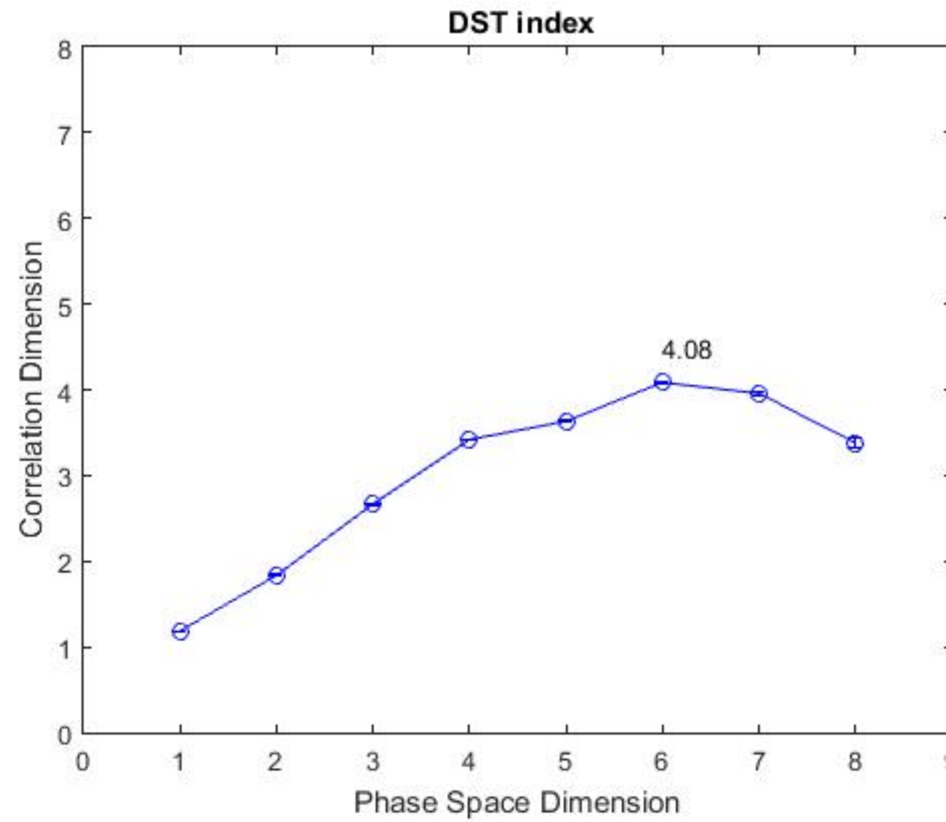




Data for: 03.2013 -12.2013.
Kp(avg) ~ 16;
DST(avg) ~ -9,6;

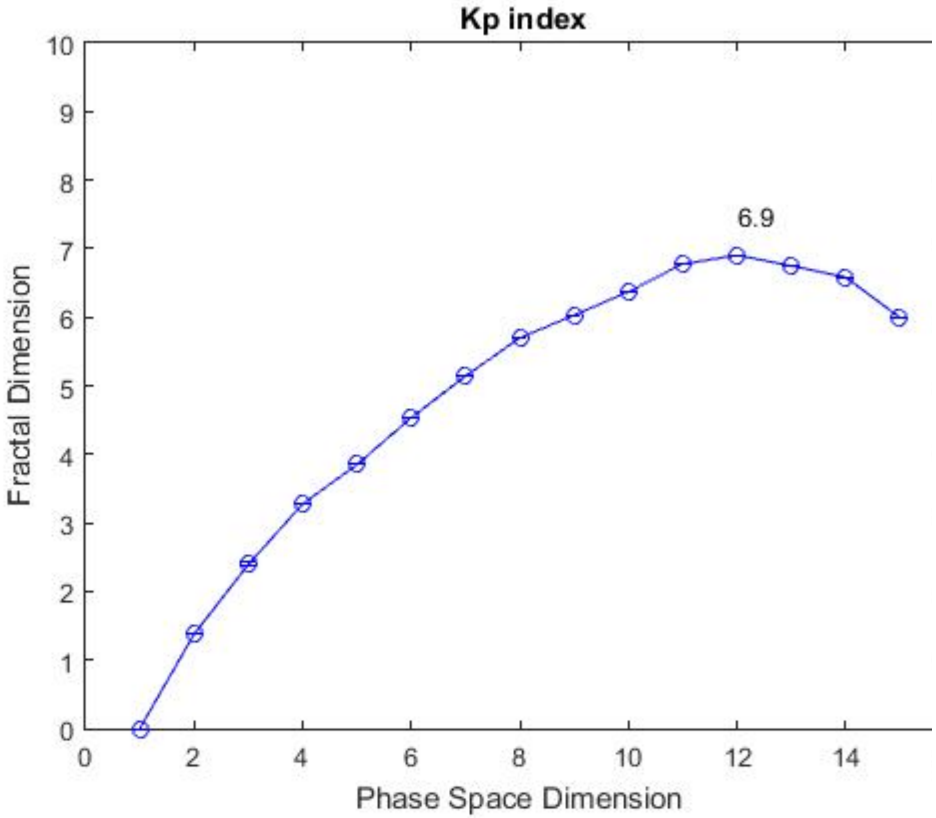
Correlation and Phase dimensions of Кр & DST indices

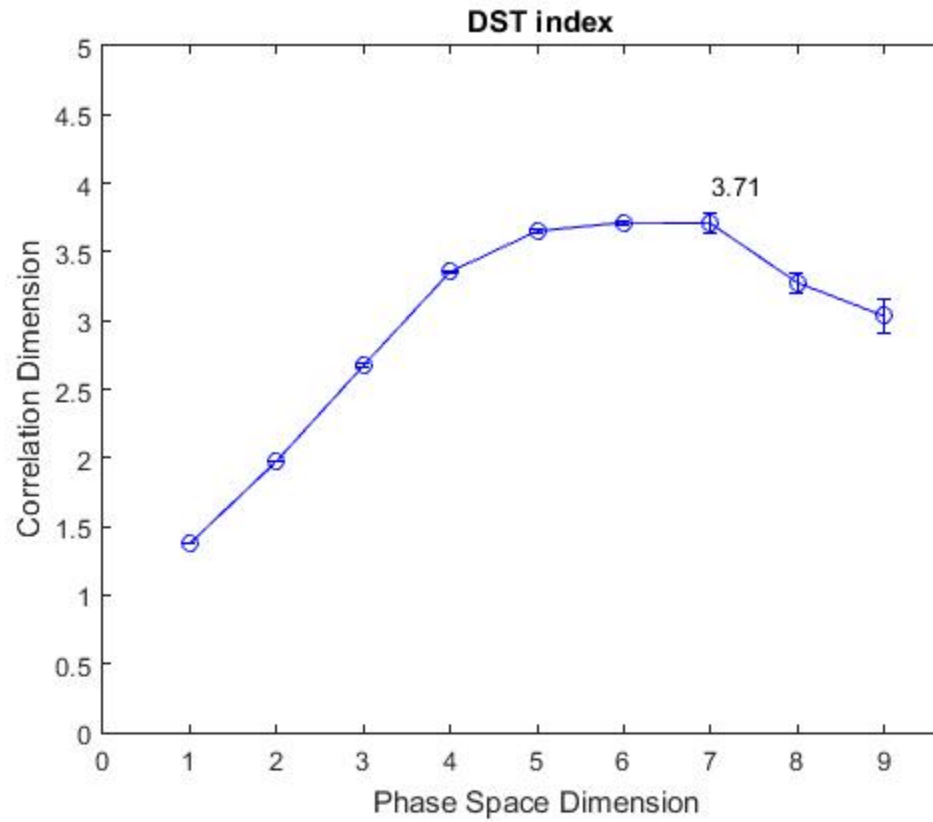




Data for: 06.2015 -04.2016.
Kp(avg) ~ 20;
DST(avg) ~ -18;

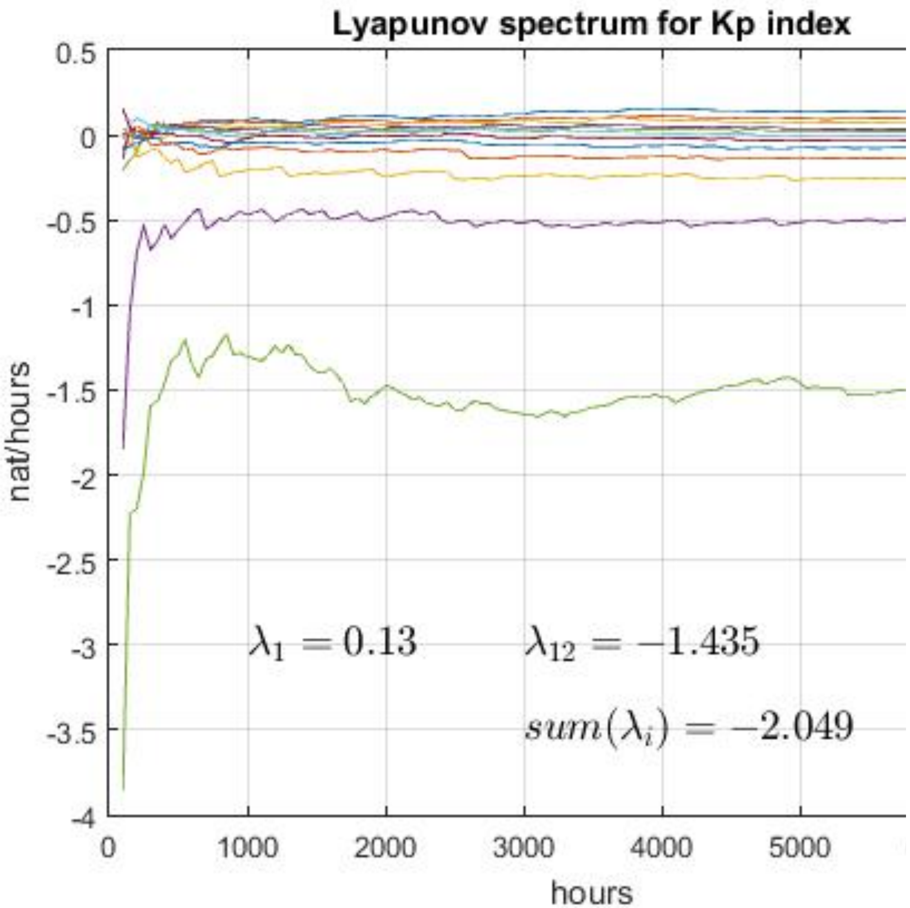
Correlation and Phase dimensions of Кр & DST indices

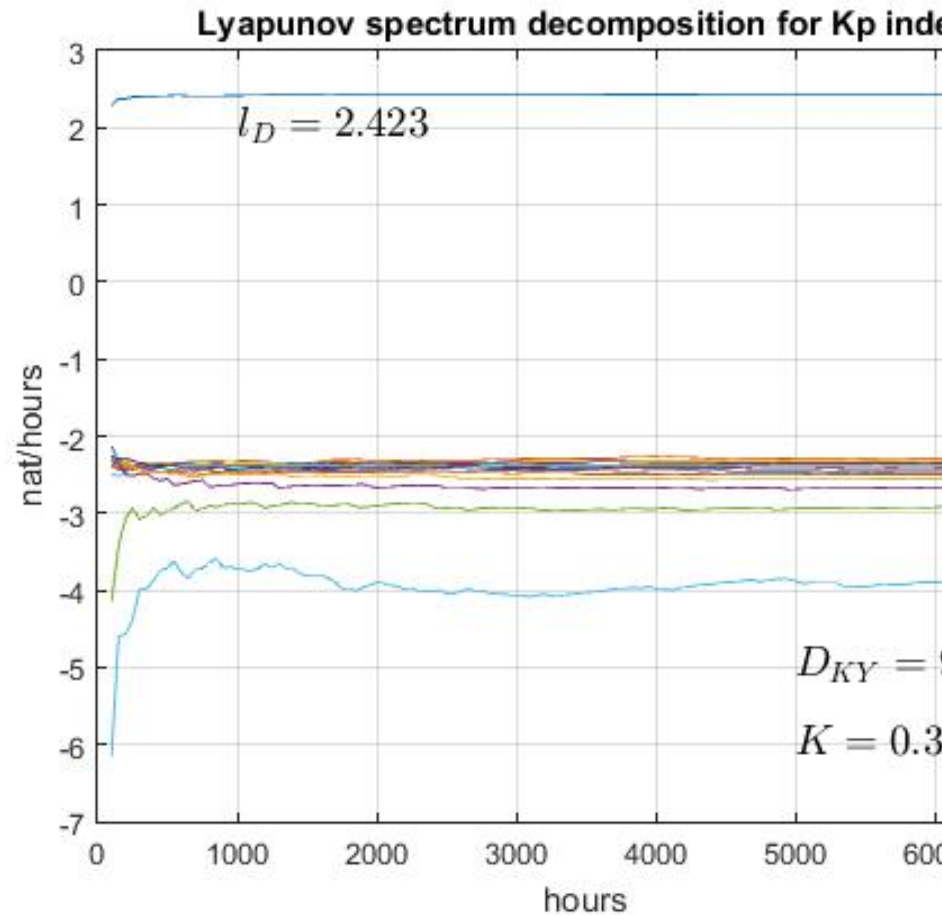




Data for: 03.2013 -12.2013.
Kp(avg) ~ 16;
DST(avg) ~ -9,6;

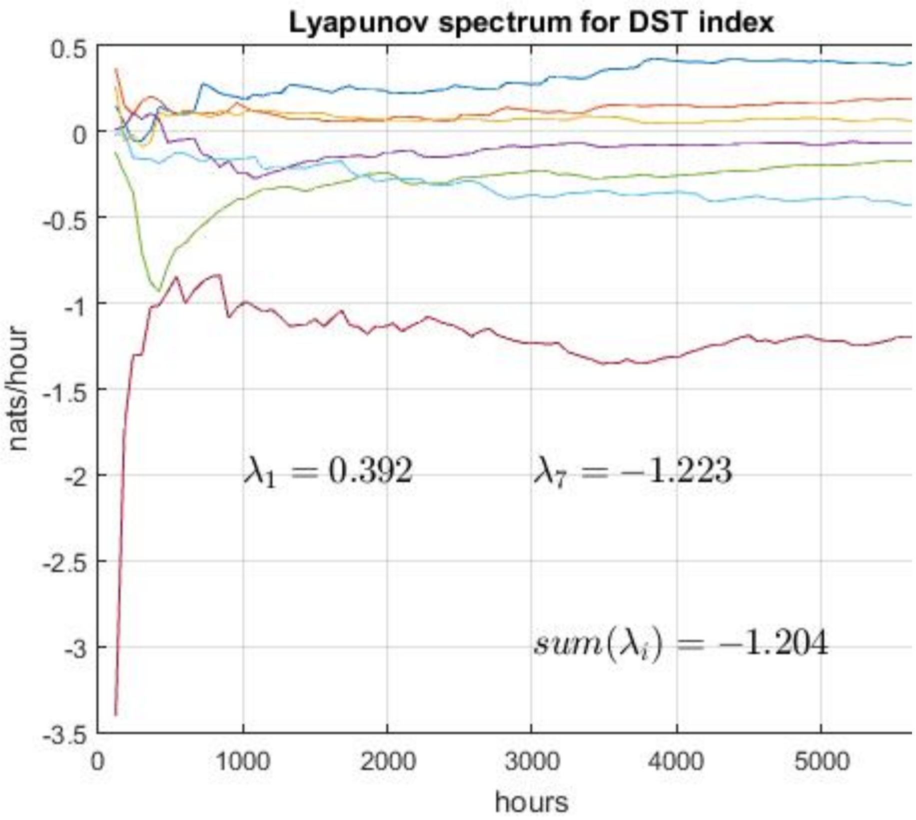
Lyapunov spectrum decomposition

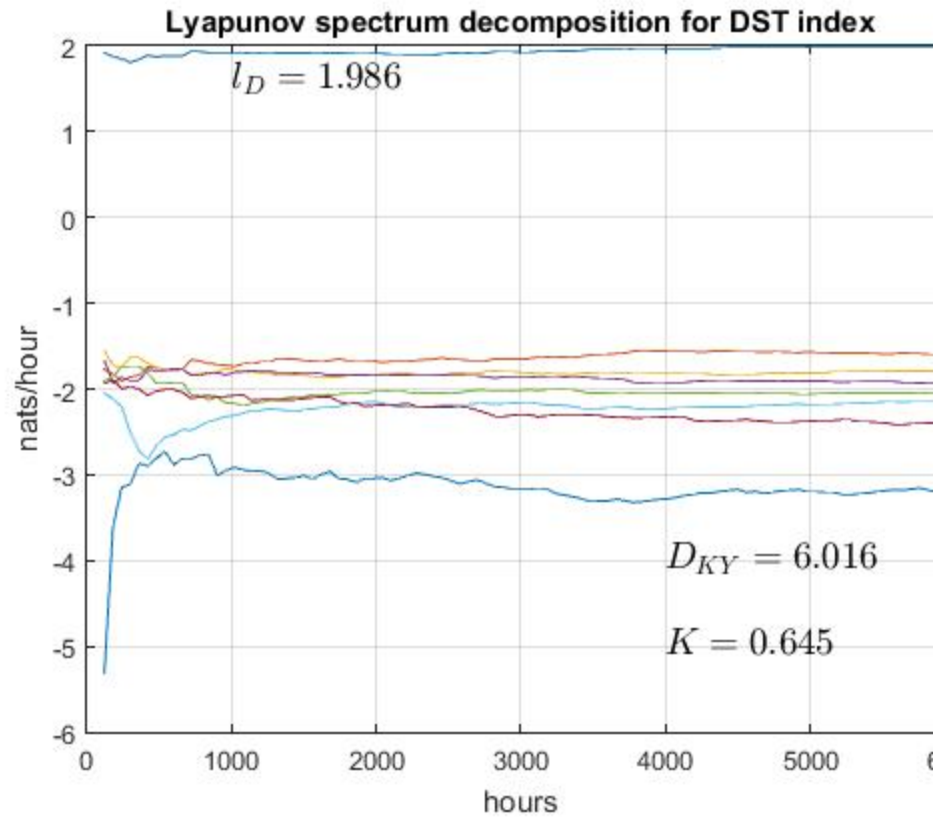




Data for: 06.2015 -04.2016.
Kp(avg) ~ 20;
DST(avg) ~ -18;

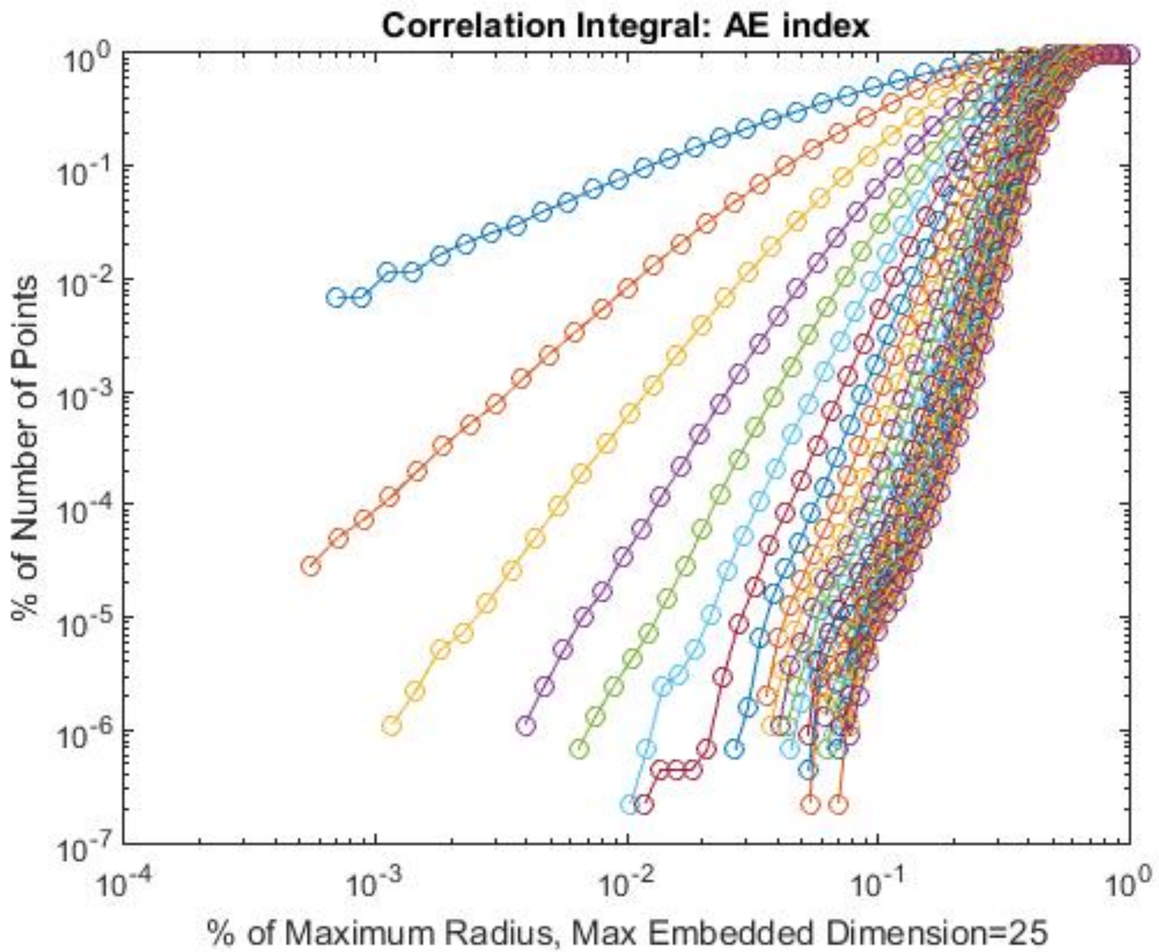
Lyapunov spectrum decomposition





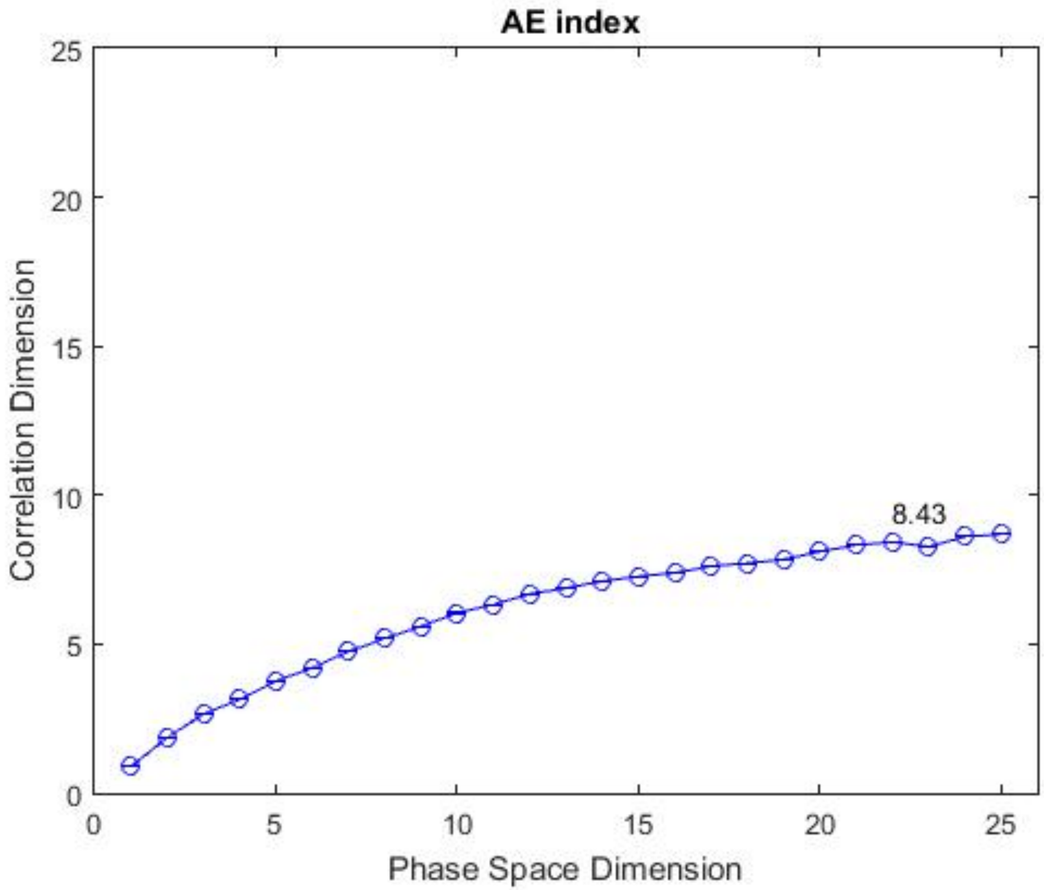
Data for: 06.2015 -04.2016.
Kp(avg) ~ 20;
DST(avg) ~ -18;

Correlation integral of AE index



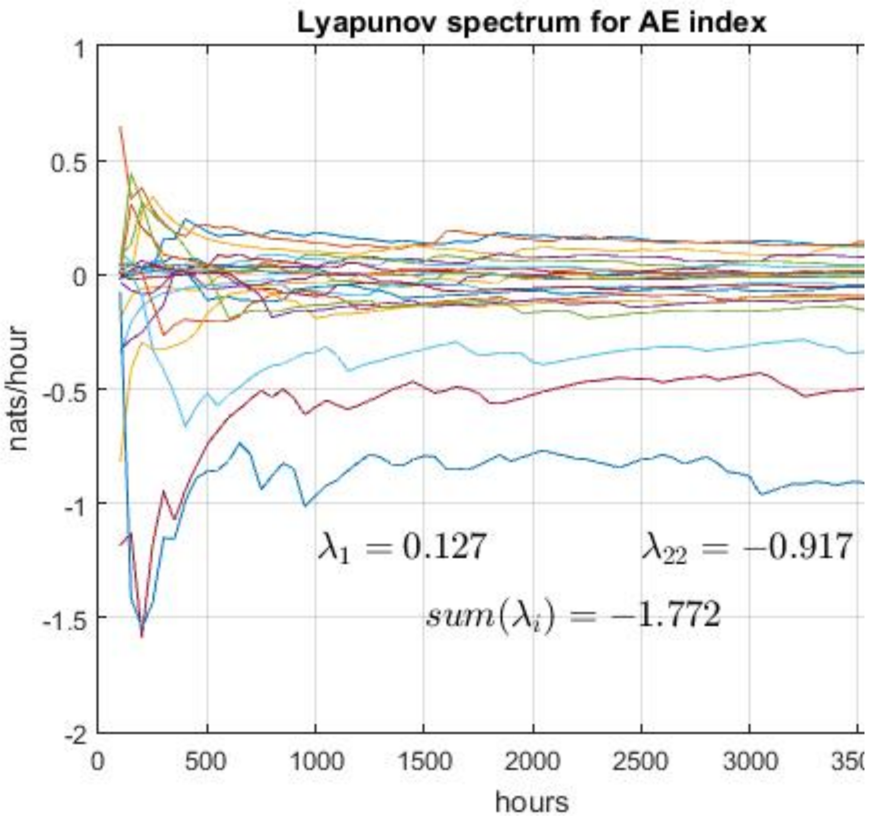
Data for: 06.2015 -04.2016.
AE(avg) ~ 258 nT;

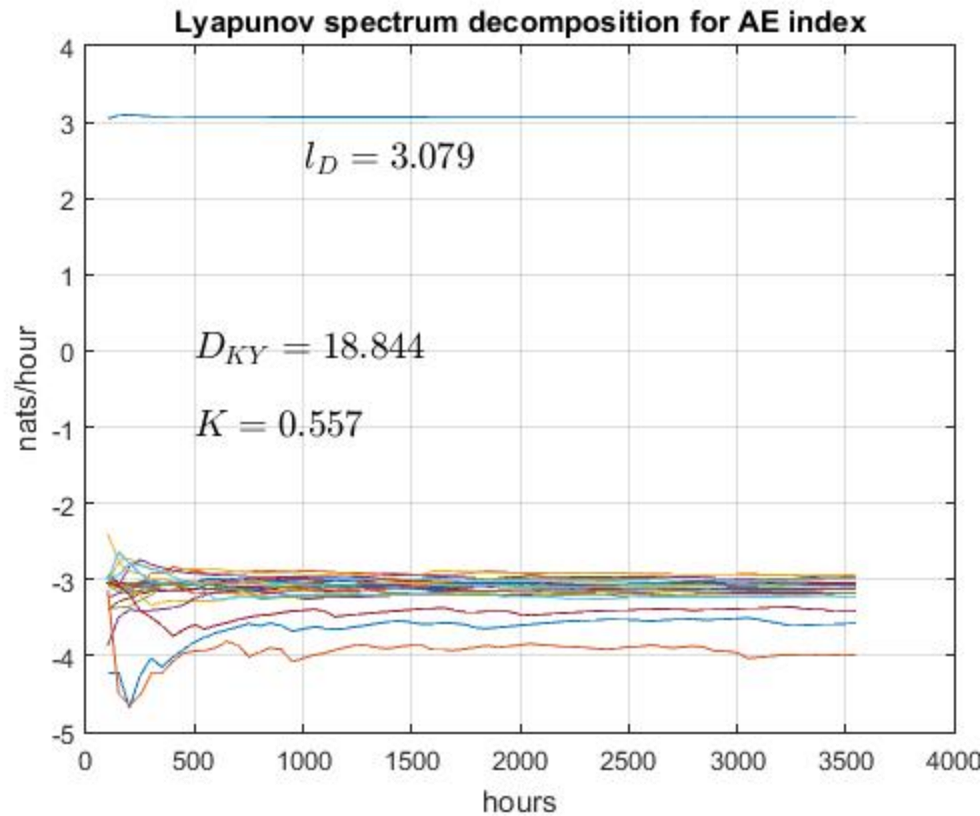
Correlation and Phase dimensions of AE index



Data for: 06.2015 -04.2016.
AE(avg) ~ 258 nT;

Lyapunov spectrum decomposition for AE index





Data for: 06.2015 -04.2016.
AE(avg) ~ 258 nT;

Risk analysis

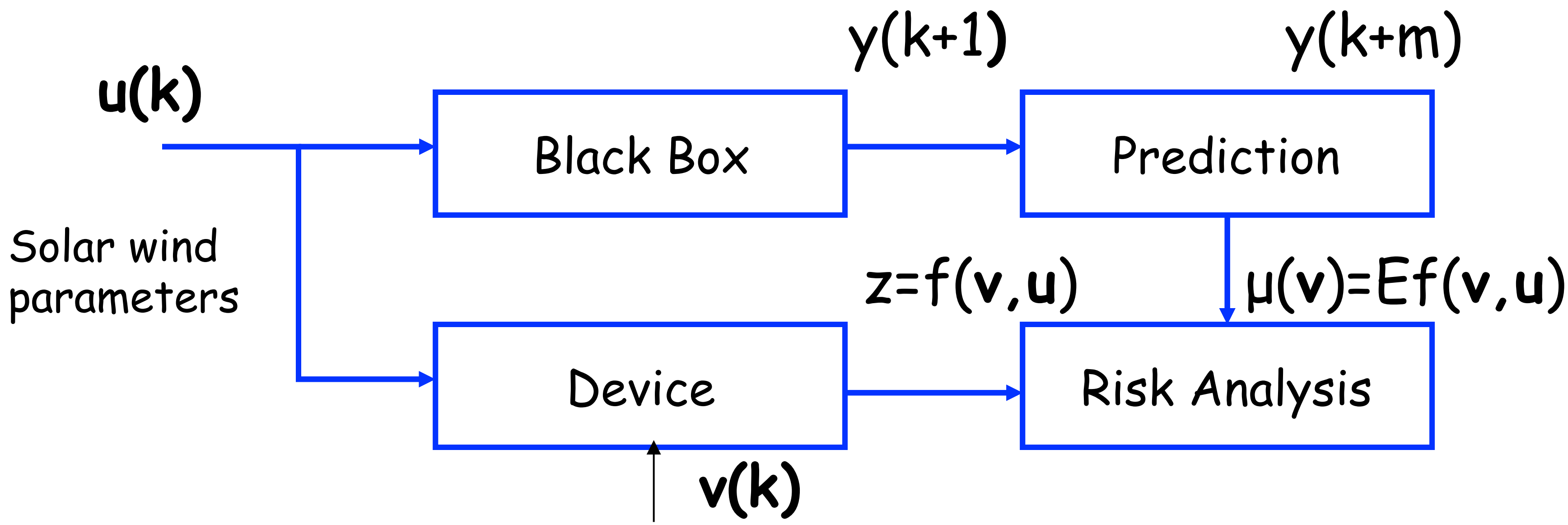


Fig. 1 Prediction and Risk Analysis

Optimization problem with constraints on risk

Let z=f(v,u) be a loss function of a device depending upon the control vector v and a random vector u. The control vector v belongs to a feasible set V, satisfying imposed requirements. We assume that the random vector u has a probability density p(u). We can define a function

$$\Phi_\beta(v,\beta) = (\alpha - \beta)^{-1} \int_{f(v,u)>\alpha} (f(v,u)) - \alpha) p(u) du.$$

Optimization model

$$\min \mu(v)$$

$$v \in V, \Phi_\beta(x) \le C_\beta, \Phi_\gamma(x) \le C_\gamma.$$

Applications

- Hybrid energy storage device based on supercapacitors
- Space accelerometers
- Superconducting gravimeter
- Lasers

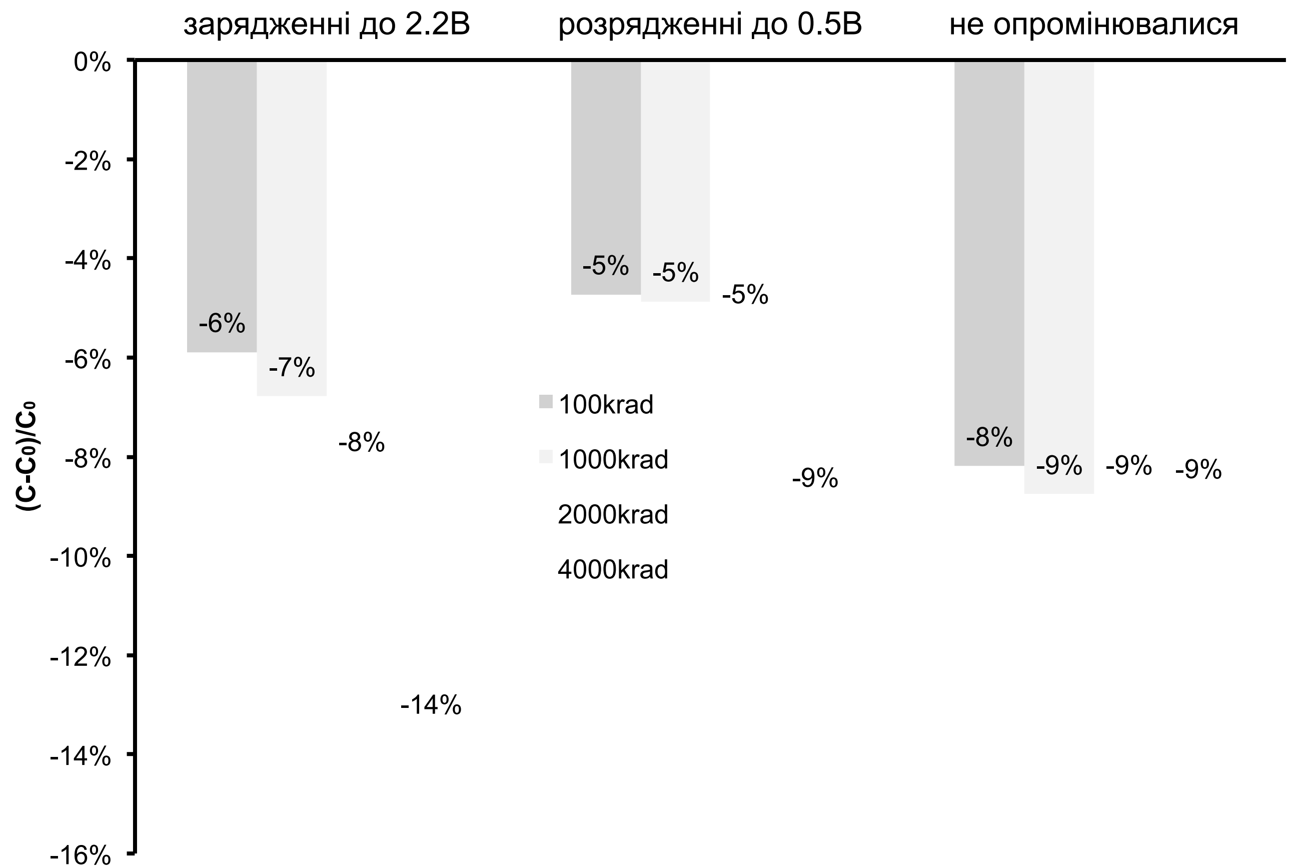
Applications

Hybrid energy storage system based on supercapacitors

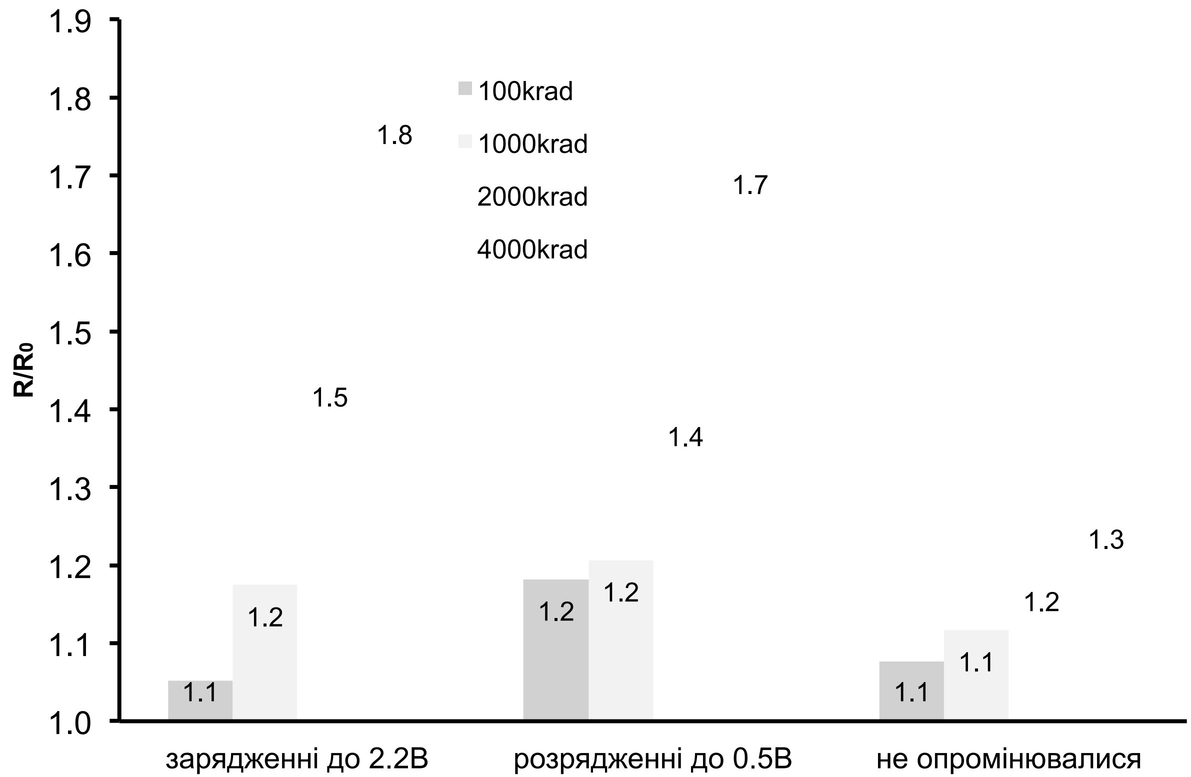
P, кВт

E, Вт·год

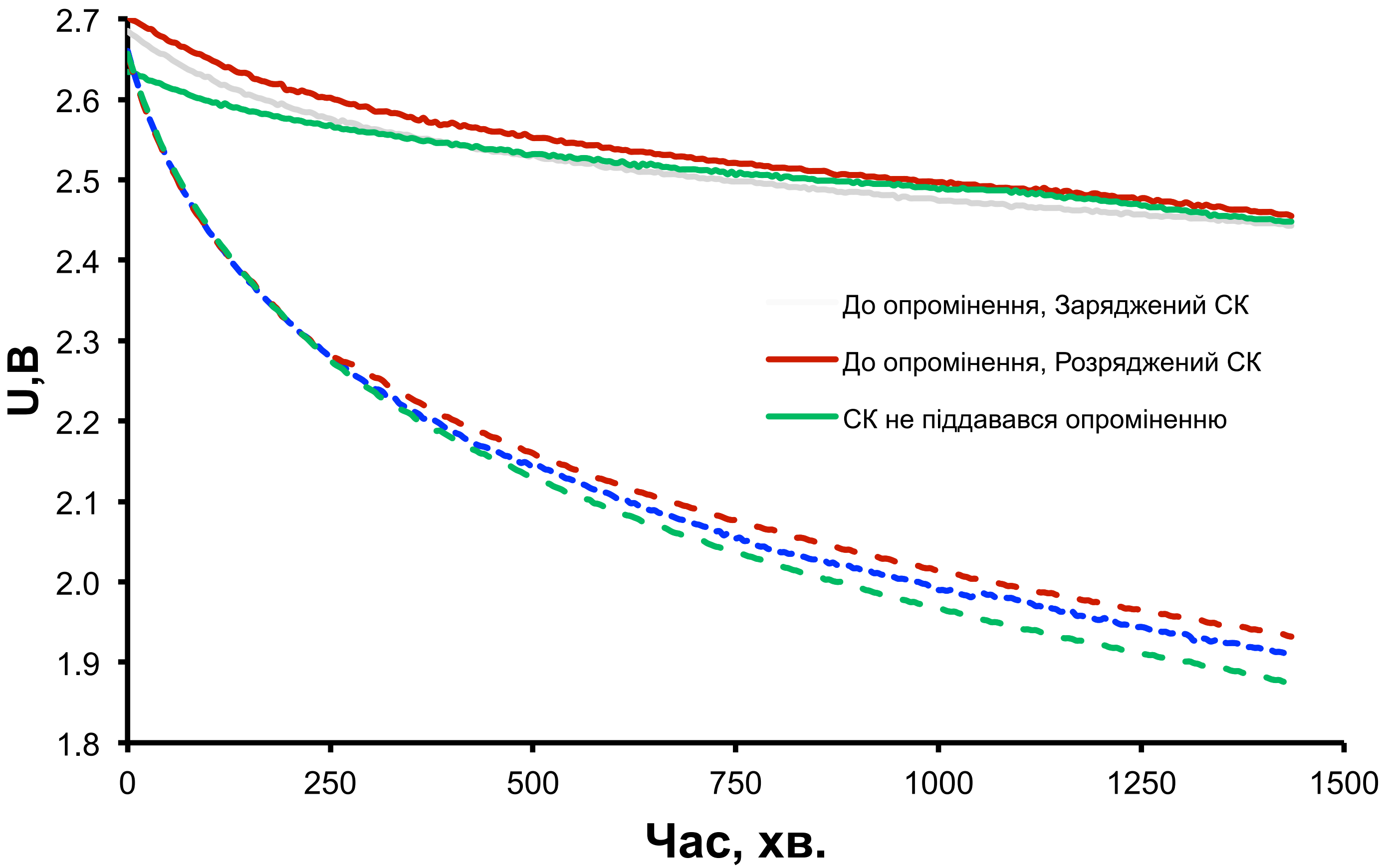
Impact γ-irradiation on capacity of hybrid energy storage device



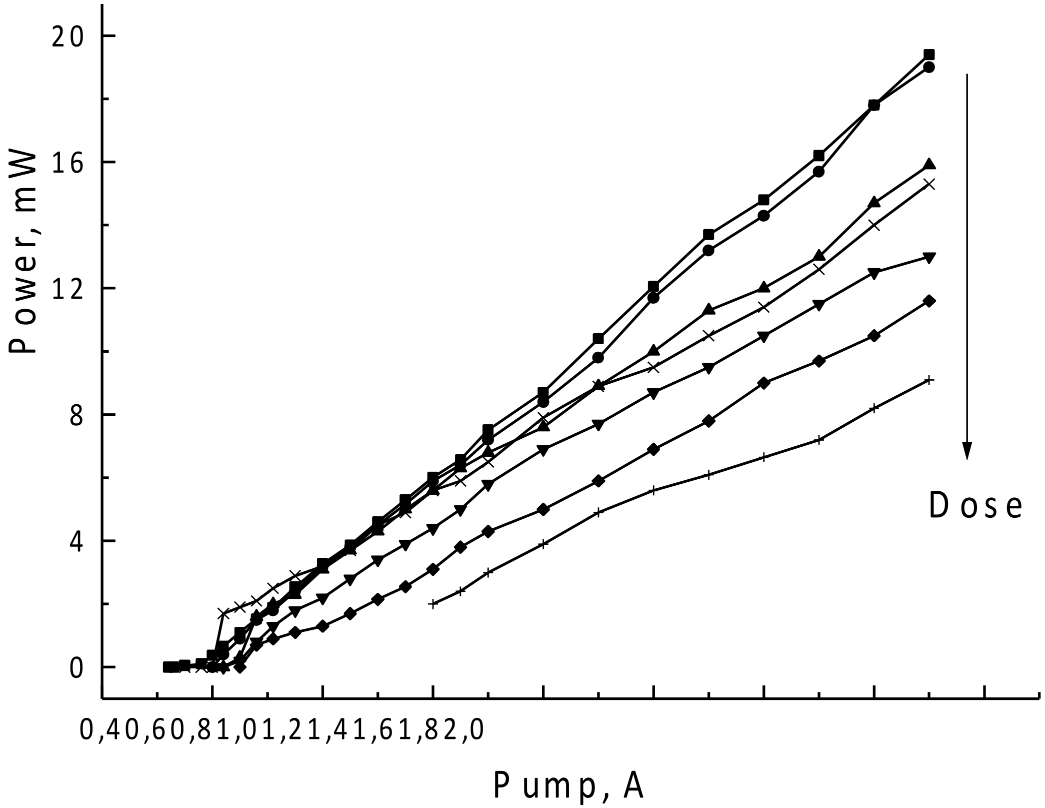
Resistance increase by γ-irradiation of hibrid energy storage device



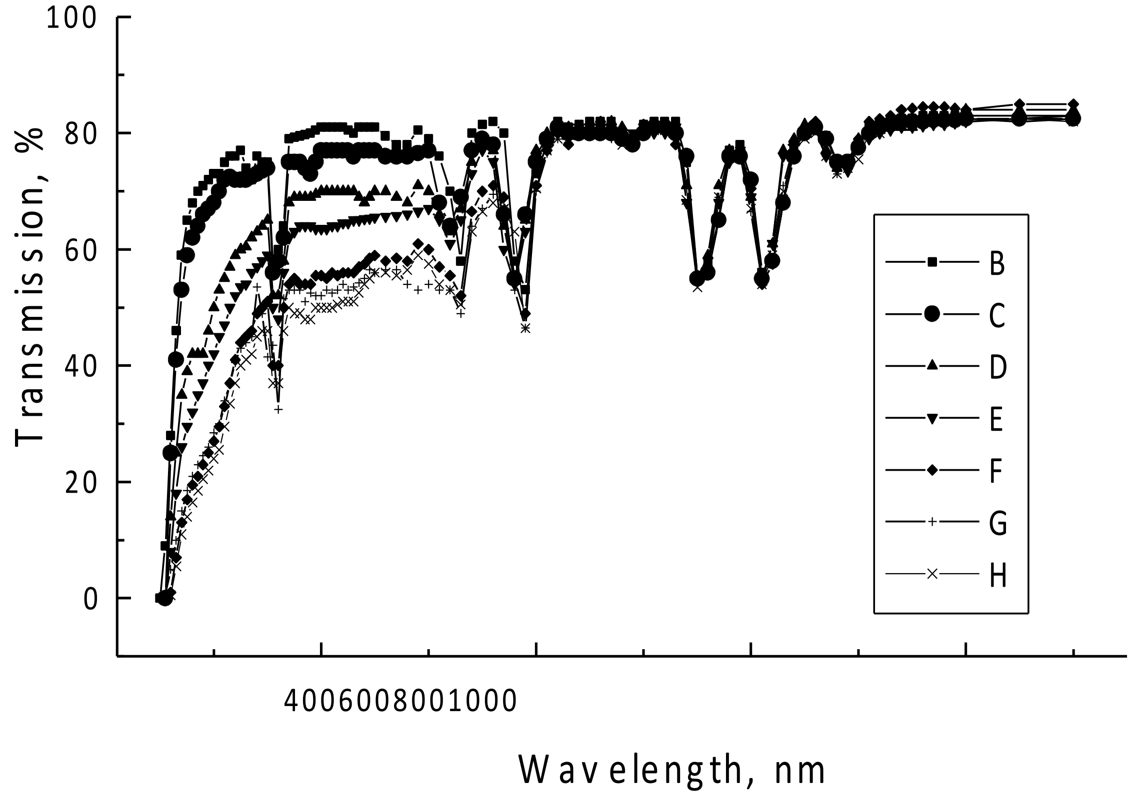
Voltage decreases of supercapacitors before and after γ-irradiation



Output of the diode laser after irradiation by gamma radiation



Transmission of Nd YAG crystal plate



Conclusions

- The following methods and models have been proposed:

  (a) dynamical-information approach to NARMAX system identification;

  (b) combination of NARMAX model and Lyapunov dimension;

  (c) guaranteed prediction;

  (d) robust models.

  (e) risk assessment in safety analysis.

The End