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A comparison of extended electricity price models considering the impact of wind energy feed-in

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Agenda

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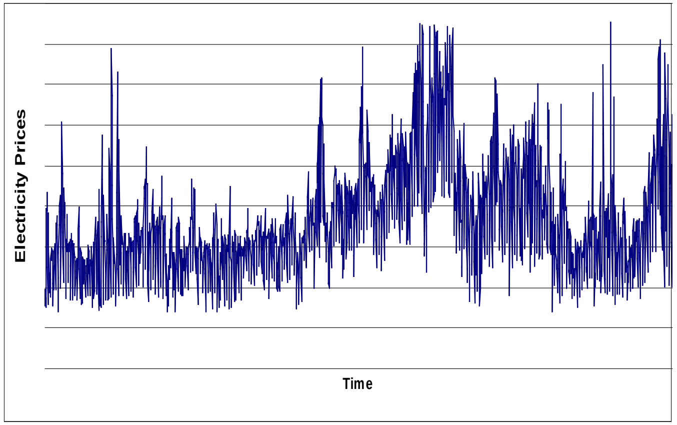
1. Background
2. Impact of wind power feed-in on electricity prices
3. Modelling electricty prices via stochastic processes
4. Simulation of wind-power feed-in
5. Extended electricity price modeling comsidering the impact of wind power feed-in
6. Conclusions and Outlook

Background

- High uncertainties in energy markets due to liberalization and structural changes
- Electricity prices have become very volatile

→ **Stochastic simulation to capture these volatilities**



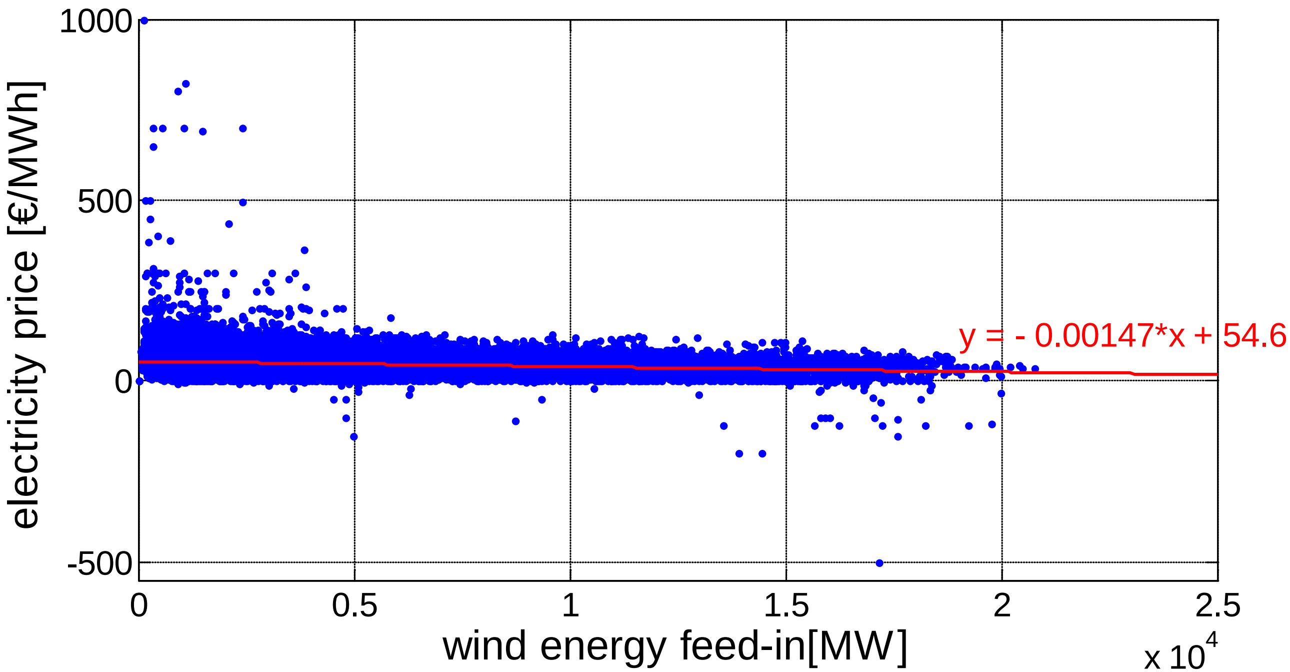
- Volatile feed-in of large amount wind power into grid
- Wind power feed-in (WPF) has a significant impact on the electricity price
- Long-term effects on power plant mix

→ Evaluation of new investments need to consider uncertain prices and WPF

→ Therefore a basic knowledge of the interrelations is necessary

Impact of wind power feed-in (WPF) on electricity prices

- historical couples of electricity prices and WPF (2006-2009)



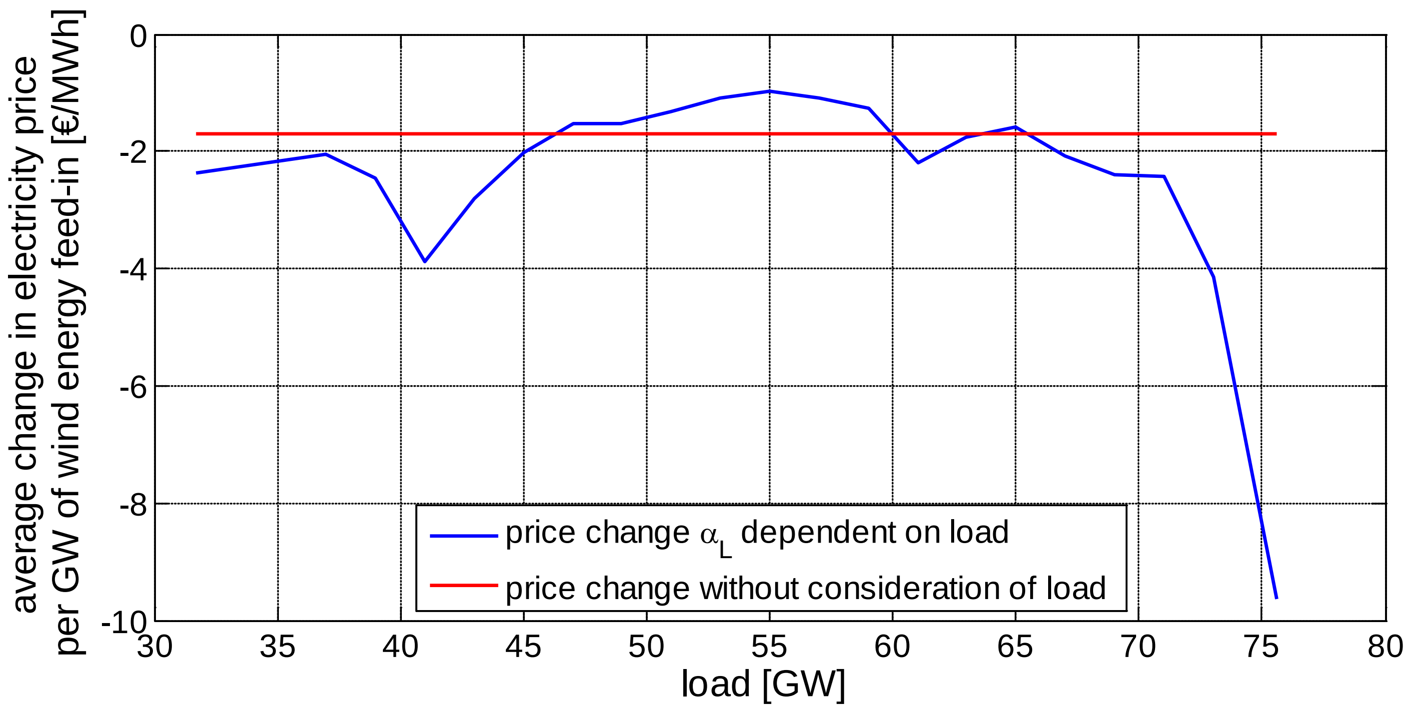
→ the electricity price declines by 1,47 €/MWh on an average per Gigawatt wind power feed-in

→ reason: merit order effect of WPF

→ the average price reduction of 1,47 €/MWh per GW does not explain extreme price decreases of up to -500€/MWh

Impact of wind power feed-in (WPF) on electricity prices

- change of electricity prices depending on the current load

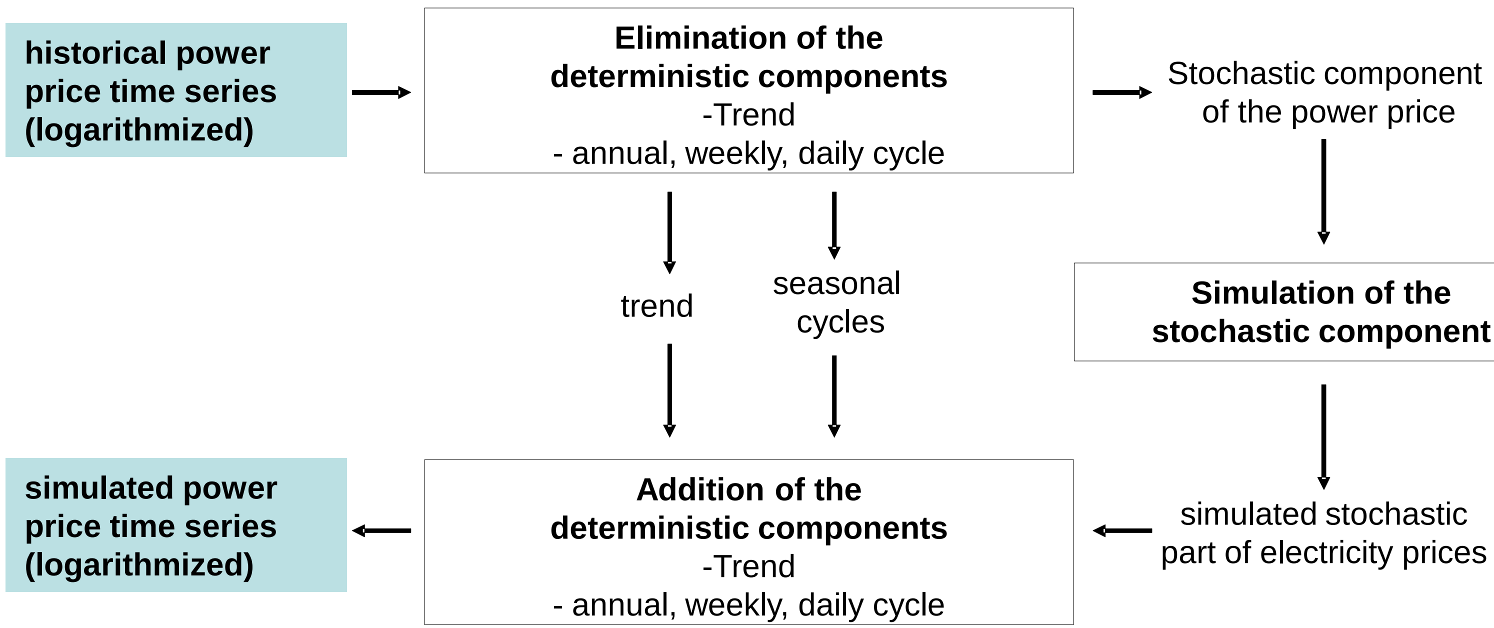


→ the average price change caused by WPF varies according to the demand level

→ possible cause: irregular structure of the merit order curve

Modeling electricity prices via stochastic prices

- basic model for power price simulation:



→ Division of the power price into a deterministic and a stochastic components

→ Simulation of the stochastic portion via models of financial mathematics

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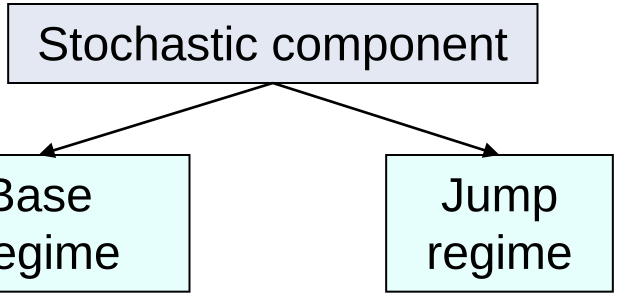
Modelling of the stochastic component:

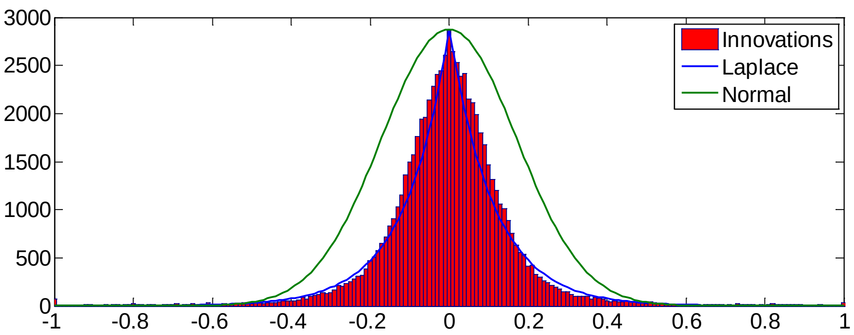


Base regime:

- **Autoregressive mean-average (ARMA(p,q))- process**
  - Assumption: Price X_t^s depend on the last p prices and X_{t-p} and q innovations ε_{t-p}

$$X_t^{BASE,s} = \sum_{i=1}^{p} \alpha_i X_{t-i}^{R} + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j} + \varepsilon_t$$

  - Parameters are estimated via MLE (Garch-Toolbox in MATLAB)
  - Innovations: ε_t ~ Laplace(μ_ε,b_ε)



- **Integrated ARMA (ARIMA)-process**
- **GARCH-Process**
- **Mean-Reversion process**

Modeling electricity prices via stochastic prices

Jump regime: extension of the base processes

$$X_t^{s,JUMP} = X_t^{s,BASE} + \ln J_t \qquad \ln J_t \sim N\left(\mu_{\ln J}, \sigma_{\ln J}^2\right)$$

- Prices in X_t^s beyond a confidence interval $[\mu - 3\cdot\sigma, \mu + 3\cdot\sigma]$ are declared as jumps
- Calculation of switching probabilities as the relative frequency of price switches between the one in and out the confidence interval:

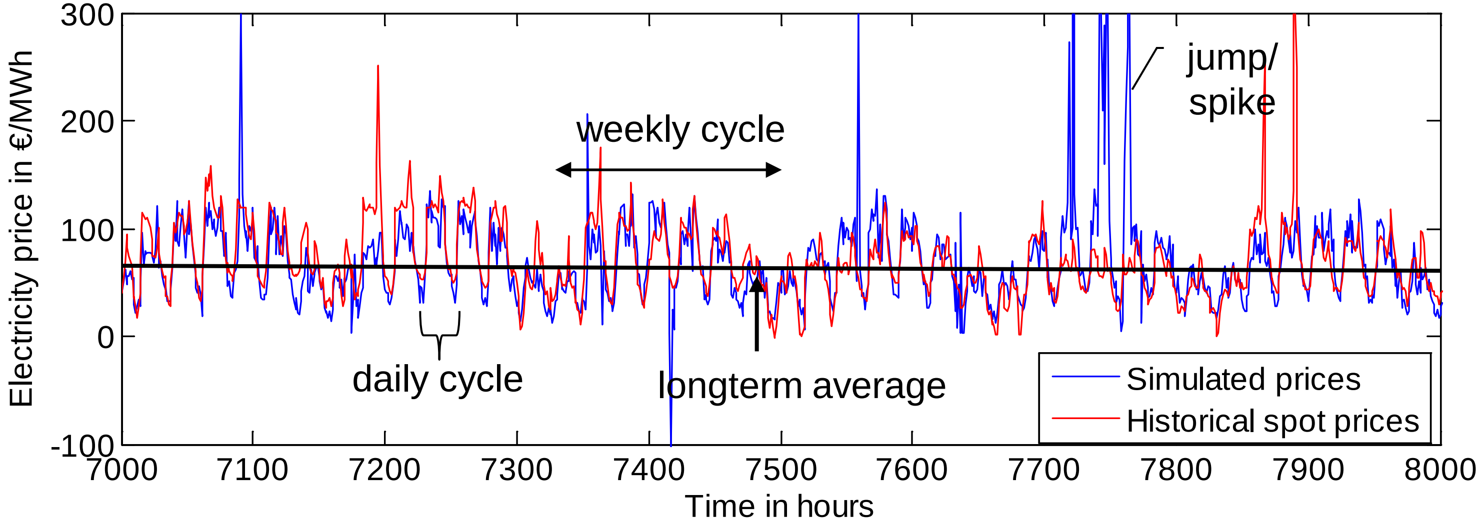
$$P_{12} = \frac{card\left\{l \mid X_{l,t}^{SR} \in [\mu - 3\sigma, \mu + 3\sigma] \wedge X_{l,t+1}^{SR} \in (\mu + 3\sigma, \ln 3000]\right\}}{card\left\{l \mid X_{l,t}^{SR} \in [\mu - 3\sigma, \mu + 3\sigma]\right\}} \qquad T = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}$$

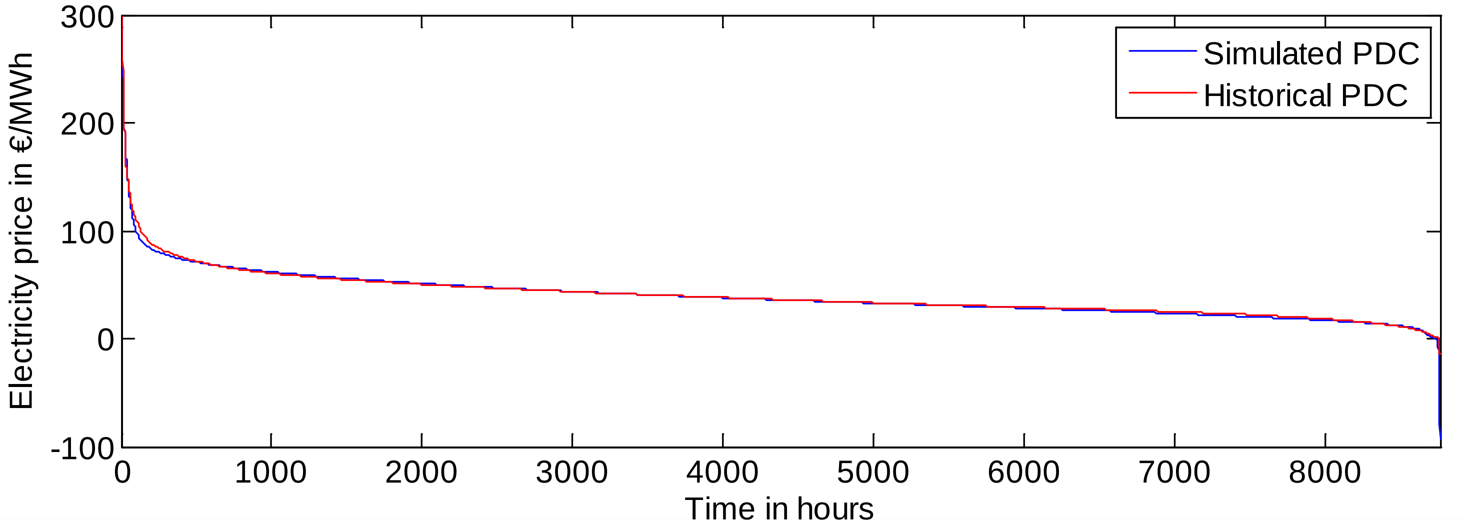
- Differentiation of switching probabilities for summer weekdays, winter weekdays and weekends

→ *Simulation of the stochastic component* X_t^s *with the regime-switching model and addition of the deterministic ones*

➡ **Simulated electricity price paths**

Modeling electricity prices via stochastic prices – simulation results



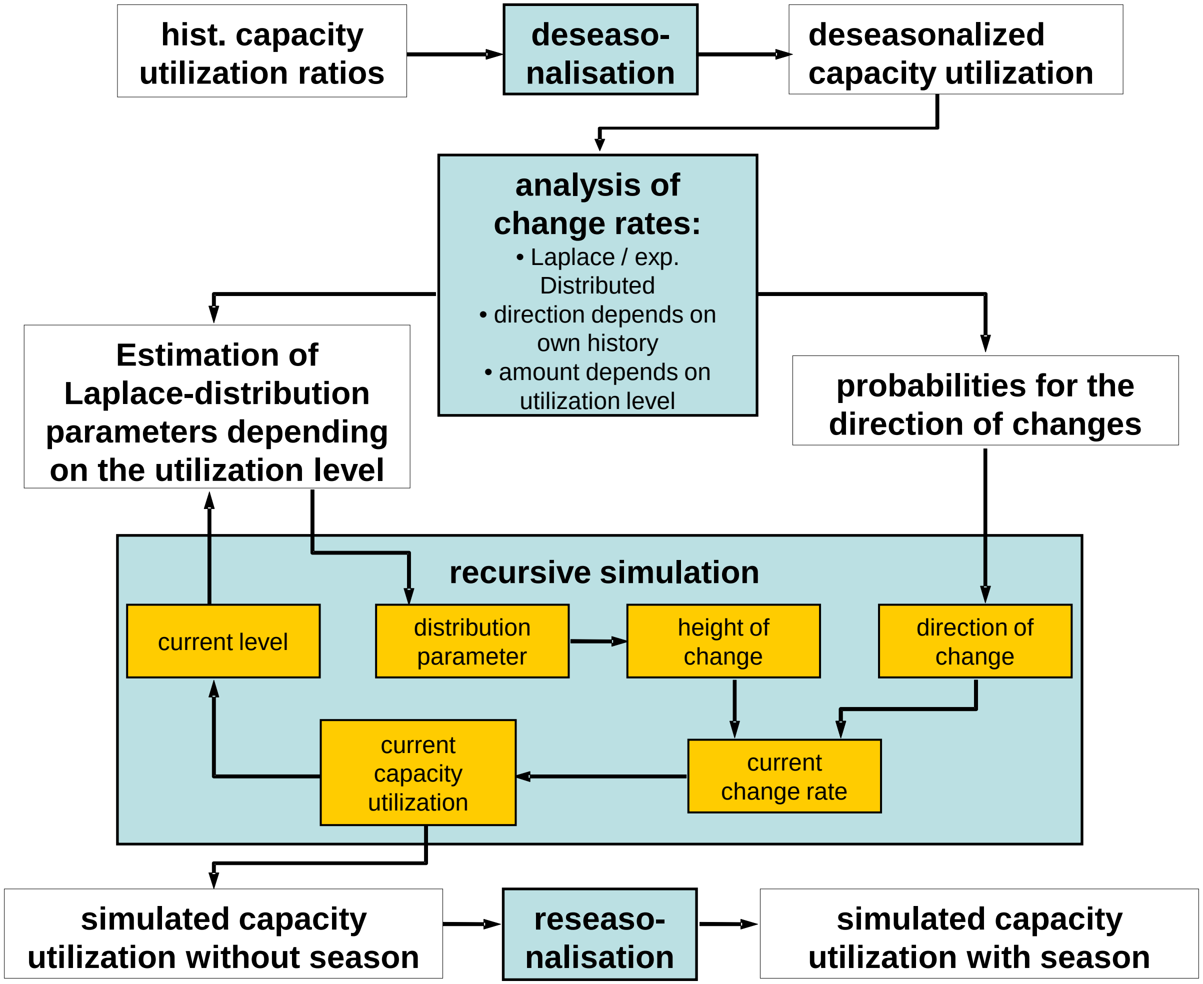


Modeling electricity prices via stochastic prices – simulation results

	MRSE [€/MWh]			R2		
Stochastic Model	**2009**	**2008**	**2002-2008**	**2009**	**2008**	**2002-2008**
Mean-Reversion (MR)	8.51	6.11	2.40	37%	52.53%	20.98%
ARMA(1,1), *(5,5)	8.63, 8.62	6.86, 7.12	2.73, 2.77	30.97%, 31.24%	43.93%, 44.70%	18.67%, 18.83%
ARIMA(1,1,1), *(5,1,5)	8.15, 8.19	5.91, 5.55	2.70, 2.64	33.21%, 33.02%	47.05%, 50.25%	19.41%, 20.18%
GARCH(1,1),*(5,5)	15.10, 17.85	9.03, 11.07	3.21, 4.18	13.57%, 10.03%	34.69%, 31.88%	13.48%, 12.53%
MR without RS	19.92	17.52	6.39	18.90%	31.49%	26.93%
GARCH without RS	109.18, 111.84	102.01, 102.97	47.12, 49.23	1.47%, 1.36%	3.89%, 3.63%	1.89%, 1.84%
ARIMA without deseasonalizing	9.94, 21.96	14.92, 13.00	9.95, 609.30	0.21%, 2.67%	0.13%, 0.11%	3.00%, 1.45%

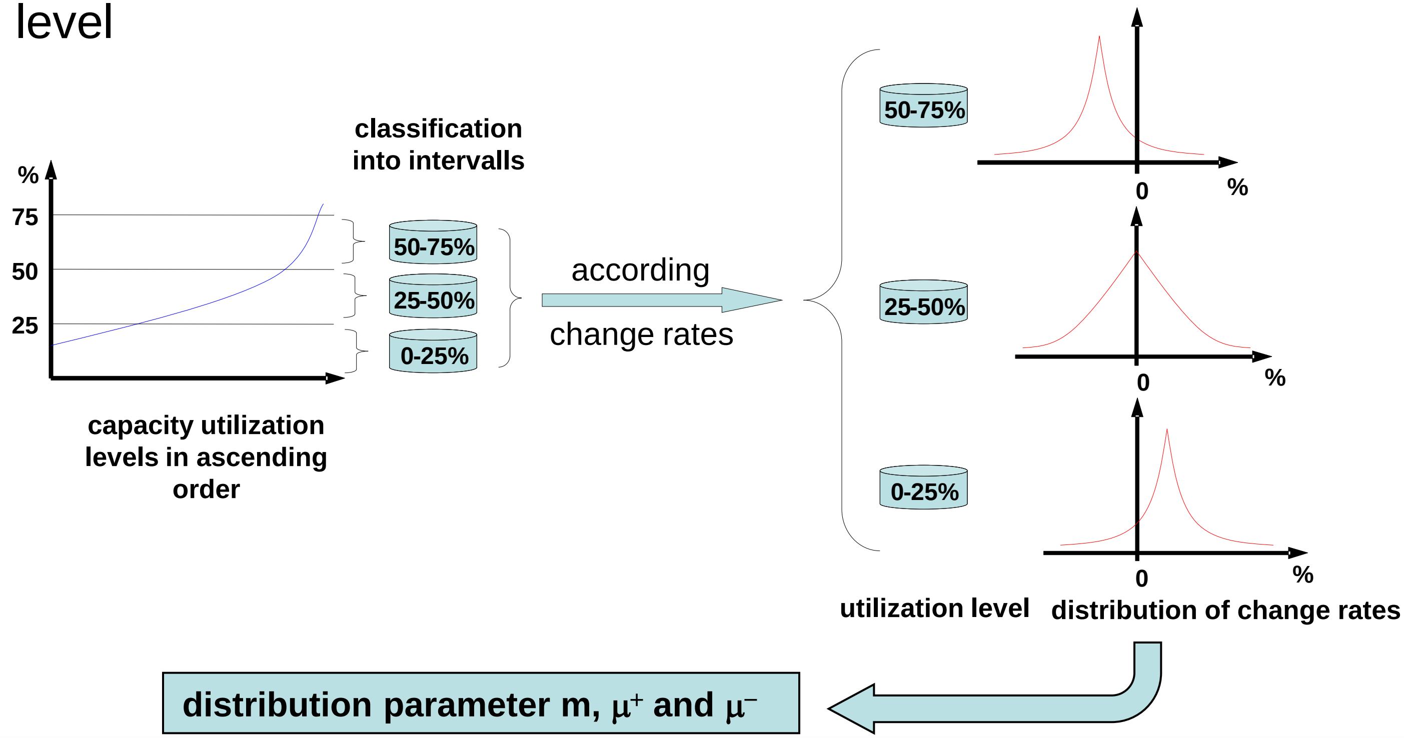
Simulation of wind power feed-in

- Overview of the simulation model



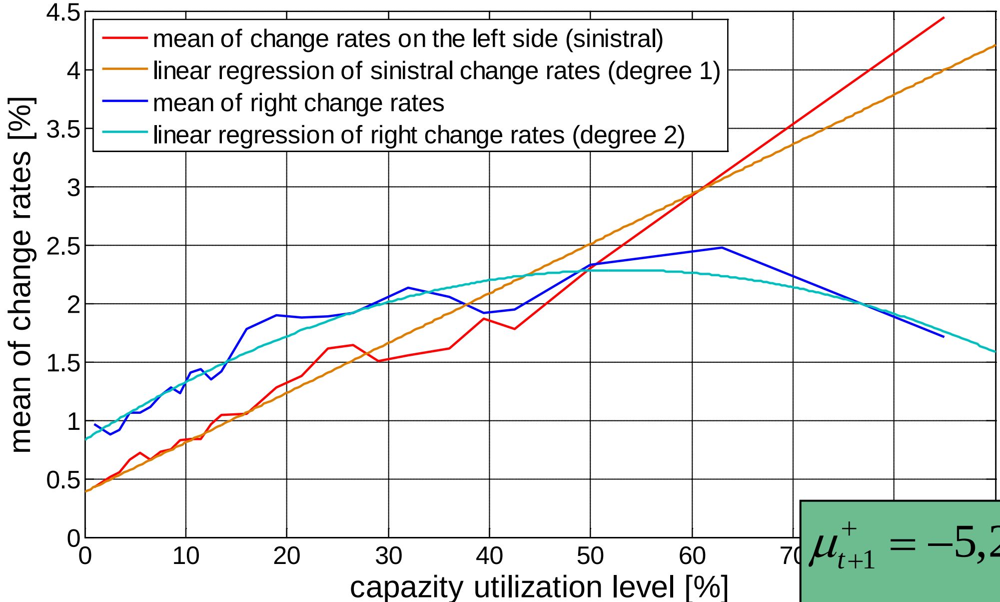
Simulation of wind energy feed-in (WEF)

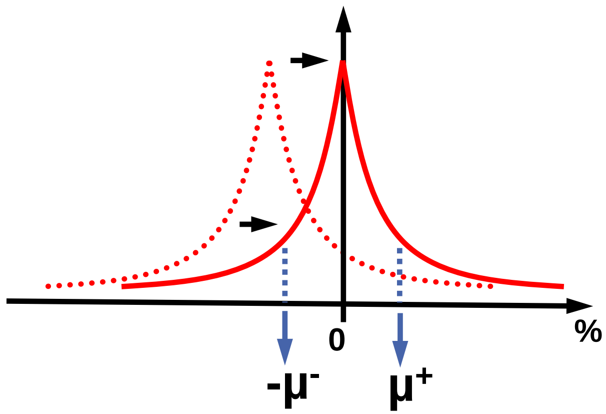
- utilization levels are classified by height
- the distribution of change rates is analysed separately for each class and parameters are determined
- with the help of these distribution parameters the height of the change is determined as a random number dependent on the recent utilization level



Simulation of wind energy feed-in (WEF)

- parameters µ+ und µ-





$$\mu_{t+1}^{+} = -5{,}2 \cdot 10^{-4} \cdot Niv(X_t)^2 + 0{,}055 \cdot Niv(X_t) + 0{,}83$$

$$\mu_{t+1}^{-} = 0{,}042 \cdot Niv(X_t) + 0{,}38$$

→ µ+ and µ- correspond to the mean of the positive and negative changes, that were moved by the modal value

→ the height of negative change rates grows with increasing utilization level

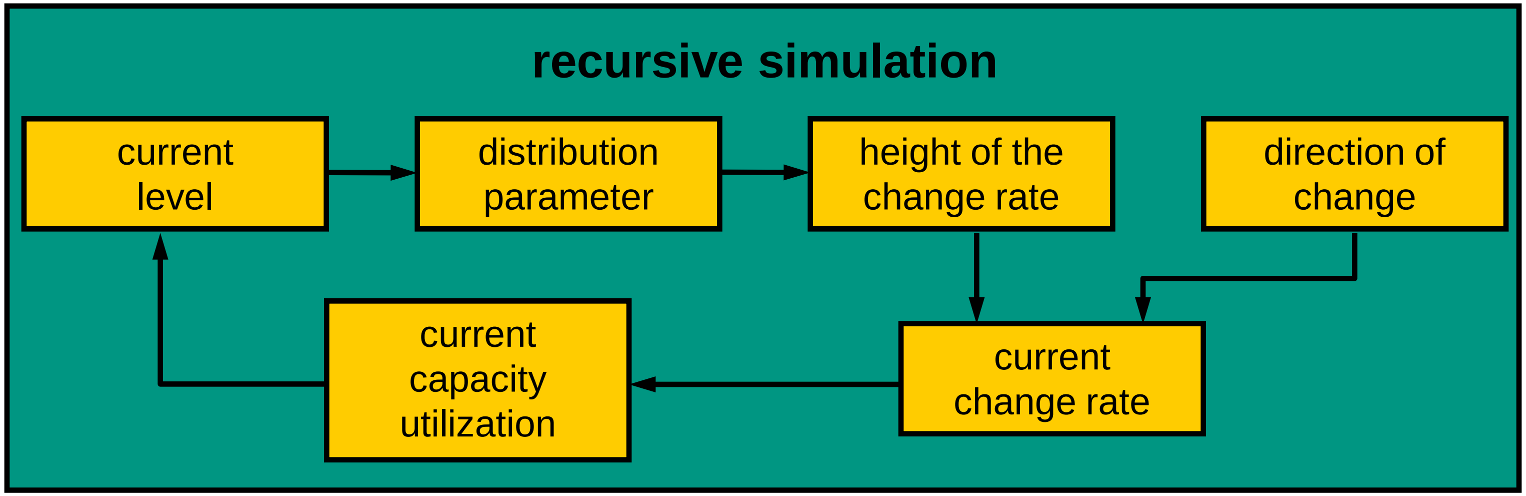
→ the height of positive change rates reaches its maximum at medium utilization rates

Simulation of wind energy feed-in (WEF)

- Simulation approach

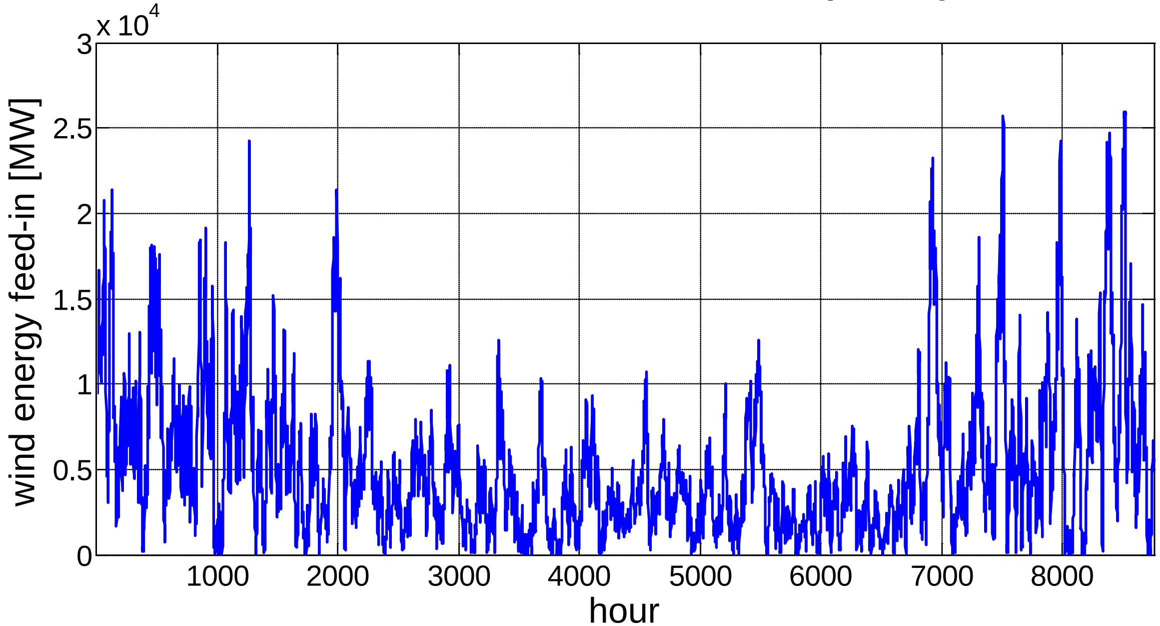
→ Recursive simulation of the hourly capacity utilization X_t^{sim} based on the model of the change rates ΔX_t^{sim}

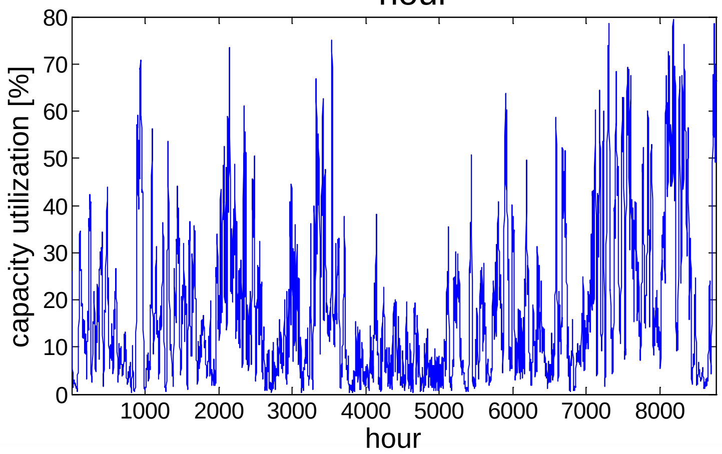
$$X_t^{sim} = X_{t-1}^{sim} + \Delta X_{t-1}^{sim}$$



Simulation of wind power feed-in (WPF)

- Simulation results for an actual installed capacity of 26 GW wind power





Extended modeling of power prices including the impact of wind power feed-in

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- extension of the base model

historical power price time series → **Elimination of the deterministic components**
-Trend
- annual, weekly, daily cycle
→ stochastic component → **Elimination of the impact of wind power feed-in**
↓ remaining stochastic price component
↓ **Simulation of the remaining stochastic price component via financial models**
↓ simulated stochastic power price path
↓ **Addition of the impact of wind power feed-in**
↑ simulated time series of wind energy feed-in
↑ **Simulation of wind power feed-in levels**

Addition of the impact of wind power feed-in → simulated stochastic component → **Addition of the deterministic components**
-Trend
- annual, weekly, daily cycle
→ **simulated power price series**

Elimination of the deterministic components → trend, seasonal cycles → Addition of the deterministic components

$$SP^{hist,stoch} = SP^{hist} - SP^{hist,\det} - \Delta SP(WEF^{hist})$$

→ impact of the WPF is included to the stochastic, but explainable price component and thus it is treated like a deterministic price component

Modeling electricity prices under volatile WPF – simulation results

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Comparison of the electricity price simulation results **without** and **with** consideration of wind power simulation:

	2009			2008		
	W/O Wind	**with Wind**	**HISTORICAL**	**W/O Wind**	**with Wind**	**HOSTORICAL**
MRSE [€/MWh]	8.51	6.67	-	6.11	5.57	-
MAPE	13.93%	10.64%	-	6.40%	4.98%	-
R2	36.60%	38.38%	-	52.53%	54.80%	-
Mean [€/MWh]	41.25	38.86	38.85	67.65	65.73	65.76
σ [€/MWh]	23.94	20.16	19.41	33.87	26.02	28.66
skewness	1.49	-1.16	-3.23	2.01	0.01	1.16
kurtosis	20.08	8.66	83.90	37.85	3.42	11.84

→ the consideration of the impact of wind power leads to significant improvement of the price simulation

Summary

- The simulation results of the mean-reversion and the ARMA-models do not differ significantly, both models are suitable for electricity price simulation
- However, the GARCH approach is less suitable, the MRSE is very high in this case
- Regime switching approach improves the simulation immensely, the error is reduced by more than half
- Consideration of the seasonal components leads also to a significant improvement of the electricity price simulation
- Impact of wind power:
  - Depends strongly on the actual load level
  - Wind power feed-in can be simulated via Laplace-distrubuted change rates
  - The separation of the stochastic component into a “wind power driven” one and remaining stochastic one improves also the electricity price simulation

Thank you!

Questions?

Impact of wind energy feed-in (WEF) on electricity prices

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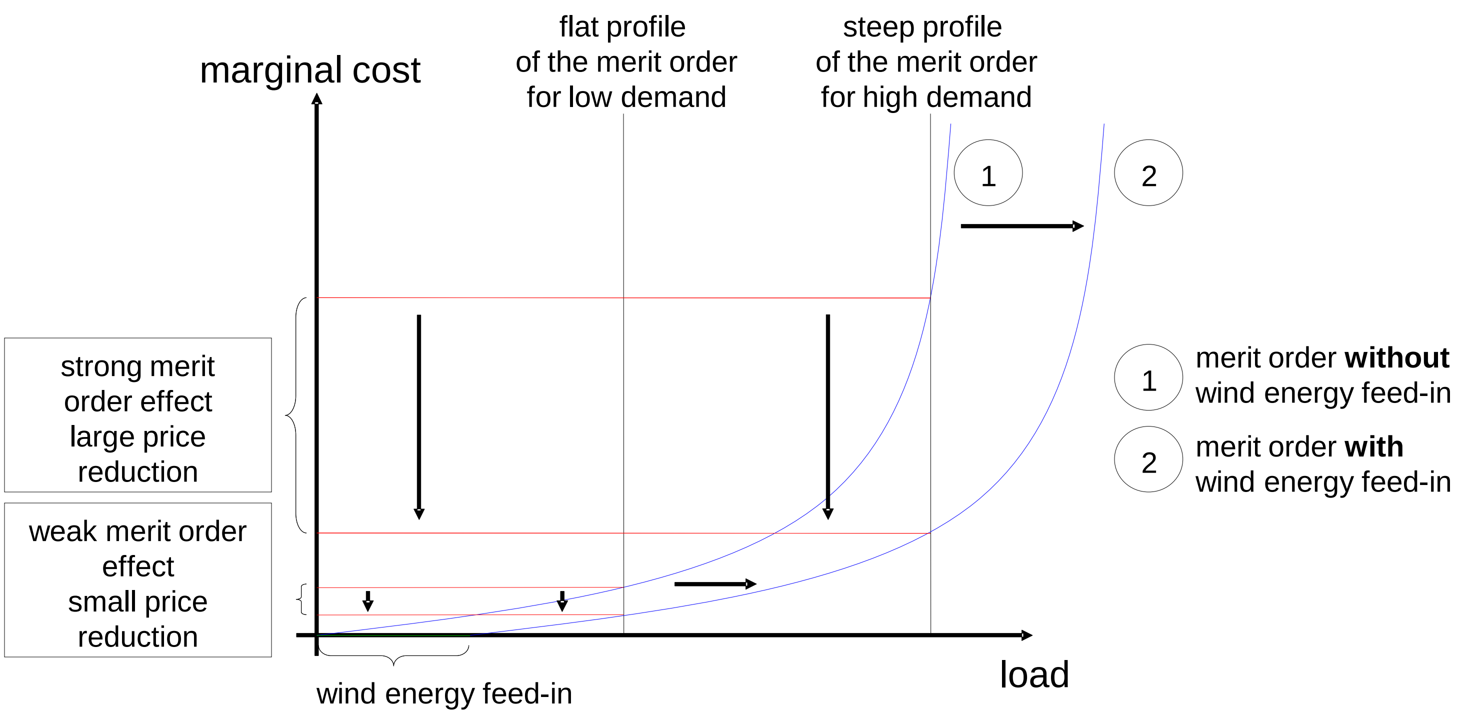
- structure of the merit order



→ exponential structure, jumps and constant levels

→ depending on merit order characteristics equal WEF can cause different price reductions

Impact of wind energy feed-in (WEF) on electricity prices

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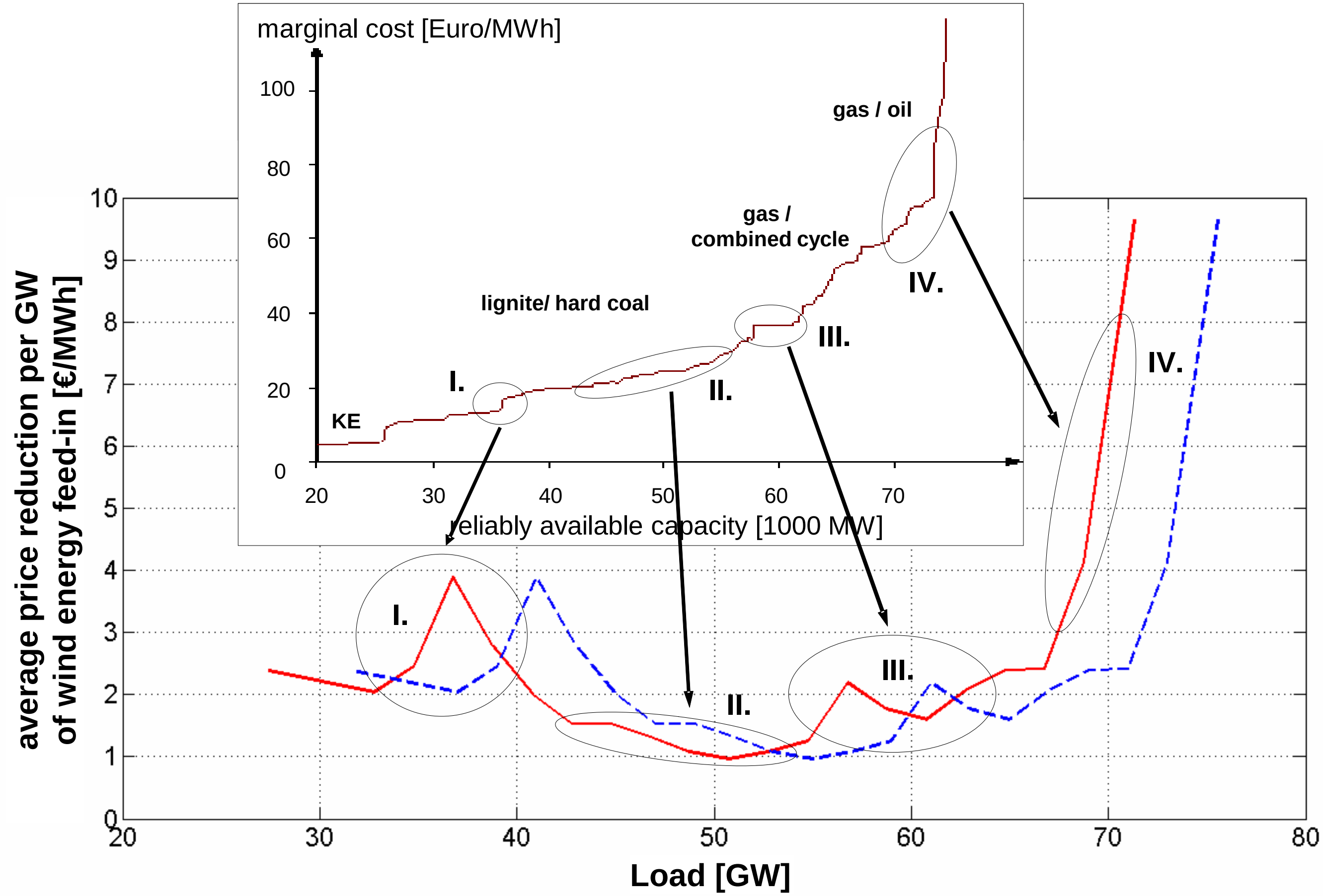
- Comparison of the merit order structure and price reductions



→ merit order structure and extreme market situations explain fluctuations within price reductions by WEF

Modeling electricity prices via stochastic prices

Modeling of the deterministic parts:

Logarithmised prices (2002 - 2009)

$$X_t = \ln p_t$$

- Negative prices are set to 0.01€/MWh
- Log. leads to variance stabilization

↓

Trend of price logs

$$X_t^{trend} = X_0 + \lambda \cdot t$$

↓ remove

Annual cycle

$$X_{dh}^{annual\,cycle}(t) = \alpha_{dh} + \beta_{dh} \cos\left(2\pi \frac{t-\tau}{8760}\right) + \gamma_{dh} \sin\left(2\pi \frac{t-\tau}{8760}\right)$$

↓ remove

Weekly cycle

$$X_t^{weekly\,cycle} = \alpha + \beta \left| \sin\left(\frac{\pi \cdot t}{168} - \varphi\right) \right|$$

↓ remove

Daily cycle

$$X_{i,season}^{daily\,cycle} = \frac{24}{T} \sum_{t=0}^{(T/24)-1} X_{i+24t,season}$$

$$\forall\ i \in \{1, 2, \ldots, 24\} \wedge \forall season \in \{winter, spring, summer, autumn\}$$

↓ remove

Stochastic residues

$$X_t^s = X_t - X_t^{trend} - X_t^{annual\,cycle} - X_t^{weekly\,cycle} - X_t^{daily\,cycle}$$

Modelling electricity prices

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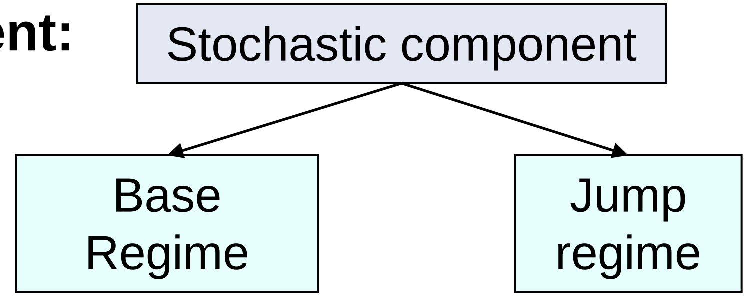
Modelling of the stochastic component:



Base regime:

Mean-reversion process

- Assumption: prices return to the long-term mean *μ with the speed κ*

$$dX_t = \kappa(\mu - X_t) \cdot dt + \sigma \cdot dW_t$$

- Wiener Process $dW_t = \varepsilon_t \, dt^{1/2}$, whereas ε_t is a standard normally distributed error term
- Exact solution: $E(X_t) = ae^{-\theta t} + \mu(1 - e^{-\theta t})$ $\quad \mathrm{Cov}(X_s, X_t) = \frac{\sigma^2}{2\theta}\left(e^{-\theta|s-t|} - e^{-\theta(s+t)}\right).$

$$X_t \sim \mathcal{N}\left(ae^{-\theta t} + \mu(1 - e^{-\theta t}), \frac{\sigma^2}{2\theta}(1 - e^{-2\theta t})\right)$$

- Parameter estimation via MLE

Simulation of wind powwer feed-in

- Analysis of change rates: dependencies

→ Dependency of change rates on historical values (Autocorrelation):

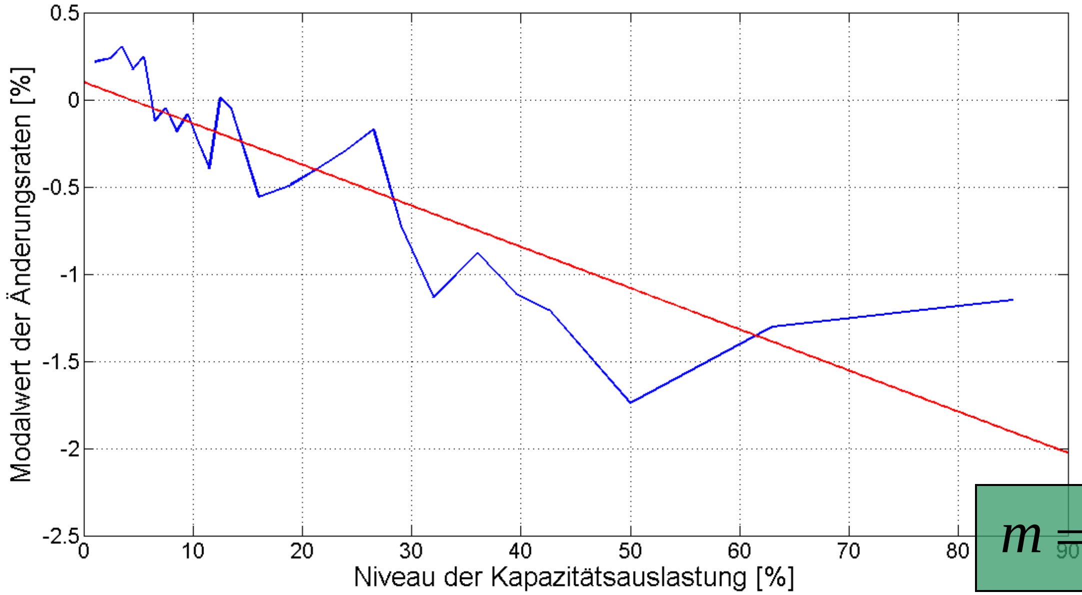
  - Direction of a change depends on previous change
  - Probability, that change will be positive or negative, results from how many directly preceding changes were positiv or negative
  - With historical date probabilities can be determined and thus for each hour in the simulation time frame the direction can be provided

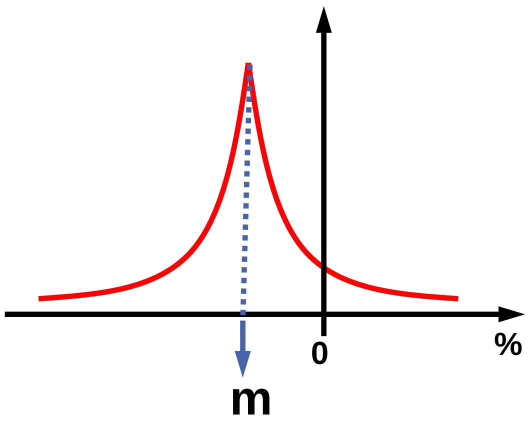
→ Dependency of change rates on historical values of capacity utilization:

  - historical capacity utilization determine the amount of the following change
  - this history is described by the level of utilization, defined as the moving average of the past 11 hours

Simulation of wind energy feed-in (WEF)

- parameter m





$$m = -0{,}024 \cdot Niv(X) + 0{,}10$$

→ m corresponds to the mode of change rates

→ the higher the utilization level, the smaller (or more negative) the average change amount

Simulation of wind energy feed-in (WEF)

- Modelling the change rates Δx_t^{sim}

$$\Delta X_t^{sim} = \begin{cases} e_t + m_t & , l_t = 1 \\ -e_t + m_t & , l_t = -1 \end{cases}$$

$$e_t \sim \begin{cases} Exp(\mu_t^+) & , l_t = 1 \\ Exp(\mu_t^-) & , l_t = -1 \end{cases}$$

$$m_t, \mu_t^+, \mu_t^- = f\left[Niv_t\left(X_t\right)\right]$$

$$t = 1,\dots, N^{sim}$$

→ Amount of the change rate is generated with a exponentially distributed random number, that is moved by the modal value of the original Laplace distribution

→ The direction of the change is determined by the series l of algebraic signs, that provides the direction of the change in each hour t