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Markus Dietz, Anna Chekhanova, Hans-Jörg Starkloff

Technische Universität Bergakademie Freiberg

Faculty for Mathematics und Computational Science

Institute for Stochastics

On a stochastic arc furnace model

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Workshop Mathematik in Forschung und Lehre,
Saalfelder Höhe

- Based on the instantaneous power balance (Acha et al (1990)) the nonlinear ordinary differential equation

$$k_1 r^n(t) + k_2 r(t) \frac{dr(t)}{dt} = \frac{k_3}{r^{m+2}(t)} i^2(t) \quad (\text{EAF})$$

describes the dynamics of the arc radius $r(t)$ with time t and

- $i(t)$ the arc current;
 - $k_1, k_2, k_3 > 0$ model coefficients determined experimentally;
 - $m, n \in \{0, 1, 2\}$ parameters, reflecting different working conditions of the furnace.
- The arc voltage is represented by $u(t) = \frac{k_3}{r^{m+2}(t)} i(t)$.
 - Assumption $n = 2$ and substitution $y = r^{m+4} \implies$ (EAF) results in

$$\frac{dy}{dt} = -\beta y(t) + f(t)$$

where $f(t) := \frac{(m+4)k_3}{k_2} i^2(t)$, $\beta := \frac{(m+4)k_1}{k_2} > 0$.

A stochastic model:

- One proposal: Replace the deterministic parameter k_3 by

$$\left(k_3 (1 + X_t)^2 \right)_{t \in \mathbb{R}}$$

with a mean square continuous second order stochastic process $(X_t)_{t \in \mathbb{R}}$ with continuous paths.

- Random ordinary differential equation:

$$\begin{aligned} \frac{dY_t}{dt} &= -\beta Y_t + F_t \\ F_t &= f(t)(1 + X_t)^2 = c_f i^2(t) (1 + X_t)^2 \\ i(t) &= a \sin(\omega t) \end{aligned}$$

- With pathwise and mean square random solution $(Y_t)_{t \in [t_0, \infty]}$:

$$Y_t = y_0 e^{-\beta(t-t_0)} + \int_{t_0}^t e^{-\beta(t-s)} F_s ds, \quad Y_{t_0} = y_0$$

Stationary excitation and solution

- Assume $(X_t)_{t \in \mathbb{R}}$ as mean square continuous strong stationary stochastic process with continuous paths
 $\Rightarrow ((1 + X_t)^2)_{t \in \mathbb{R}}$ is a stationary process.
- \implies Periodically correlated solution on \mathbb{R}

$$Y_t^{\text{per}} = \int_0^\infty e^{-\beta s} F_{t-s} \, ds = \int_0^\infty e^{-\beta s} f(t-s)(1 + X_{t-s})^2 \, ds$$

(steady state solution, limit for $t_0 \rightarrow -\infty$).

- Mean value for periodically correlated solution

$$\begin{aligned} \mathbb{E}[Y_t^{\text{per}}] &= y_{\text{per}}(t) \mathbb{E}[(1 + X_0)^2] \\ &= c_1 [1 - c_2 \sin(2\omega t + \psi)] \mathbb{E}[(1 + X_0)^2]. \end{aligned}$$

Stationary excitation and solution

- For covariance function $\text{Cov}_{Y^{\text{per}}}(s, t) = \text{Cov}[Y_s^{\text{per}}, Y_t^{\text{per}}]$ an integral formula can be derived.
- Moment functions for random arc radius $(R_t)_{t \in [0, T]}$ or random voltage $(U_t)_{t \in [0, T]}$ cannot be calculated without further assumptions.
- **Reason:** nonlinear relationship between the functions R and Y , and respectively U , Y and X . So it holds

$$R_t = Y_t^{\frac{1}{m+4}}, \quad U_t = k_3 (1 + X_t)^2 Y_t^{-\frac{m+2}{m+4}} i(t).$$

Stationary Ornstein-Uhlenbeck process (O-U process)

- $(X_t)_{t \in \mathbb{R}}$ stationary Gaussian process with continuous paths and $E[X(t)] = 0$, $\text{Cov}[X_t, X_s] = \frac{\sigma^2}{2\theta} \exp(-\theta|t-s|)$ with $\theta > 0$, $\sigma > 0$, $t, s \in \mathbb{R}$.
- Can for $t \geq 0$ be considered as solution of stochastic differential equation

$$dX_t = -\theta X_t dt + \sigma dW_t$$

with standard Wiener process $W = (W_t; t \geq 0)$ and initial value $X_0 \sim N\left(0, \frac{\sigma^2}{2\theta}\right)$ independent of W .

- ⇒ Possibility of investigating the coupled system of nonlinear stochastic differential equations

$$d \begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \begin{pmatrix} -\beta Y_t + f(t)(1 + X_t)^2 \\ -\theta X_t \end{pmatrix} dt + \begin{pmatrix} 0 \\ \sigma \end{pmatrix} dW_t.$$

Mean function of u with Monte-Carlo method

- Simulating 1000 paths $(x_t)_{t \in [0, T]}$ of the Ornstein-Uhlenbeck process (here with $\theta = 1.3$ and $\sigma = 6$).
- Numerical computation of

$$y_t = y_0 e^{-\beta t} + \int_0^t e^{-\beta(t-s)} f(s) (1 + x_s)^2 ds, \quad t \in [0, T]$$

as the solution of the initial value problem of the ordinary differential equation.

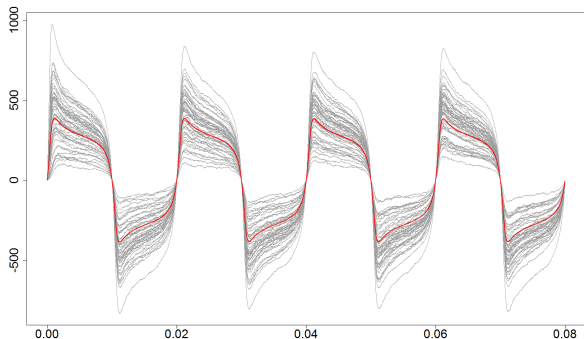
- Computation of arc voltage paths with the formula

$$u_t = \sqrt{2} k_3 (1 + x_t)^2 |I| y_t^{-\ell} \sin(\omega t), \quad \ell = \frac{m+2}{m+4}, \quad t \in [0, T]$$

Mean function of u with Monte-Carlo method

- First 50 simulations of u (grey lines) and estimated mean function (red line) with parameters

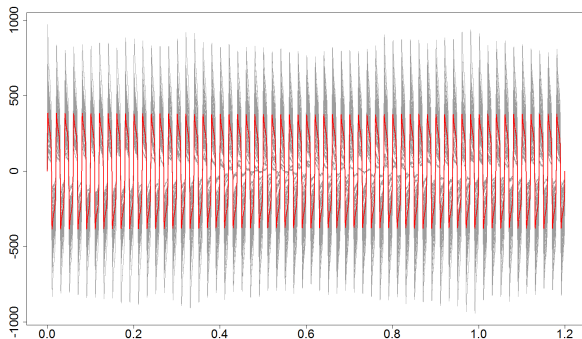
t_0	y_0	$ I $	ω	m	k_1	k_2	k_3	θ	σ
0	0.01	50	100π	0	3 000	1	12.5	1.3	6



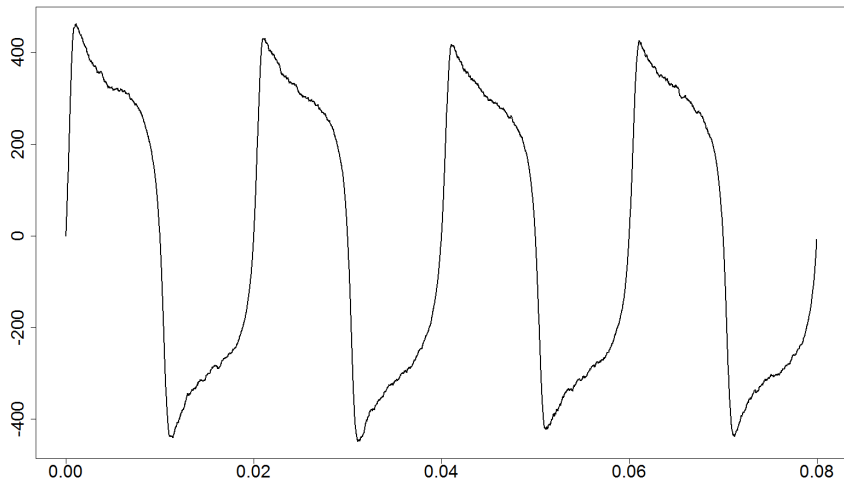
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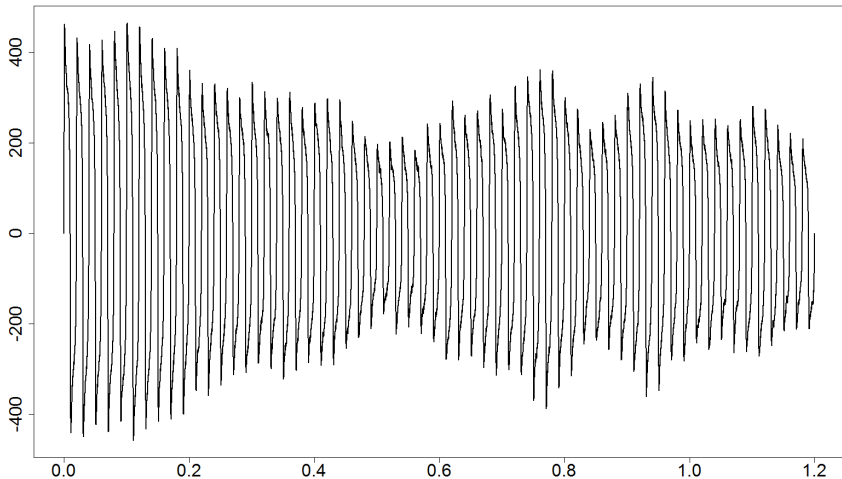
t_0	y_0	$ I $	ω	m	k_1	k_2	k_3	θ	σ
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Karhunen-Loève expansion of O-U process

- On time interval $[0, T > 0]$ a.s and in mean square

$$X_t = \sum_{k \in \mathbb{N}} \sqrt{\lambda_k} \xi_k \phi_k(t), \quad t \in [0, T],$$

with i.i.d. $N(0, 1)$ random variables $\xi_k = \frac{1}{\sqrt{\lambda_k}} \int_0^T X_t \phi_k(t) dt$.

- Covariance operator $C_X : L^2([0, T]) \rightarrow L^2([0, T])$ is defined by

$$(C_X g)(s) := \int_0^T \text{Cov}[X_t, X_s] g(t) dt = \int_0^T \frac{\sigma^2}{2\theta} e^{-\theta|s-t|} g(t) dt.$$

- $\lambda_k > 0, \phi_k(\cdot)$ eigenvalues and corresponding orthonormalized (in $L^2[0, T]$) eigenfunctions of the covariance operator:

$$C_X \phi_k = \lambda_k \phi_k \quad \text{for } k \in \mathbb{N}.$$

- Eigenvalues can be calculated numerically (solutions of transcendental equations), eigenfunctions for given eigenvalue can be calculated analytically (eg. cf. Corlay, S.; Pages, G. (2010)).
- For numerical computations we need to truncate the Karhunen-Loève expansion:

$$X_t^N = \sum_{k=1}^N \sqrt{\lambda_k} \xi_k \phi_k(t), \quad N \in \mathbb{N}.$$

- Y^N pathwise solution, where X is replaced by X^N :

$$Y_t^N = y_0 e^{-\beta(t-t_0)} + \int_{t_0}^t e^{-\beta(t-s)} f(s) (1 + X_s^N)^2 ds.$$

- Can be represented as polynomial chaos expansion:

$$Y_t^N = \sum_{k=0}^M y_k(t) \Psi_k,$$

with $M = \frac{(N+2)(N+1)}{2} - 1$. $(\Psi_k)_{k \in \mathbb{N}_0}$ are orthogonal random variables with properties:

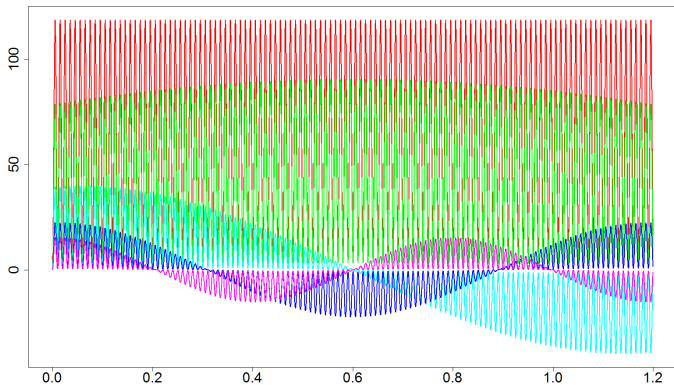
- For every Ψ_k exists a N -variate polynomial p_k , such that

$$\Psi_k = p_k(\xi_1, \xi_2, \dots, \xi_N).$$

- $\Psi_0 = 1$ and $\Psi_k = \xi_k$ for $k \in \{1, \dots, N\}$.
- To consider are only the multivariate Hermite polynomials up to degree 2.

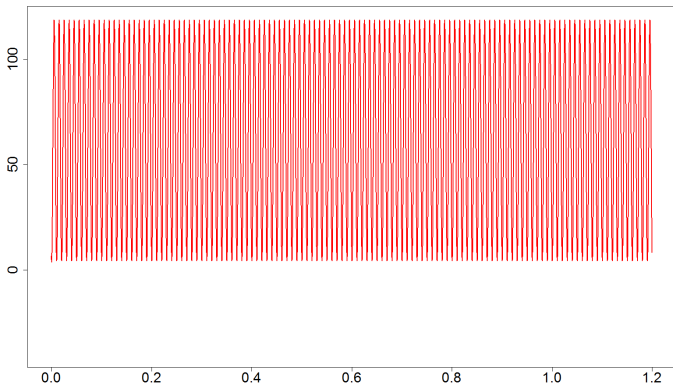
Numerical computations

- Selected parameters: $N = 20 \implies M = \frac{(N+2)(N+1)}{2} - 1 = 230$,
 $T = 1.2$
- y_0 in red, y_1 in green, y_2 in light blue, y_3 in blue, y_4 in purple:



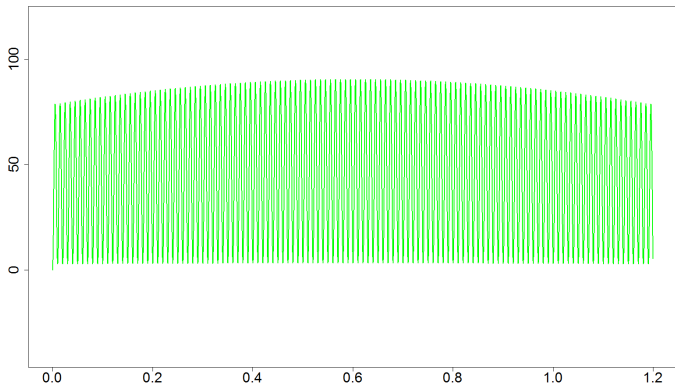
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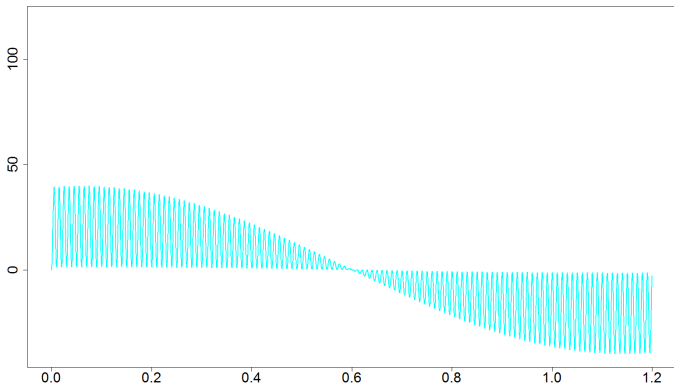
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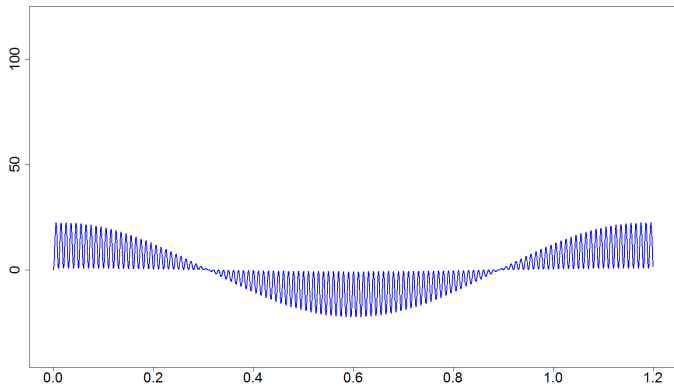
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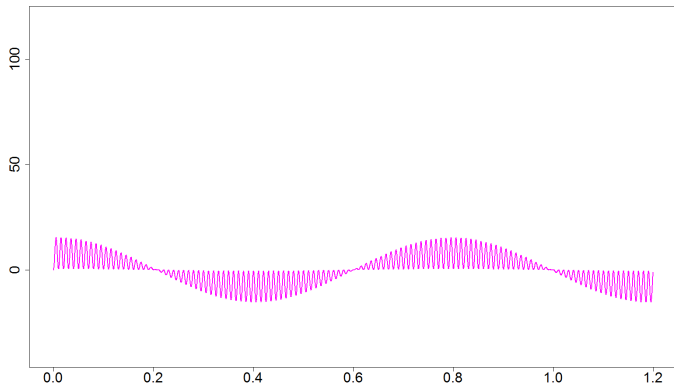
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- Consider here the case $m = 0$, then

$$R^N := (Y^N)^{\frac{1}{4}} = \sqrt{\sqrt{Y^N}}$$

- The arc radius can be represented as polynomial Chaos expansion:

$$R^N = \sum_{k=0}^{\infty} r_k(t) \Psi_k$$

- Step 1: Series development of $\left(\sqrt{Y^N}\right)_t = \sum_{k=0}^{\infty} \tilde{y}_k(t) \Psi_k$

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Approximately it holds

$$\sum_{k=0}^M y_k(t) \Psi_k = Y_t^N = \left(\sqrt{Y_t^N} \right)^2 \approx \left(\sum_{k=0}^M \tilde{y}_k(t) \Psi_k \right)^2$$

For all $\ell \in \{0, \dots, M\}$ it follows

$$y_\ell(t) \mathbb{E}[\Psi_\ell^2] \approx \sum_{j=0}^M \sum_{k=0}^M \tilde{y}_j(t) \tilde{y}_k(t) \mathbb{E}[\Psi_j \Psi_k \Psi_\ell]$$

with $M_{jkl} := \frac{\mathbb{E}[\Psi_j \Psi_k \Psi_\ell]}{\mathbb{E}[\Psi_\ell^2]}$, this results in the nonlinear equation

$$\begin{pmatrix} y_0(t) \\ \vdots \\ y_M(t) \end{pmatrix} = \begin{pmatrix} \sum_{j=0}^M \sum_{k=0}^M M_{jk0} \tilde{y}_j(t) \tilde{y}_k(t) \\ \vdots \\ \sum_{j=0}^M \sum_{k=0}^M M_{jkM} \tilde{y}_j(t) \tilde{y}_k(t) \end{pmatrix}$$

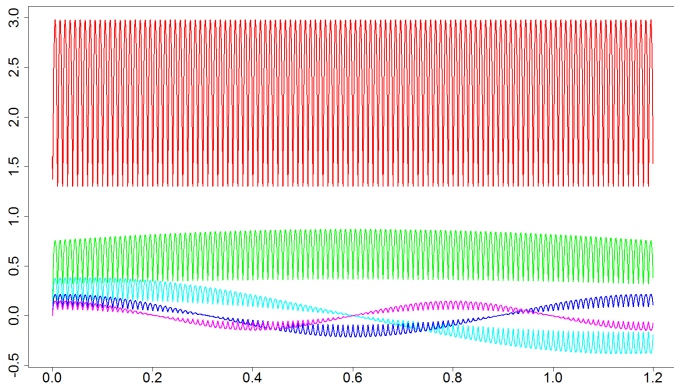
Step 2: Series development of $R_t^N = \sqrt{\sqrt{Y_t^N}} \approx \sqrt{\sum_{k=0}^M \tilde{y}_k(t) \Psi_k}$ with the same method as in step 1 \implies

$$R_t^{N,M} = \sum_{k=0}^M \tilde{r}_k(t) \Psi_k \quad t \in [0, T]$$

as presumed approximation of $(R_t^N)_{t \in [0, T]}$.

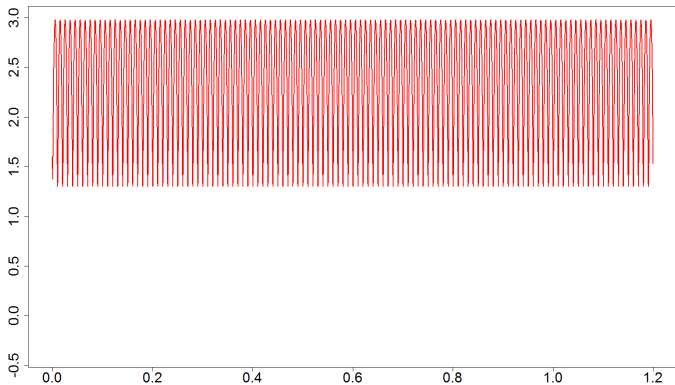
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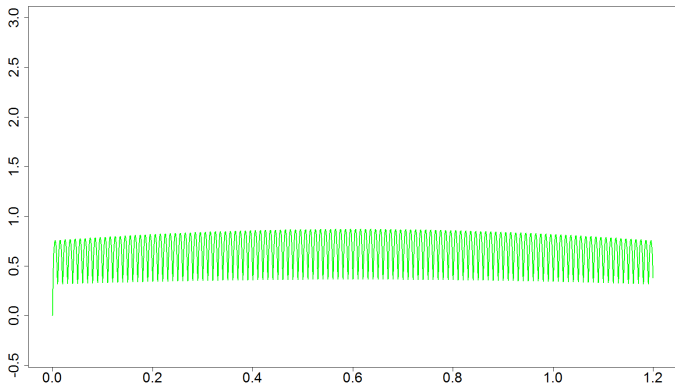
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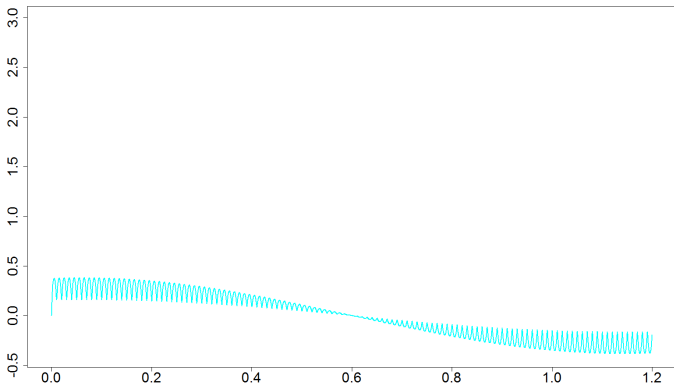


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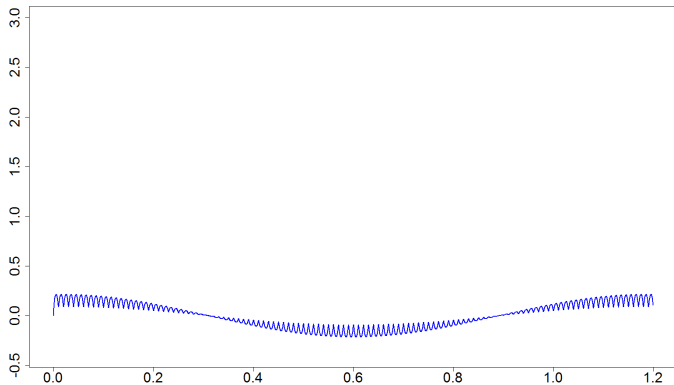


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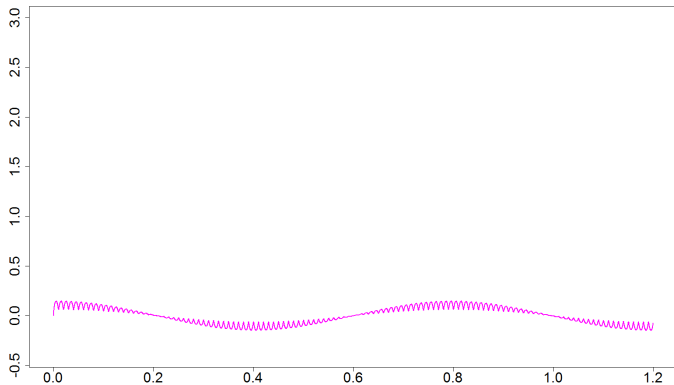
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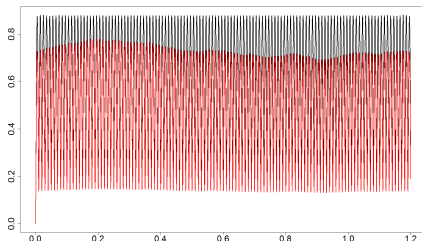


Variance function of the arc radius

- **Black line:** variance function of $R_t^{N,M} = \sum_{k=0}^M \tilde{r}_k(t) \Psi_k$:

$$\text{Var} \left[R_t^{N,M} \right] = \sum_{k=0}^M \tilde{r}_k^2(t) \text{E} \left[\Psi_k^2 \right]$$

- **Red line:** estimated variance function of $R^N = (Y^N)^{\frac{1}{4}}$ by Monte-Carlo method (2000 simulations).



- Consider here the case $m = 0$, then

$$U_t^N := \frac{k_3 (1 + X_t^N)^2}{\sqrt{Y_t^N}} i(t)$$

- The arc radius can be represented as polynomial Chaos expansion:

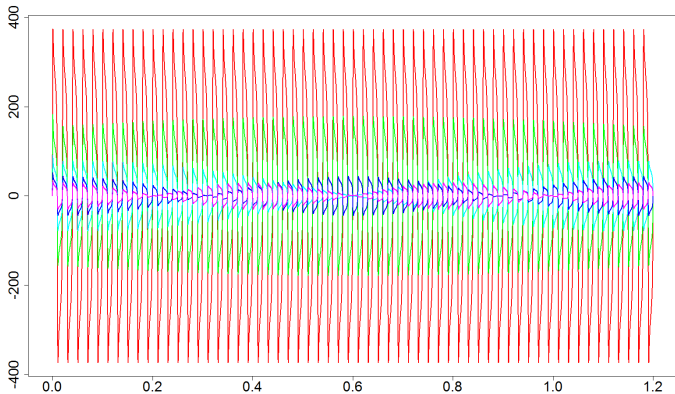
$$U_t^N = \sum_{k=0}^{\infty} u_k(t) \Psi_k$$

- A similar method as for the arc radius leads to a series development as presumed approximation of U_t^N :

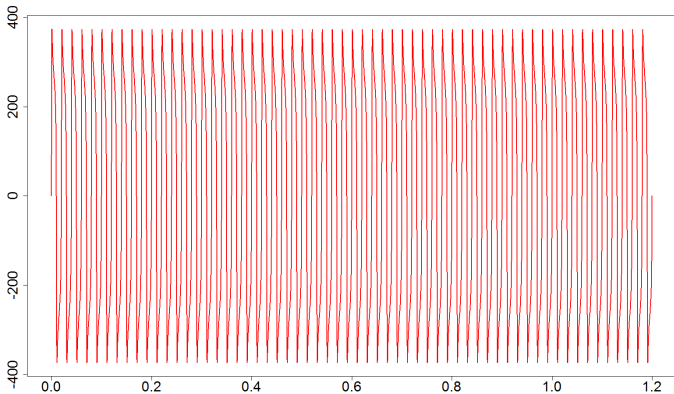
$$U_t^{N,M} = \sum_{k=0}^M \tilde{u}_k(t) \Psi_k$$

Numerical computations

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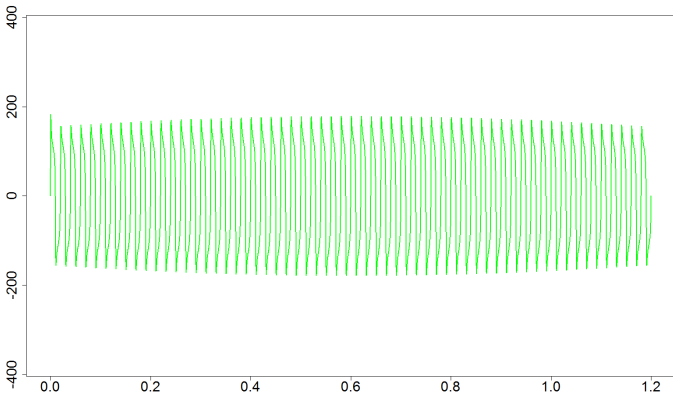


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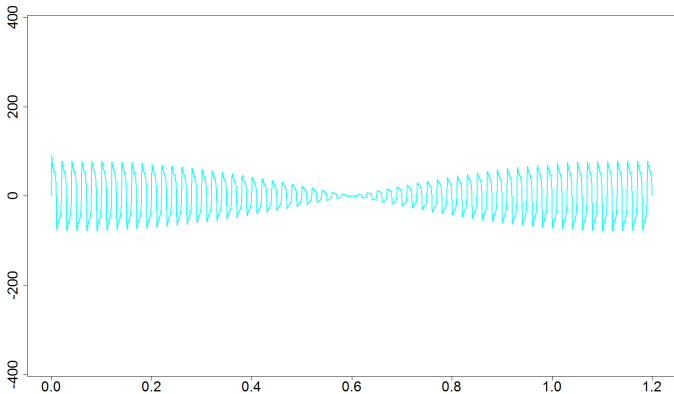
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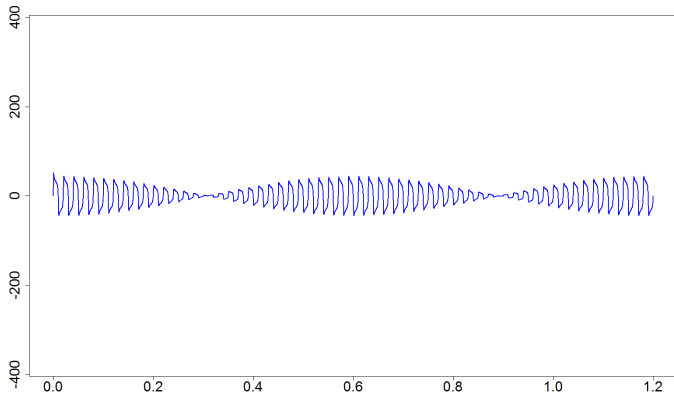
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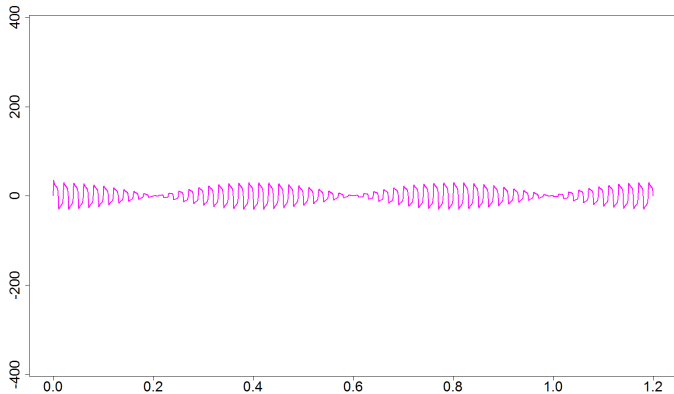
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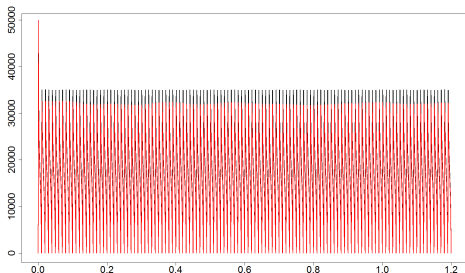


Variance function of the arc voltage

- **Black line:** variance function of $U_t^{N,M} = \sum_{k=0}^M \tilde{u}_k(t) \Psi_k$:

$$\text{Var} \left[U_t^{N,M} \right] = \sum_{k=0}^M \tilde{u}_k^2(t) \text{E} [\Psi_k^2]$$

- **Red line:** estimated variance function of U^N by Monte-Carlo method (2000 simulations).



Some open questions:

- Characteristics of the stochastic processes $R(t)$ and $U(t)$.
- Statistical analysis of the model.
- Fitting the model to real world data.

List of References

- **Grabowski, D.; Walczak, J., Klimas, M.:** “Electric arc furnace power quality analysis based on a stochastic arc model”. IEEEIC/I&CPS Europe, pp. 1–6, 2018, IEEE.
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Thank you for your attention!