M. Arpogaus, M. Voss, B. Sick, M. Nigge-Uricher und O. Dürr, "Short-Term Density Forecasting of Low-Voltage Load using Bernstein-Polynomial Normalizing Flows," *IEEE Transactions on Smart Grid*, doi: 10.1109/TSG.2023.3254890, 2023.

Short-Term Density Forecasting of Low-Voltage Load using Bernstein-Polynomial Normalizing Flows

Marcel Arpogaus, Marcus Voss, Beate Sick, Mark Nigge-Uricher and Oliver Durr

Motivation

Quelle: https://www.smarter-fahren.de/smart-grid-fuer-elektroautos/

CER – Data set

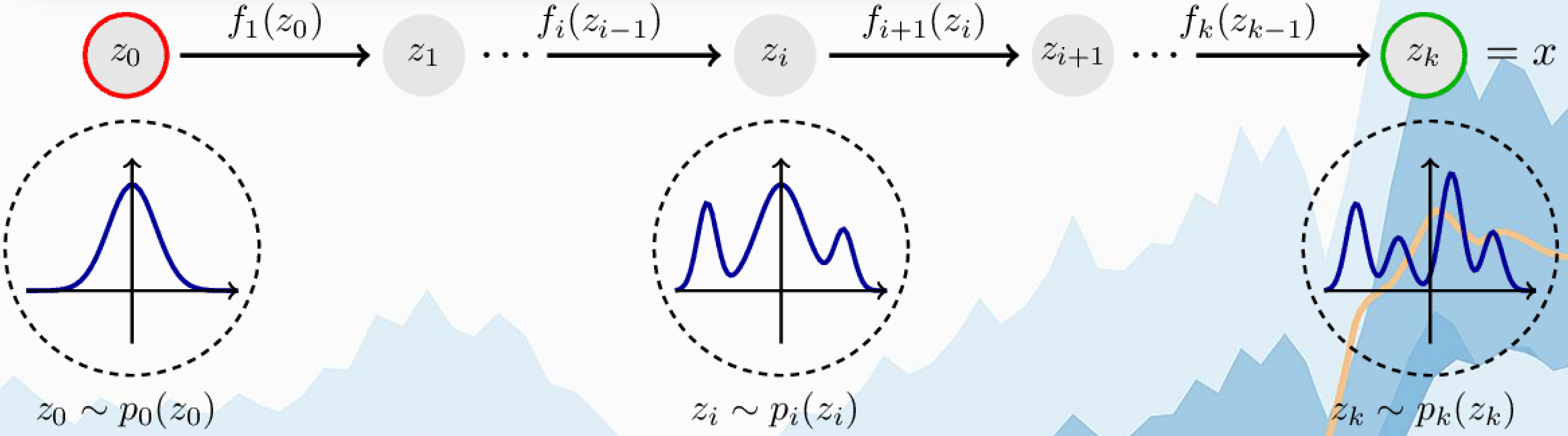
Data from smartmeters in private households (N =3639)

Period: 14.07.09 – 31.12.10

Resolution: Sample every 30min

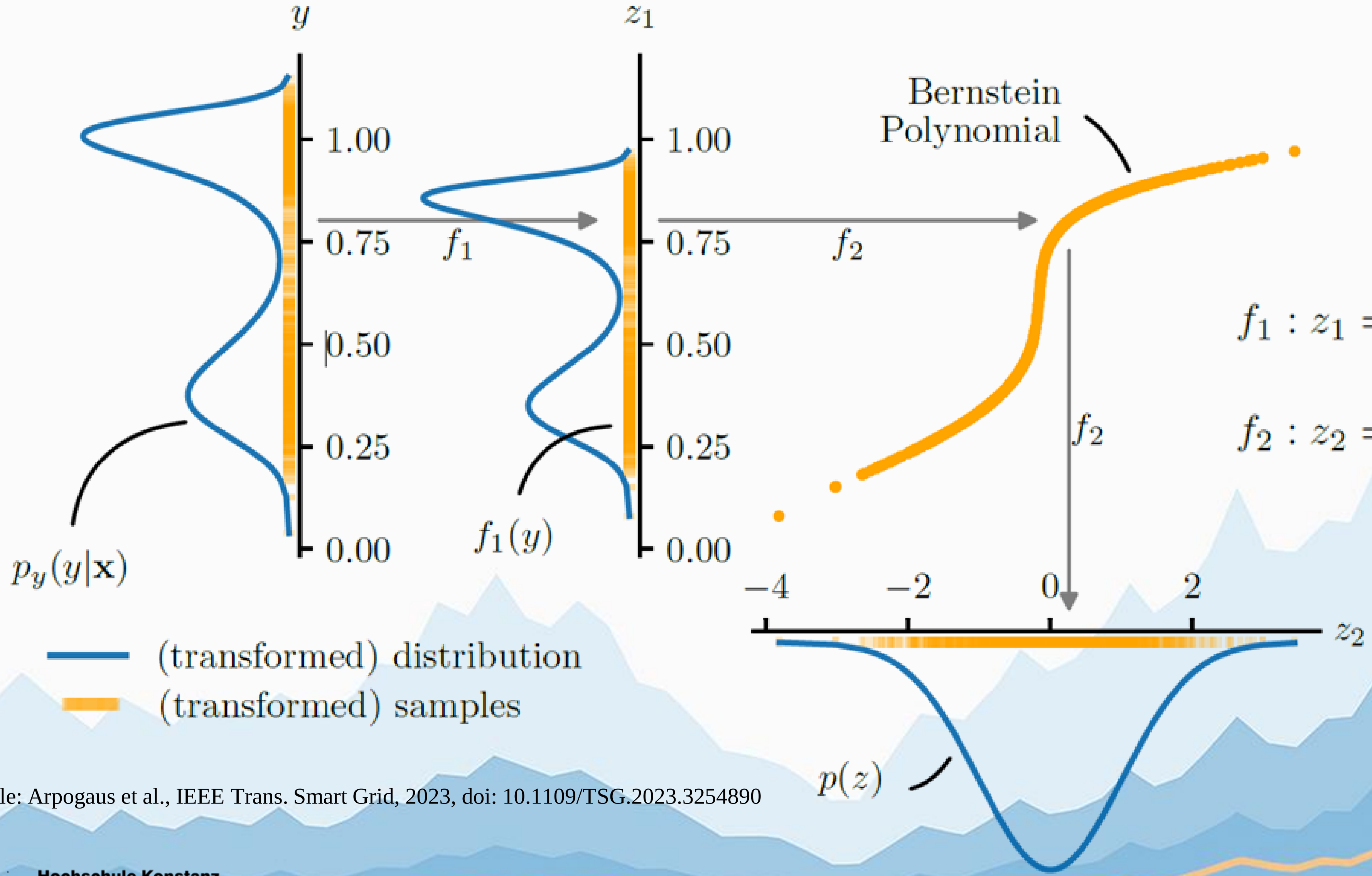
Normalizing Flows

$$p_y(y|\mathbf{x}) = p_z\left(f(y)|\theta(\mathbf{x})\right)\left|\det \nabla f(y|\theta(\mathbf{x}))\right|$$



Quelle: Arpogaus et al., IEEE Trans. Smart Grid, 2023, doi: 10.1109/TSG.2023.3254890
https://github.com/janosh/awesome-normalizing-flows

Normalizing Flows using Bernstein-Polynomials

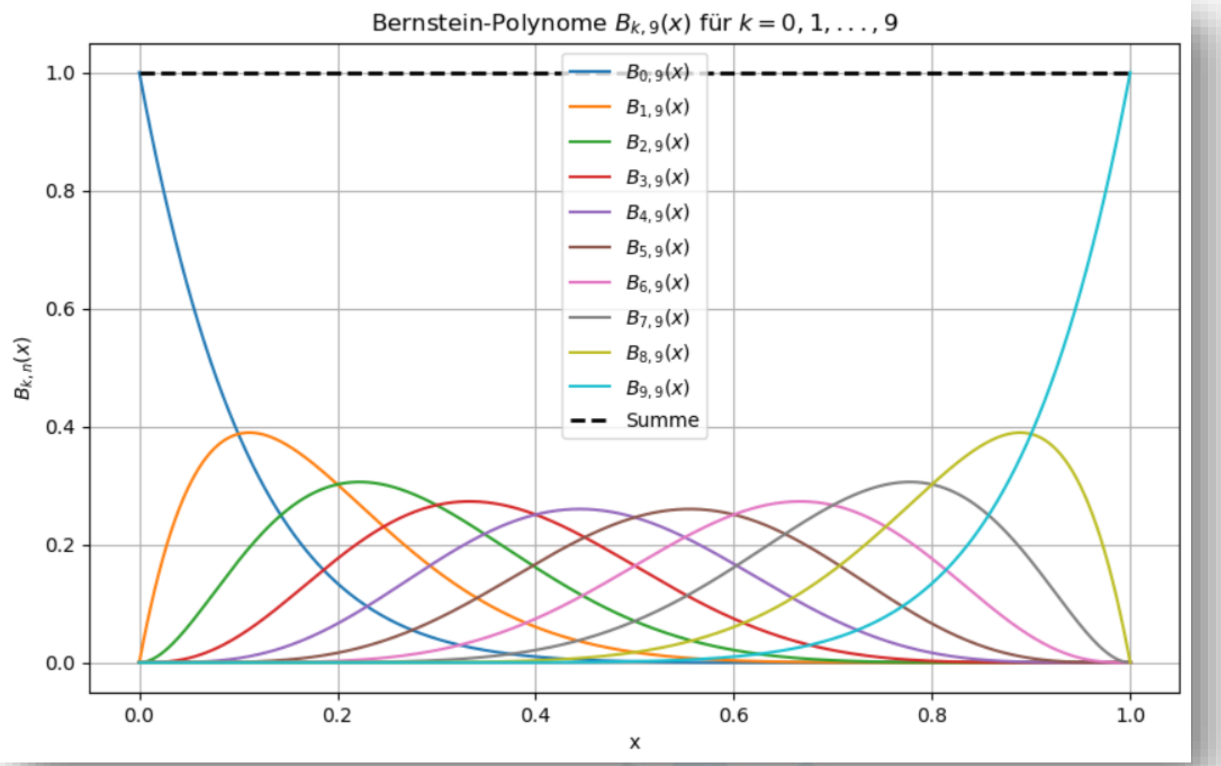


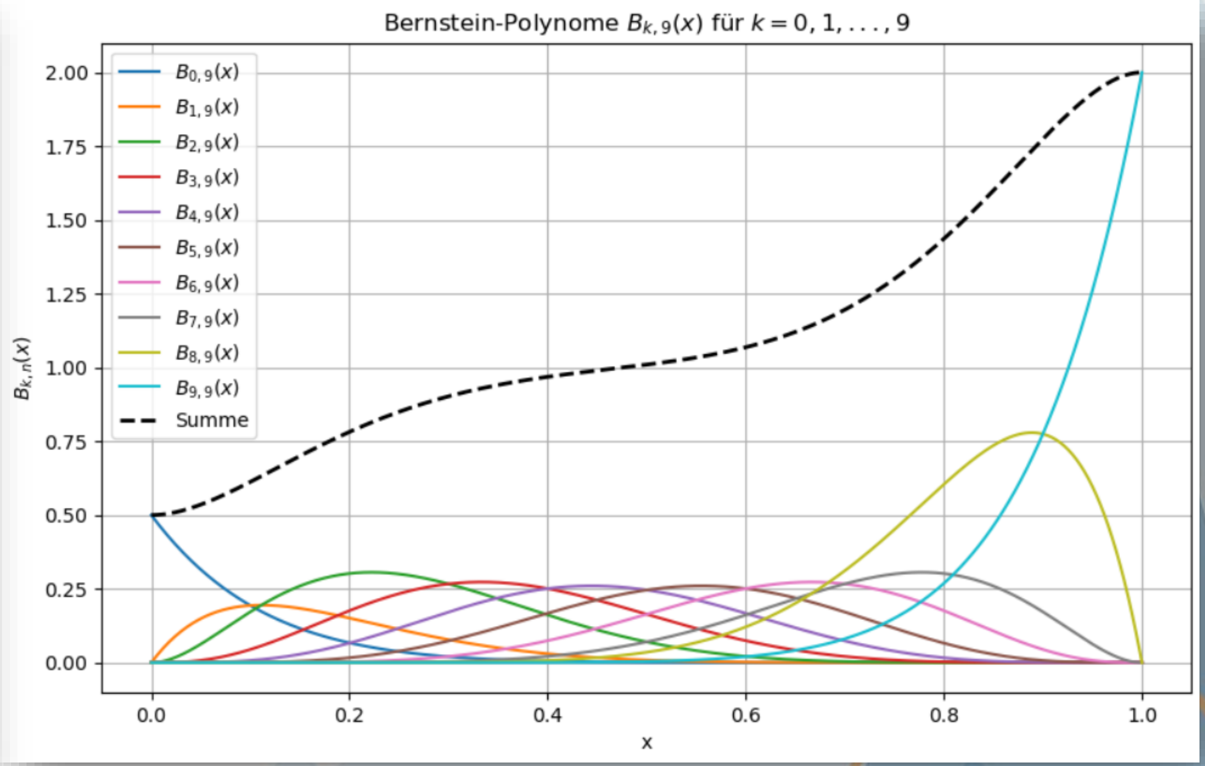
$$f_1 : z_1 = a_1(\mathbf{x}) \cdot y - b_1(\mathbf{x})$$

$$f_2 : z_2 = \frac{1}{M+1} \sum_{i=0}^{M} \mathrm{Be}_i^M(z_1)\vartheta_i(\mathbf{x})$$

Quelle: Arpogaus et al., IEEE Trans. Smart Grid, 2023, doi: 10.1109/TSG.2023.3254890

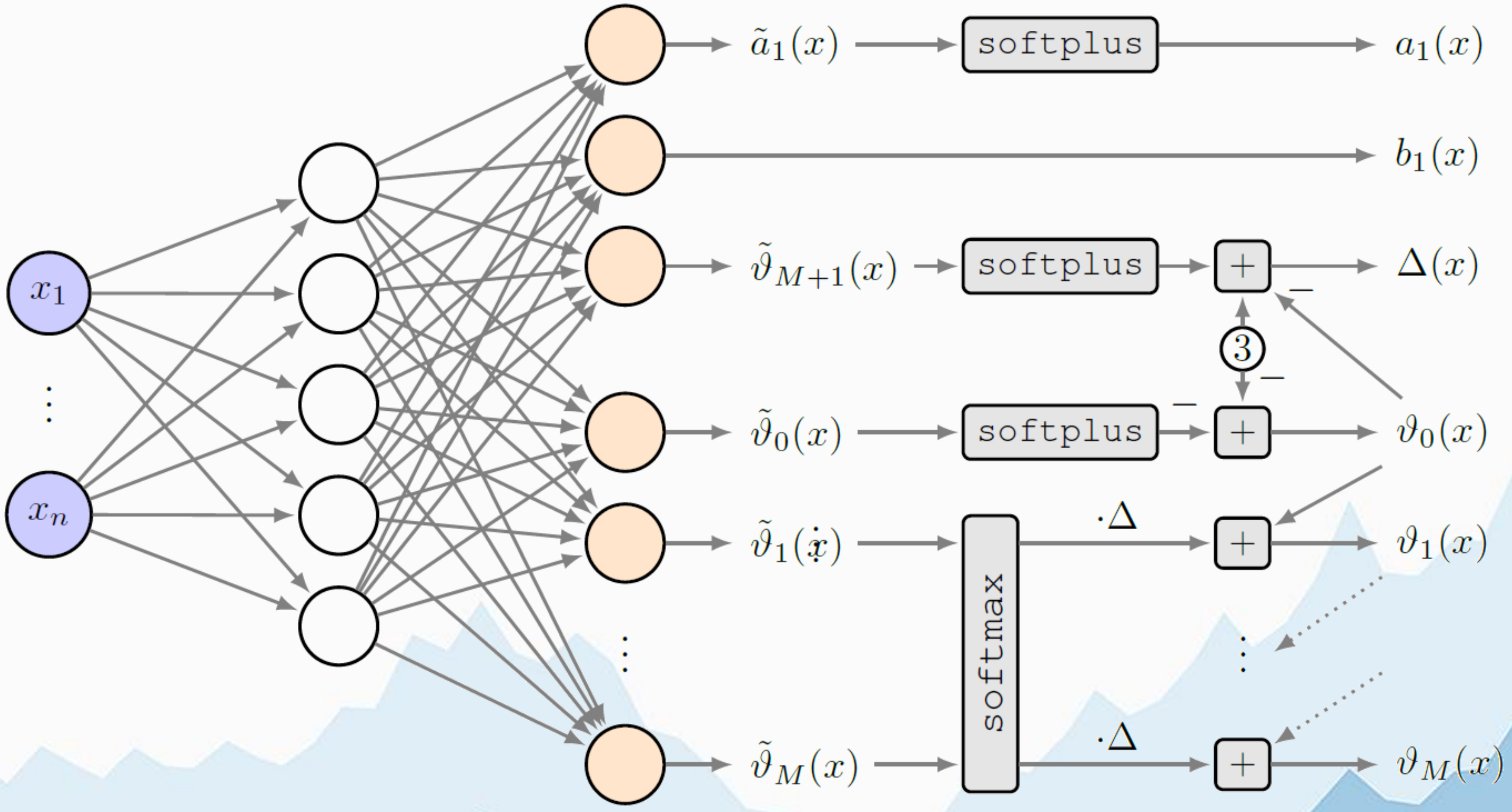
Bernstein-Polynomials





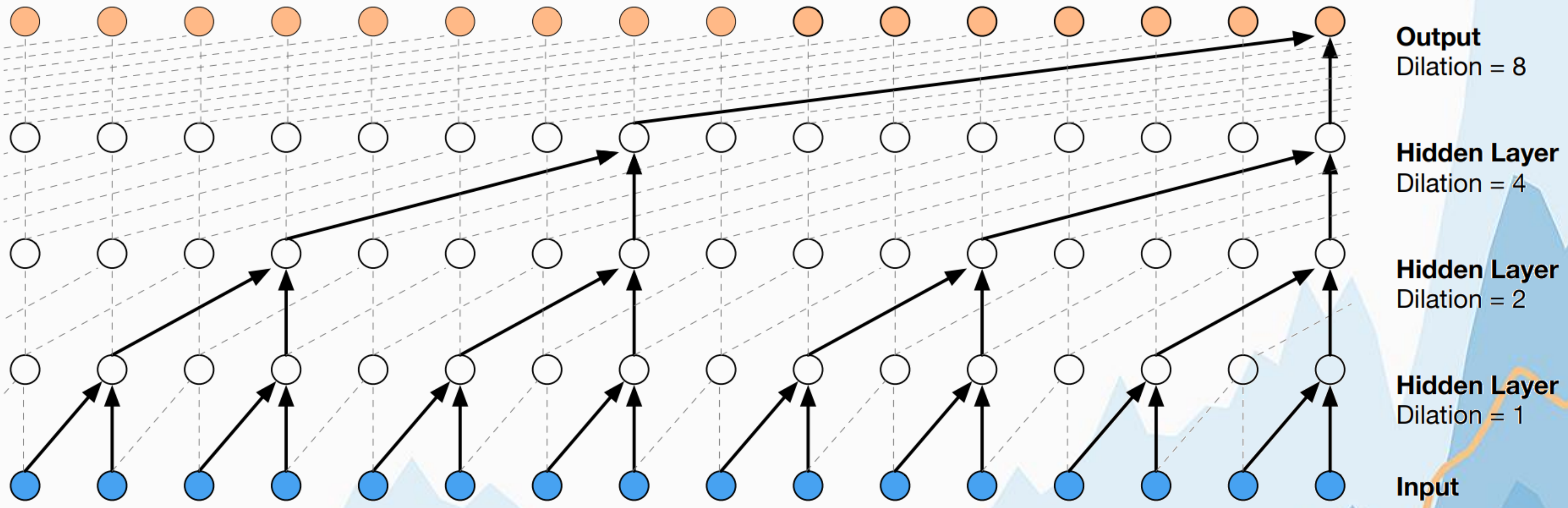
Quelle: eigene Abbildungen

Normalizing Flows using Bernstein-Polynomials



Quelle: Arpogaus et al., IEEE Trans. Smart Grid, 2023, doi: 10.1109/TSG.2023.3254890

1D-CNN



Quelle: https://arxiv.org/abs/1609.03499

Forcasting Model / Training

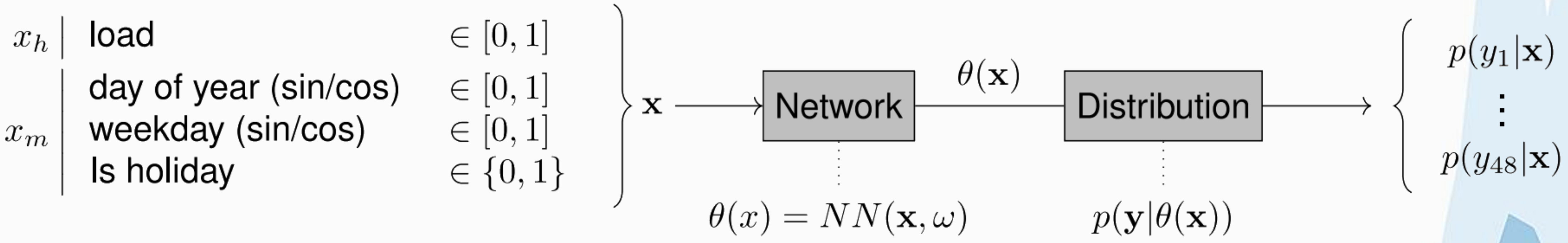


TABLE I
THE DATASET [45] WAS SPLIT BY CUSTOMERS AND DATE-RANGES INTO ONE TRAIN AND THREE TEST SETS. ONLY THE TRAIN DATA WAS USED TO OPTIMIZE THE WEIGHTS OF THE NNS

	households	
date range	used in training	hold-out
14/07/2009 – 31/07/2010	Train	Test 2
01/08/2010 – 31/12/2010	Test 1	Test 3

TABLE II
NUMBER OF TRAINABLE PARAMETER AND THE CORRESPONDING OUTPUT SHAPE FOR ALL MODELS

NN	Distribution	Parameters	Output shape
FC	BNF	463,168	(48, 20)
	GMM	395,056	(48, 9)
	GM	351,712	(48, 2)
	QR	952,336	(48, 99)
1DCNN	BNF	4,436,794	(48, 20)
	GMM	3,895,594	(48, 9)
	GM	3,551,194	(48, 2)
	QR	8,323,594	(48, 99)

Quelle: Arpogaus et al., IEEE Trans. Smart Grid, 2023, doi: 10.1109/TSG.2023.3254890

Comparison of Models

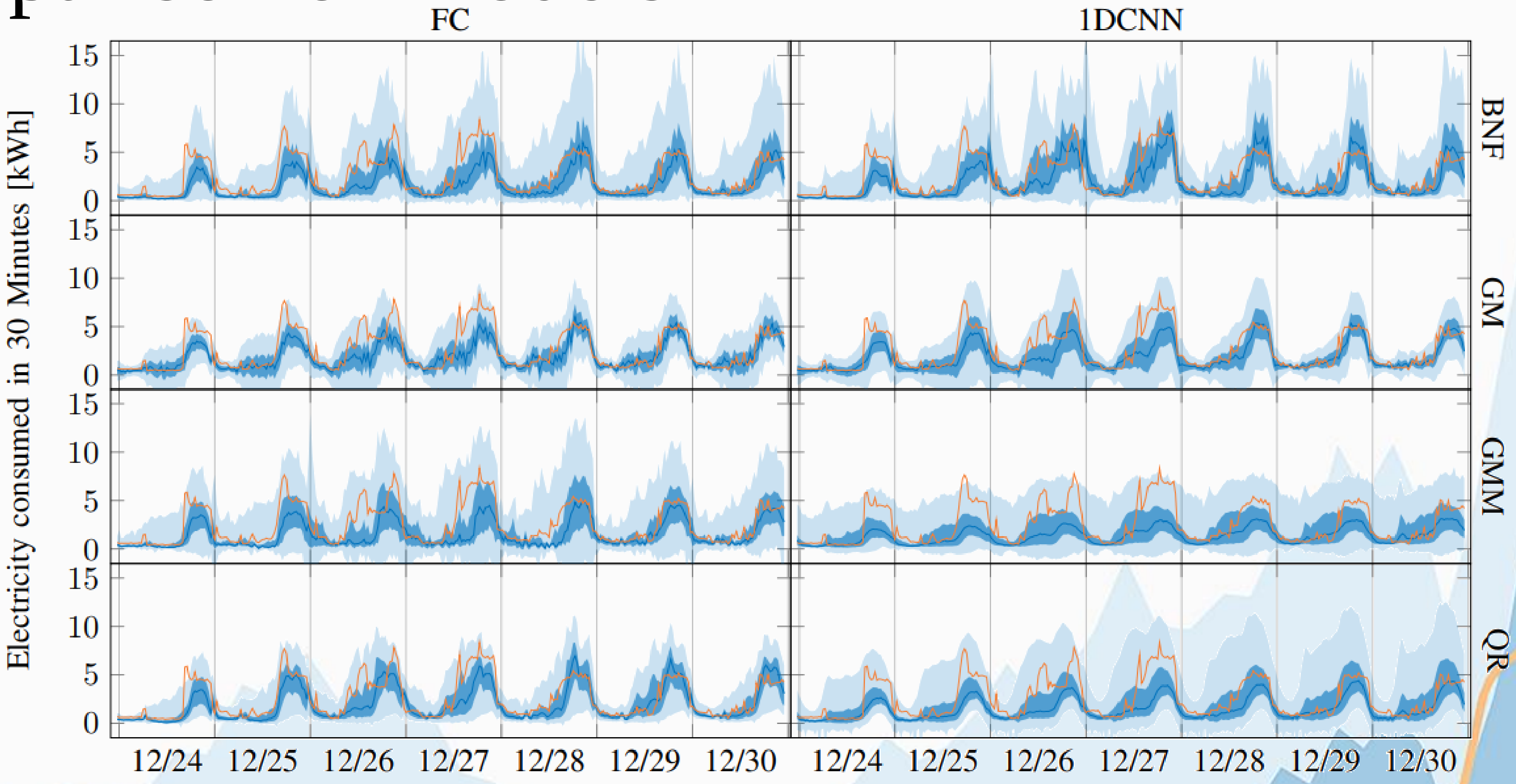


Fig. 5. The plots show the 98% ( ) and 60% ( ) confidence intervals, along with the median ( ) of the predicted CPD and the measured observations ( ) for one household with unusual high load during the Christmas week. Data from [45].

Quelle: Arpogaus et al., IEEE Trans. Smart Grid, 2023, doi: 10.1109/TSG.2023.3254890

Comparison of Models

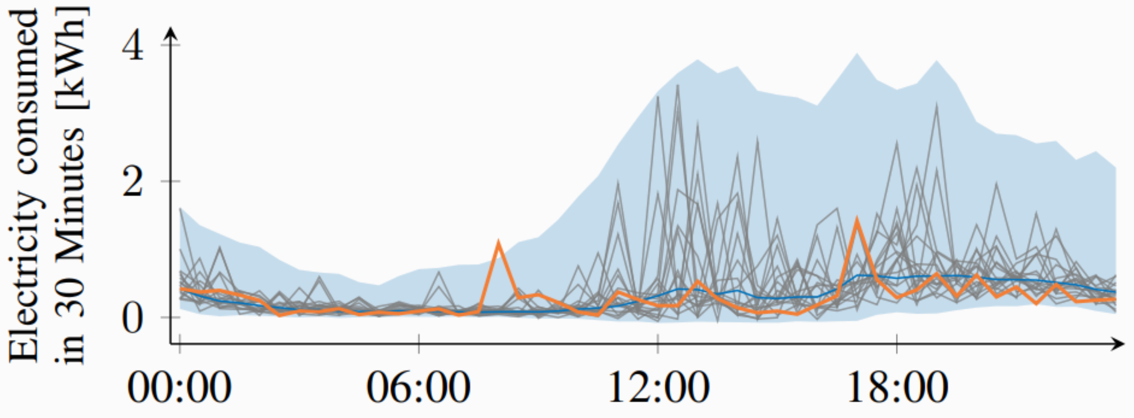
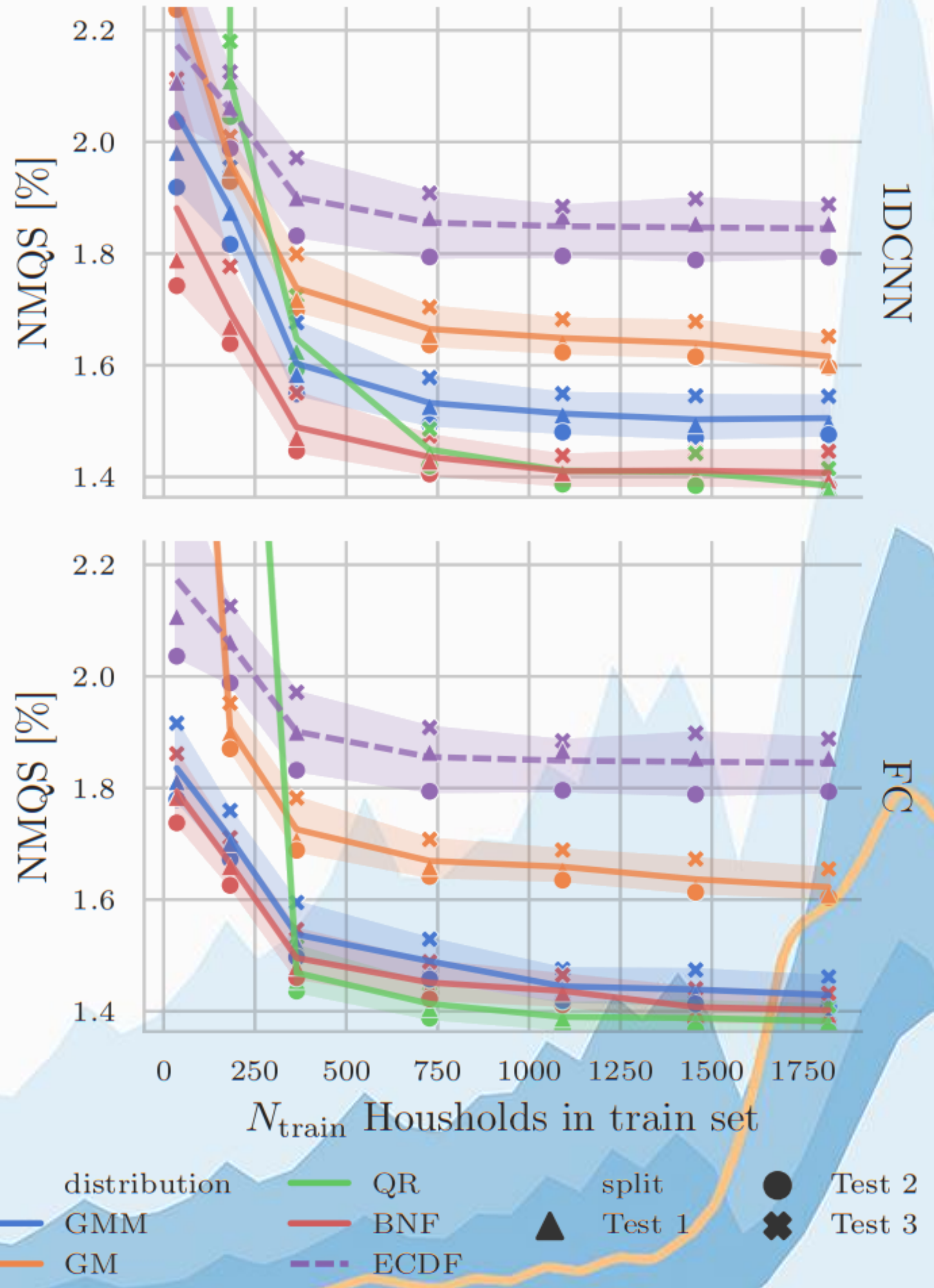


Fig. 8. Our BNF approach allows sampling from the learned distributions. The plot shows the 99% ( ) confidence intervals, median (——), the observed values (——), and 15 samples (——) drawn from the predicted CPD.



Quelle: Arpogaus et al., IEEE Trans. Smart Grid, 2023, doi: 10.1109/TSG.2023.3254890

Comparison of Models

N_{train}	NN	kind Distribution	NLL	NCRPS [%]	NMQS [%]
363	Baseline	ECDF	-111.702	1.920	1.900
	FC	BNF	**-135.616 (±0.388)**	**1.502 (±0.007)**	**1.486 (±0.007)**
		GMM	-129.663 (±0.642)	1.542 (±0.008)	1.526 (±0.008)
		GM	-100.973 (±0.893)	1.743 (±0.015)	1.724 (±0.014)
		QR	–	–	2.303 (±0.587)
	1DCNN	BNF	**-137.040 (±1.640)**	**1.495 (±0.017)**	**1.479 (±0.016)**
		GMM	-132.622 (±0.560)	1.613 (±0.017)	1.596 (±0.017)
		GM	-100.040 (±0.408)	1.742 (±0.011)	1.724 (±0.011)
		QR	–	–	1.625 (±0.006)
1091	Baseline	ECDF	-114.777	1.886	1.867
	FC	BNF	**-139.262 (±0.361)**	**1.443 (±0.009)**	1.428 (±0.009)
		GMM	-135.029 (±0.754)	1.464 (±0.009)	1.449 (±0.009)
		GM	-104.128 (±0.402)	1.660 (±0.010)	1.642 (±0.010)
		QR	–	–	**1.393 (±0.003)**
	1DCNN	BNF	**-142.385 (±0.904)**	**1.426 (±0.011)**	**1.411 (±0.011)**
		GMM	-135.767 (±0.692)	1.541 (±0.015)	1.525 (±0.014)
		GM	-103.335 (±1.027)	1.659 (±0.022)	1.641 (±0.021)
		QR	–	–	**1.400 (±0.008)**

Quelle: Arpogaus et al., IEEE Trans. Smart Grid, 2023, doi: 10.1109/TSG.2023.3254890