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Stochastic Geometry

A toolbox for mathematical analysis, modeling and simulation of complex geometrical patterns on various length scales

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Motivation/Goals

Overview

2D patterns on geographical scales

3D patterns on microscopic scales

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 Representing the essential information of huge databases by a small number of model parameters

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 $\Rightarrow$  object-oriented modeling (grid-free, fast algorithms)



Main roads

Simulated main roads



- Main roads
- Side streets

Simulated side streets



- Main roads
- Side streets
- Network components:
  - High-level components (green)
  - Low-level components (blue)

Network components along the roads/streets



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- Serving zones of high-level components (black)

Serving zones



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- shortest-path tree in serving zones

Serving zones

developing a toolbox of stochastic network models ('to be kept in stock')

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Basic tessellation models







Iterated tessellation models

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  - $\Rightarrow$  establish quantitative (functional) relationships between
    - spatial distribution of infrastructure/network components and
    - network performance
  - $\Rightarrow$  combined modeling and simulation of
    - spatial network structure and
    - network transport/performance (transport-relevant cost functionals)

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Models of stochastic geometry for

two-dimensional patterns on geographical scales

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  - $\Rightarrow$  Li-ion batteries
  - $\Rightarrow$  organic solar cells
  - $\Rightarrow$  fuel cells
  - $\Rightarrow$  polycristalline alloys

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### Stochastic modelling of network components



- Main roads and side streets modelled by stationary random graph Twith length intensity  $\gamma = \mathbb{E}\nu_1(T^{(1)} \cap [0, 1]^2)$
- Network components:
  - High-level components: Cox process X<sub>H</sub> with linear intensity λ<sub>ℓ</sub> (HLC)
  - Low-level components: Cox process  $X_L$  with linear intensity  $\lambda'_{\ell}$  (LLC)

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- Serving zones of high-level components
  - to connect LLC to closest HLC



► consider the Voronoi tessellation T<sub>H</sub> = {Ξ<sub>H,n</sub>} induced by the points X<sub>H,n</sub> of the Cox process X<sub>H</sub> = {X<sub>H,n</sub>}

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Cox-Voronoi cell

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### Shortest-path length



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- distribution of shortest-path lengths depends both on  $\lambda_\ell$  and  $\gamma$
- ▶ however, for PVT, PLT and PDT we have a certain scaling invariance ⇒ suffices to consider the ratio  $\kappa = \frac{\gamma}{\lambda_e}$  called scaling parameter

► choose one of the serving zones at random ⇒ typical serving zone

- $\blacktriangleright$  choose one of the serving zones at random  $\Rightarrow$  typical serving zone
- more formally, consider Palm version X<sup>\*</sup><sub>H</sub> of X<sub>H</sub> whose distribution has representation formula

$$\mathbb{E}g(X_H^*) = \frac{1}{\lambda_H} \mathbb{E}\sum_{i: X_{H,i} \in [0,1]^2} g(\{X_{H,n}\} - X_{H,i}),$$

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$$\Xi_{H}^{*} = \{ x \in \mathbb{R}^{2} : \, \|x\| \leq \|x - X_{H,j}^{*}\| \, \text{ for all } j \geq 1 \}$$





Typical serving zone  $\Xi_{H}^{*}$ (dashed) and corresponding segment system  $S_{H}^{*}$  (solid)

Shortest-path tree *G* with origin *o* as root

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- closely related with capacity problems
- and cost estimation for telecommunication networks

#### Main branches of G



Half-trees  $G_1^h$  (solid) and  $G_2^h$ (dashed) of *G* emanating from the root



Main branches *LSP* (dashed) and *LSP'* (dot-dashed) of the corresponding half-trees

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### Definition (bivariate copula)

A function  $K : [0, 1]^2 \rightarrow [0, 1]$  is called a bivariate copula if there exists a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$  supporting a random vector  $\mathbf{U} = (U_1, U_2)$  such that  $U_i \sim U[0, 1]$  for  $i \in \{1, 2\}$  and

 $K(u_1, u_2) = \mathbb{P}(U_1 \le u_1, U_2 \le u_2), \quad u_1, u_2 \in [0, 1]$ 

 $\implies$  the bivariate joint distribution function of the random vector  $\mathbf{C} = (C_{LSP}, C_{LSP'})$  can be written as

$$F_{\mathbf{C}}(\mathbf{c}) = \mathcal{K}_{\mathbf{C}}(F_{C_{LSP}}(c_1), F_{C_{LSP'}}(c_2))$$

where  $\mathbf{c} = (c_1, c_2), c_1, c_2 > 0$  (Sklar's theorem)

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#### Maximum-likelihood method (ML)

► assume parametric models for  $F_{C_{LSP}}(\cdot | \eta_1)$ ,  $F_{C_{LSP'}}(\cdot | \eta_2)$  and  $K_{C}(\cdot | \eta)$  with parameter vectors  $\eta_1$ ,  $\eta_2$  and  $\eta$ 

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► for a sample  $\mathbf{c}_i = (c_{LSP,i}, c_{LSP',i}), i = 1, ..., n$ , consider the loglikelihood  $\log L(\eta_1 \eta_2, \eta) = \sum_{i=1}^n (\log f_{C_{LSP}}(c_{LSP,i} | \eta_1) + \log f_{C_{LSP'}}(c_{LSP',i} | \eta_2) + \log [k_{\mathbf{C}}(F_{C_{LSP}}(c_{LSP,i} | \eta_1), F_{C_{LSP'}}(c_{LSP',i} | \eta_2) | \eta)])$ 

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#### Examples

- Hurricane Andrew, Florida, Louisiana, 1992: 26 fatalities, caused damages amounting to 25.5 billion U.S. Dollars
  - $\rightarrow$  at this time costliest hurricane in U.S. history, 11 insurers went bankrupt
- Hurricane Katrina, Florida, Louisiana, Mississippi, 2005: 1500 fatalities, caused damages amounting to 81 billion U.S. Dollars
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- Necessity to assess risks posed by cyclones as precisely as possible



Andrew, the Miami area



Katrina, New Orleans

Aftermath of hurricanes Andrew and Katrina

- Problems
  - reliable cyclone track data only given for about 100 years
  - insurers interested in risks caused by the largest cyclones having very small occurrence probability (< 0.1%)</li>
  - tropical storm could occur that is more intense or causes more damage than any historical measurement

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- Motivation for development of a stochastic simulation model for tropical cyclone tracks

 $\rightarrow$  joint research project between UIm University and Munich RE

- Consider two ocean basins: Western North Pacific (WNP) and North Atlantic (NA) since ...
  - ... they offer the most comprehensive historical cyclone data bases
  - ... the most endangered coastal areas belong to these regions
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- Storm track is modeled as polygonal line by connecting each two successive storm locations
- ► Additionally, translational speed and movement direction along each storm segment can be computed → both characteristics suffice to completely determine the pathway of a storm track



Observation window of the NA split into 4 zones

Criteria for the classification of cyclone tracks in the NA

start in zone	touched zones	end in zone	class	sta
0	0	0	0	
1	1	1	5	
2	2	2	2	
3	3	3	3	
0	0 and 1	0	0	
1	0 and 1	0	1	
0	0 and 1	1	1	
1	0 and 1	1	1	
0 or 3	0 and 3	0 or 3	3	
1	1 and 2	1	1	
1 or 2	1 and 2	2	2	
2	1 and 2	1	2	
1 or 3	1 and 3	1 or 3	4	
2 or 3	2 and 3	2 or 3	4	
0	0, 1 and 2	Ó	0	
1 or 2	0, 1 and 2	Ó	2	0

start in zone	touched zones	end in zone	class
0 or 1	0, 1 and 2	1	1
2	0, 1 and 2	1	2
0, 1, or 2	0, 1 and 2	2	2
0	0, 1 and 3	0	0
1 or 3	0, 1 and 3	0	3
0, 1 or 3	0, 1 and 3	1	1
0, 1 or 3	0, 1 and 3	3	3
0, 2 or 3	0, 2 and 3	0, 2 or 3	2
2	1, 2 and 3	1, 2 or 3	2
1 or 3	1, 2 and 3	1	1
1 or 3	1, 2 and 3	2 or 3	2
0	0, 1, 2 and 3	0	0
1, 2 or 3	0, 1, 2 and 3	0	2
1	0, 1, 2 and 3	1	1
0, 2 or 3	0, 1, 2 and 3	1	2
0, 1, 2 or 3	0, 1, 2 and 3	2 or 3	2

Some cyclones that have been sorted into class 1 and satisfy certain conditions are moved to class 4 or 5

2D patterns on geographical scales

### Historical cyclone observations - NA



Historical cyclone tracks of class 0



Historical cyclone tracks of class 1



Historical cyclone tracks of class 2





Historical cyclone tracks of class 3



Historical cyclone tracks of class 4



Historical cyclone tracks of class 5
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- Synthetic storms are modeled as polygonal lines, where each line segment represents movement of the storm during 6 hours
- Stochastic simulation model includes the following components:
  - model for points of storm genesis
  - track propagation (including maximum sustained wind speeds)
  - termination of cyclone tracks

#### Poisson point processes in $\mathbb{R}$

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  - ▶  $\Phi_{B_1}, \Phi_{B_2}, \ldots$  are independent random variables for all  $B_1, B_2, \ldots \in \mathcal{B}_0(\mathbb{R}^d)$  pairwise disjoint
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  - $\Phi_B \sim \mathsf{Poi}(\mu(B))$  for each  $B \in \mathcal{B}_0(\mathbb{R}^d)$
- Assumption:  $\mu$  is absolutely continuous, i.e.  $\Phi$  has an intensity function  $\lambda : \mathbb{R} \to [0, \infty)$  such that

$$\mu(B) = \int_B \lambda(x) \, dx$$
 for all  $B \in \mathcal{B}$ 

 $\rightarrow \lambda$  completely determines the distribution of  $\Phi$ 

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- $\rightarrow \lambda$  completely determines the distribution of  $\Phi$
- ▶  $\Phi$  can be considered as random counting measure  $\rightarrow$  there is a sequence of random vectors  $S_1, S_2, ...$  in  $\mathbb{R}$  such that  $\Phi_B = \#\{i : S_i \in B\}, B \in \mathcal{B}$

# **Points of genesis**

The estimator λ̂ for the intensity function λ is given by a generalized nearest-neighbor estimator, i.e.

$$\hat{\lambda}(x) = rac{1}{r_k(x)^2} \sum_{i=1}^n \mathcal{K}\left(rac{S_i - x}{r_k(x)}
ight) \qquad ext{for } x \in \mathbb{R}^2,$$

#### where

- $S_1, \ldots, S_n$ : starting points of historical cyclone observations
- kernel function K: Epanechnikov kernel

$$\mathcal{K}(x) = \begin{cases} \frac{2}{\pi} (1 - x^\top x) & \text{if } x^\top x < 1, \\ 0 & \text{else} \end{cases}$$

- $r_k(x)$ : distance from x to k-th nearest starting point
- $k = \lfloor \sqrt{n} \rfloor$

#### Points of genesis - WNP



Starting points of historical storm tracks for class 0 in the WNP together with the estimated intensity function

#### **Points of genesis - NA**



Starting points of historical storm tracks for class 2 in the NA together with the estimated intensity function

Appropriate cyclone track model needs to include the direction of movement X and the translational speed Y

- Appropriate cyclone track model needs to include the direction of movement X and the translational speed Y
- Assume both characteristics to be constant for intervals of 6 hours and update (X, Y)<sup>⊤</sup> after each of these intervals
  - $\rightarrow$  the cyclone's location can be calculated in 6-hour steps
  - $\rightarrow$  connecting these storm points yields a polygonal line

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- Appropriate cyclone track model needs to include the direction of movement X and the translational speed Y
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  - ightarrow the cyclone's location can be calculated in 6-hour steps
  - $\rightarrow$  connecting these storm points yields a polygonal line
- Additionally, for risk assessment purposes at each storm point the maximum wind speed Z is considered
- The characteristics X<sub>i</sub>, Y<sub>i</sub> and Z<sub>i</sub> after the *i*-th track segment are considered to be sums of initial values and the changes in these values after each step

$$\left(\begin{array}{c}X_i\\Y_i\\Z_i\end{array}\right) = \left(\begin{array}{c}X_0\\Y_0\\Z_0\end{array}\right) + \sum_{j=1}^i \left(\begin{array}{c}\Delta X_j\\\Delta Y_j\\\Delta Z_j\end{array}\right)$$















#### **Comparison of cyclone tracks - NA**



Historical cyclone tracks of class 0



Historical cyclone tracks of class 1



Simulated cyclone tracks of class 0



Simulated cyclone tracks of class 1

#### **Comparison of cyclone tracks - NA**



Historical cyclone tracks of class 2



Historical cyclone tracks of class 3



Simulated cyclone tracks of class 2



Simulated cyclone tracks of class 3

#### **Comparison of cyclone tracks - NA**



Historical cyclone tracks of class 4



Historical cyclone tracks of class 5



Simulated cyclone tracks of class 4



Simulated cyclone tracks of class 5

210

180

150

120

#### Validation - NA - hazard maps





Simulated

# Estimated hazard maps for storm event sets representing a time span of $T_{hist} = 111$ years return period 5 years

210

180

150

120

# Validation - NA - hazard maps







# Estimated hazard maps for storm event sets representing a time span of $T_{hist} = 111$ years return period 25 years

210

180

150

120

#### Validation - NA - hazard maps





Simulated

Estimated hazard maps for storm event sets representing a time span of  $T_{hist} = 111$  years return period 100 years

#### Validation - NA - hazard maps









Estimated hazard maps for storm event sets representing a time span of  $T_{hist} = 111$  years return period 500 years

#### Contents

Motivation/Goals

Overview

2D patterns on geographical scales

3D patterns on microscopic scales

# **3D** patterns on microscopic scales

- Li-ion batteries
- organic solar cells
- fuel cells
- polycristalline alloys

# **3D** patterns on microscopic scales

#### Li-ion batteries

- organic solar cells
- fuel cells
- polycristalline alloys



### Synchrotron tomography image data





# Synchrotron tomography image data



- > 3D image of uncompressed graphite electrode used in Li-ion batteries
- tomography: Helmholtz Center Berlin, material: ZSW Baden-Württemberg
- yellow: graphite phase
- transparent: pore phase, volume fraction ca. 56%

#### **Goal: stochastic simulation model**



- Modeling of the 3D morphology of graphite electrodes
- Size: 100 × 100 × 100 voxels

3D patterns on microscopic scales

#### **Functionality**



- ► 3D microstructure ⇔ functionality
- Detect improved microstructures by virtual materials design




Start with random allocation of voxels given volume fraction  $\alpha$ 



- Start with random allocation of voxels given volume fraction  $\alpha$
- Coarsening of morphology by interchanging voxels.
  - ► *T* temperature,  $c(\cdot)$  cost function to be reduced (e.g. surface area)
  - Pick a pair of voxels at random
  - Swap voxels if cost function decreases, otherwise accept swap with probability exp ( c(no change) − c(change) / T
  - Decrease T with time



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  - Decrease T with time
- Stop if desired value of  $c(\cdot)$  is reached.



Simulated annealing: simple but computational expensive, limited control of microstructure



- Simulated annealing: simple but computational expensive, limited control of microstructure
- Hybrid approach: combining spatial stochastic graph modeling with simulated annealing
  - simulate random geometric graph
  - start configuration of voxels by project voxels onto the graph
  - run simulated annealing on new start configurations
  - voxels of graph fixed



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  - voxels of graph fixed
- spatial graph serves as backbone of microstructure
- fast, good control on microstructure

# Stochastic graph model



# Stochastic graph model



Extract spatial graph (V, E) from experimental data by skeletonization

- V set of vertices
- E set of edges

# Stochastic graph model



- Extract spatial graph (V, E) from experimental data by skeletonization
  - V set of vertices
  - E set of edges
- Stochastic modeling by
  - Point process model for the set of vertices
  - a stochastic model for setting edges
  - Fitting of model parameters to corresponding experimental data

#### Point process model: modulated hardcore point process



(1) Simulation of homogeneous Poisson process

#### Point process model: modulated hardcore point process



- (1) Simulation of homogeneous Poisson process
- (2) Simulation of Boolean Model

#### Point process model: modulated hardcore point process



- (1) Simulation of homogeneous Poisson process
- (2) Simulation of Boolean Model
- (3) Simulation of Poisson hardcore model inside the Boolean Model

### Stochastic model for setting edges



Cut-out of experimental graph (left) and simulated graph (right)

# Stochastic model for setting edges



Cut-out of experimental graph (left) and simulated graph (right)

#### Connecting nearest neighbors

- Connect each point S<sub>i</sub> with its n nearest neighbors.
- Start with nearest neighbor
- Connection is rejected if angle to previous edges undercuts a threshold γ<sub>1</sub>

# Stochastic model for setting edges



Cut-out of experimental graph (left) and simulated graph (right)

#### Connecting nearest neighbors

- Connect each point S<sub>i</sub> with its n nearest neighbors.
- Start with nearest neighbor
- Connection is rejected if angle to previous edges undercuts a threshold γ<sub>1</sub>
- Postprocessing of edges
  - If angles undercut threshold  $\gamma_2$ : deletion with probability  $p \in (0, 1)$ .
  - Control of angles

# **Model validation**



Cut-out of experimental (left) and simulated (right) microstructure



Spherical contact distribution from pore phase to graphite (left) and vice versa (right). Red curve displays experimental data and black curve simulated data.

# **3D** patterns on microscopic scales

- Li-ion batteries
- organic solar cells
- fuel cells
- polycristalline alloys

#### Tomographic solar cell data



5000 rpm  $\sim$  57 nm

1500 rpm  $\sim$  100 nm

1000 rpm  $\sim$  167 nm

- 3D TEM images of P3HT-ZnO solar cells with different thicknesses
- ► TEM: Technical University Eindhoven
- P3HT-phase: transparent
- ZnO-phase: yellow, volume fraction 13.3% 21.1%
- Morphology is anisotropic

# Goal: stochastic simulation model



- same model type for all layer thicknesses
- different model parameters for different layer thicknesses



- Device architecture: bulk heterojunction
- Light acitivates the polymer phase of the solar cell



- Device architecture: bulk heterojunction
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- Device architecture: bulk heterojunction
- Light acitivates the polymer phase of the solar cell
- Excitons are generated
- Diffusion of excitons in the polymer phase
- Excitons reaching the ZnO phase generate charges: quenching
- Transportation of charges to the electrodes
- ► 3D microstructure ⇔ functionality
- Detect improved microstructures by virtual materials design

#### Modeling idea: 'smart' system of spheres



- Representation of the ZnO phase as a complex system of spheres
- Contrast to compressed battery modeling: anisotropic point pattern
- Anisotropy by Markov chain of 2D point processes

### Multi-scale approach



#### 3D Representation of the macro-scale by unions of spheres



$$= \bigcup_{i=1}^{n} b(s_i, r_i)$$

- Macro-scale represented by marked point process
- Transformation of solar cells into mathematical language



Modeling in 2 steps:

- > 2D point patterns: elliptical Matérn cluster process
- 3D stack of 2D point patterns: spatial birth-and-death process



# Inversion of morphological smoothing by stochastic modeling



#### **Result: stochastic simulation model**



Good visual agreement

Important structural characteristics for the morphology

 Spherical contact distribution function (probability of a random polymer voxel to find the ZnO phase within a given distance)



Distribution functions; solid lines: simulations; dashed lines: lower & upper bounds from original data.

Important structural characteristics for the morphology

- Volume fraction
- Connectivity (existence of percolation pathways to electrodes)

		Volume fraction	Connectivity (monotonous)
57 nm	model	0.115	0.887
	data	0.133	0.928
100 nm	model	0.216	0.888
	data	0.211	0.910
167 nm	model	0.210	0.809
	data	0.210	0.851

### Physical characteristic for model validation

Quenching probability  $\eta_Q$  (probability of a random exciton to reach the ZnO-phase)

¬η<sub>Q</sub> obtained from the field {n(x), x ∈ B<sup>c</sup>} of local exciton densities in the polymer phase

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$$0=\frac{dn(x)}{dt}=-\frac{n(x)}{\tau}+D\nabla^2n(x)+g,\qquad x\in B^c,$$

D: diffusion constant,  $\tau$ : exciton life time, g: rate of exciton generation
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- ▶ boundary condition: n(x) = 0 for all  $x \in \partial B^c \setminus \partial W$ .
- $\eta_Q = 1 \bar{n}/(\tau g)$

### Physical characteristic for model validation





Model for transport processes

#### Model for morphology

Page



# Virtual Material Design

# Virtual material design



Model

$$\vec{\lambda} = (\lambda_1, \dots, \lambda_m)$$

Stochastic simulation model  $\Rightarrow$  3D morphology represented by parameter vector  $\stackrel{\rightarrow}{\lambda}$ 



Spin coating speed determines morphology

- ▶ Regression of parameter vector  $\vec{\lambda}$  allows prediction of morphologies which were not fabricated
- Manufacturing process can be realized virtually

#### **Regression of model parameters**



Spin coating speed determines morphology

- ► Regression models of type  $\lambda_i(\omega) = a_i + b_i \exp(c_i \omega) + \varepsilon_i \text{ or } \lambda_i(\omega) = a_i + b_i \omega + \varepsilon_i$
- ▶ ⇒ analytical formulae for  $\vec{\lambda}$  in dependence of  $\omega$ .
- Prediction of morphologies which were not fabricated

# Scenario analysis

#### Model for layer thickness

- layer thickness =  $c\omega^{\alpha}$ ,  $\alpha = -0.5$
- estimation of c by least squares
- simulation of virtual morphologies with 'correct' layer thickness



# Scenario analysis

- Simulation of virtual morphologies for  $\omega = 500, 750, \dots, 5250$
- Estimation of structural and physical characteristics



#### Scenario analysis - results



left: connectivity, right: mean spherical contact distance (in nm); experimental data added by filled symbols

#### Scenario analysis - results



left: quenching efficiency by bulk, right: quenched by electrodes; experimental data added by filled symbols

- Li-ion batteries
- organic solar cells
- fuel cells
- polycristalline alloys

# Modeling of non-woven GDL





#### 2D SEM image

#### 3D synchrotron data

# Two different modeling approaches

Multi-layer model

# Modeling of non-woven GDL





#### 2D SEM image

#### 3D synchrotron data

# Two different modeling approaches

- Multi-layer model
- Direct 3D modeling

# **Model assumptions**



#### Cross section of non-woven GDL

Horizontally oriented curved fibers

# **Model assumptions**



Cross section of non-woven GDL

- Horizontally oriented curved fibers
- GDL can be decomposed into independent thin horizontal layers

# **Model assumptions**



Cross section of non-woven GDL

- Horizontally oriented curved fibers
- GDL can be decomposed into independent thin horizontal layers
- Mutually penetrating fibers



### **Construction of 3D multi-layer model**



Multi-Layer model

Fiber model

2D fiber model

### **Construction of 3D multi-layer model**



Multi-Layer model

- Fiber model
- 3D-dilation

3D-dilation

## **Construction of 3D multi-layer model**



Multi-Layer model

- Fiber model
- 3D–dilation
- More layers ...

2 layers



# Validation of 3D multi-layer model



3D synchrotron data

Realization of multi-layer model

# Goodness of fit

Visual inspection



# Validation of 3D multi-layer model



3D synchrotron data

Realization of multi-layer model

## Goodness of fit

- Visual inspection
- Formal model validation

# **Discussion – multi-layer model**



Cross section of GDL

#### Advantage

Model fitting based on 2D SEM images

# **Discussion – multi-layer model**



Cross section of GDL

#### Advantage

- Model fitting based on 2D SEM images
- Short run times

### Disadvantage

Fibers mutually penetrate

# **Discussion – multi-layer model**



Cross section of GDL

### Advantage

- Model fitting based on 2D SEM images
- Short run times

### Disadvantage

- Fibers mutually penetrate
- Fibers have no gradient in z-direction

Extraction of single fibers from 3D image data



- Extraction of single fibers from 3D image data
- Stochastic modeling of single fibers



- Extraction of single fibers from 3D image data
- Stochastic modeling of single fibers
- Construction of stochastic 3D model



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- Extraction of single fibers from 3D image data
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- Validation of stochastic 3D model
- Modeling of PTFE



# Stochastic connection algorithm



Left: original fibers



#### Right: extracted fibers



# Validation by visual inspection



Extracted single fibers

Realizations of single fiber model

#### Basic idea

Monte-Carlo simulation of time series

### Basic idea

- Monte-Carlo simulation of time series
- Transformation into polygonal tracks

### Basic idea

- Monte-Carlo simulation of time series
- Transformation into polygonal tracks
- Comparison of geometric properties of extracted and simulated polygonal tracks



Measure for the amount of curvature: Volume of red area / (length of blue line)<sup>2</sup>
#### Formal validation of vectorial time series model

#### Curvature properties of single fibers



First row: Extracted polygonal tracks Second row: Simulated polygonal tracks

#### Idea of 3D GDL model



Cut-out of 3D synchrotron data

Basic idea of bar/channel modeling

- A priori information
  - Radius of fibers:  $r = 4.75 \mu m$
  - Fiber length: I = 50 mm
  - Volume fraction of fibers: 0.235
  - fiber-channel width  $c = 500 \mu m$
  - fiber-bar width  $b = 70 \mu m$

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- 3D GDL model
  - 1.  $U \sim U[0, 570]$

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  - 1.  $U \sim U[0, 570]$
  - 2. Boolean model:  $\Xi = \bigcup_{n=1}^{\infty} (B_n + S_n)$ ,
    - $\{S_n\}$  is a 3D Poisson process with intensity  $\lambda$
    - ▶  $B_n$  is the single bundle model of length *I* if  $S_n \in$  fiber-channel, i.e.,  $S_n \in [u + i(b + c) c, u + i(b + c)), i \in \mathbb{Z}$ ,
    - ▶  $B_n$  is a line segment of length *I* parallel to the x-axis if  $S_n \in$  fiber-bar, i.e.,  $S_n \in [u + i(b + c), u + i(b + c) + b), i \in \mathbb{Z}$

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  - 3. Dilate fibers with a 3D sphere:  $\Xi \oplus B(0, r)$

# Visual inspection of 3D GDL model



3D synchrotron data



#### Visual inspection of 3D GDL model



3D synchrotron data

Simulated non-woven GDL drawn from the GDL model

# Visual inspection of 3D GDL model

Alternative visualisation (with different choice of colors)



3D synchrotron data



# Visual inspection of 3D GDL model

Alternative visualisation (with different choice of colors)



3D synchrotron data

Simulated non-woven GDL drawn from the GDL model

Model validation using structural characteristics

 spherical contact distribution function (probability of a random pore voxel to reach the fiber phase within a given distance)



Model validation using structural characteristics

- spherical contact distribution function (probability of a random pore voxel to reach the fiber phase within a given distance)
- directional distribution of line segments



simulated GDL

Model validation using physical characteristics

effective tortuosity (distribution of path lengths through a porous material)





path lengths through real GDL path lengths through simulated GDL

blue colored: short paths red colored: long paths

Model validation using physical characteristics

effective tortuosity (distribution of path lengths through a porous material)



mean = 1.19 (real GDL) resp. mean = 1.15 (sim. GDL)

- Li-ion batteries
- organic solar cells
- fuel cells
- polycristalline alloys



 3D morphology of eutectic Si corals in an Al matrix (left) and corresponding skeletonization (right)



image size is 548  $\times$  761  $\times$  357 voxel with voxel size of 46 nm

#### > 3D skeletonization of Si corals (left) and corresponding stems (right)



Modeling idea of single coral:

- First the main stem is described by a random polygonal track where the endpoints of these line segments are numbered serially (0)
- Branches are added to the stem and numbered serially ((1), (2)) and
- finally branches are deleted ((3), red colored) which are too close to each other





 3D graph structure of Si corals in an AI matrix (left) and realization of the stochastic model for aggregates of corals (right)



- spherical contact distribution function (left), distribution of edge lengths (center) and distribution of maximum stem length (right)
- black: computed for the graph structure of experimental Si corals, red: drawn from the multi-coral model





 3D morphology of experimental Si corals in an Al matrix (left) and corresponding simulation of stochastic model (right)



image size is 761  $\times$  548  $\times$  357 voxel with voxel size of 46 nm

Distribution of spherical contact distances from AI to Si particles (left), and vice versa (right) for the experimental image data (black curve) and realization drawn from the stochastic model (red curve)

