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Conformal Multilayer Perceptron-Based Probabilistic Net-Load Forecasting for Low-Voltage Distribution Systems with PV

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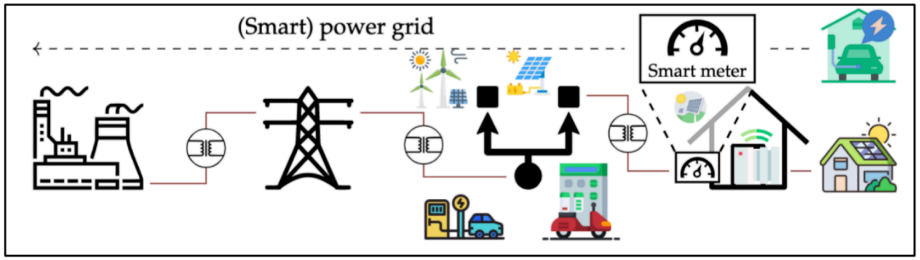
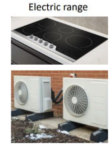
Power Load Forecasting for Future Energy Systems



Massive penetration of Distributed Energy Resources (DERS)

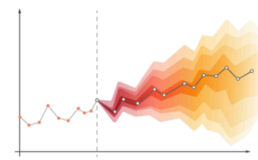
1. RES such as PV, with Energy Storage System (ESS)
2. Prosumers, such as Local Energy Communities (LECs).
3. Low carbon technologies (LCTs) such Electric Vehicle (EVs), and Electric Heating Systems (EHSs)

Electric range



Air conditioning

Forecast



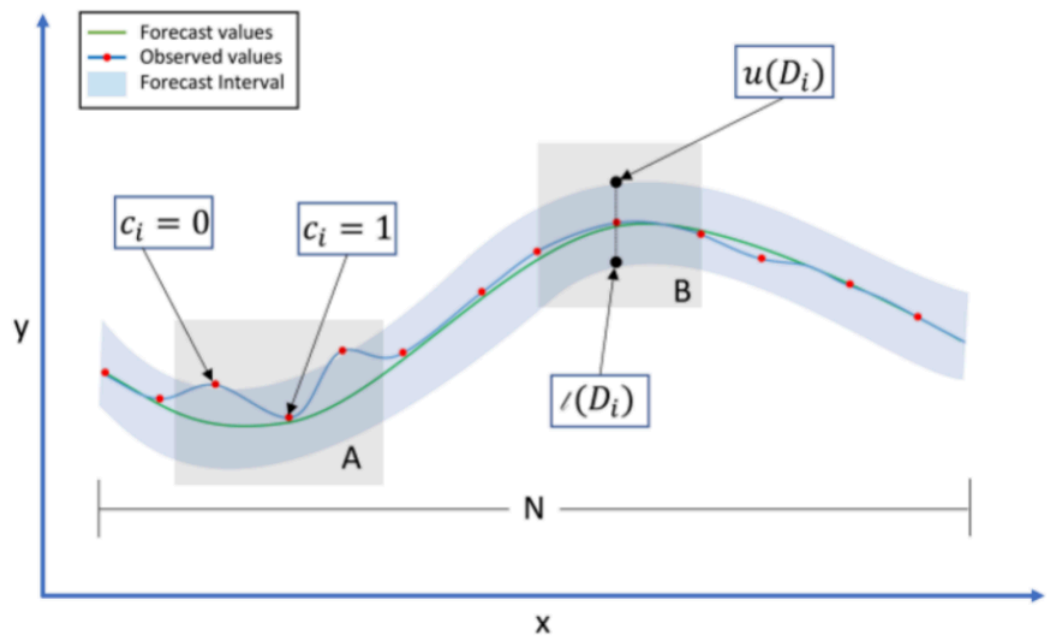
Optimise and Control

- Control & optimisation of ESS system
- Flexibility and demand response
- Co-ordinated EV Charging
- Unify planning and operation

- **More challenging =>Less predictable pattern, B-PV, and volatile RES generation.**
- **Need for uncertainty quantification=>Growing uncertainty in Load demands and generation.**

Quantifying forecast uncertainty with Intervals

Goal: Produce future forecasts with confidence



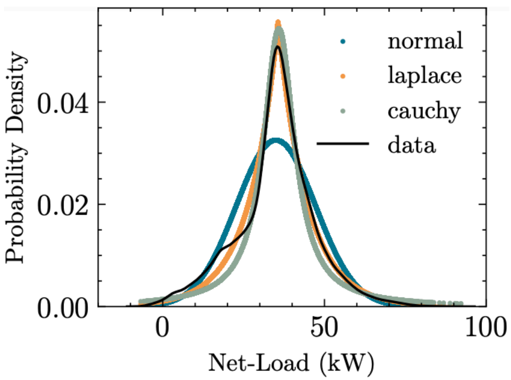
Build predicted interval $\mathcal{C}_{1-\alpha}$ such that

$$p(y_{t+h} \in \mathcal{C}_{1-\alpha}) > 1 - \alpha$$

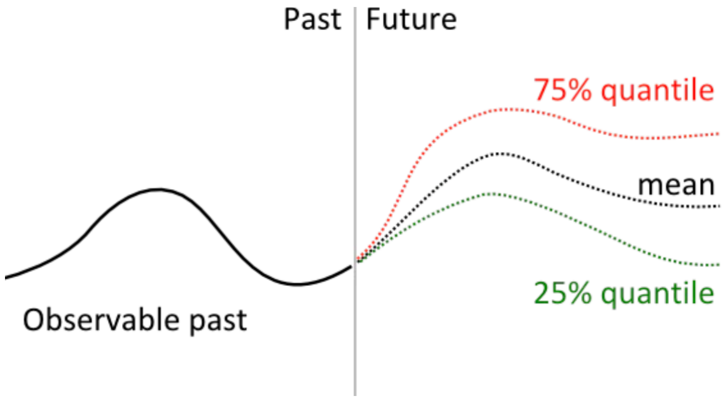
The predictive intervals should be:
agnostic to the model, data distribution and valid in finite samples.

Probabilistic Forecast Methods

- **Parametric density learning**



- **Quantile-regression**



Limitation:

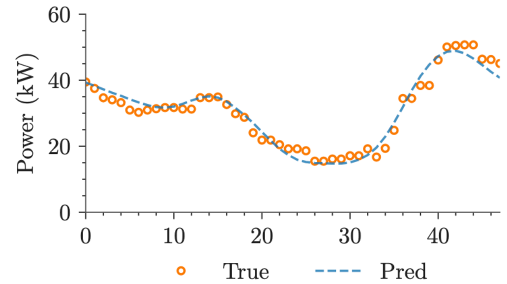
- Assume a specific distribution for the data, which might not always be accurate.
- No theoretical guarantee with a finite sample

Conformal Prediction:

- A distribution-free uncertainty estimation method that constructs valid prediction intervals.

Train algorithm f_θ

$$f_\theta(\mathbf{x}_L, \mathbf{c}_H) = \hat{\mu}_\theta$$

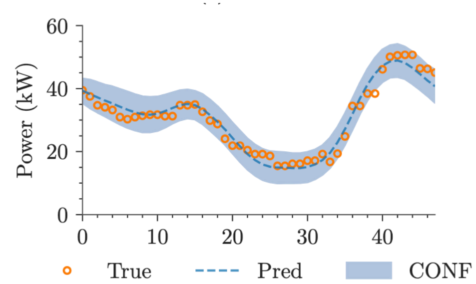


Prediction step :

1. Obtain $\mu_\theta(x)$

2. Build intervals

$$\mathcal{C}_{1-\alpha} = [\mu_\theta \pm \varepsilon]$$



On calibration set $\mathcal{D}_{cal}$

1. Get the conformity score

$$\gamma_k = |y_k - \mu_\theta(x_k)|$$

2. Compute $1-\alpha$ **quantiles**

$$\varepsilon = \mathcal{Q}_p\left(\{\gamma_0, \ldots \gamma_k\}\right)$$

Conformalised MLPF

- Combine the MLPF with SCP to quantify the uncertainty of the point net-load forecast in a predictive interval.

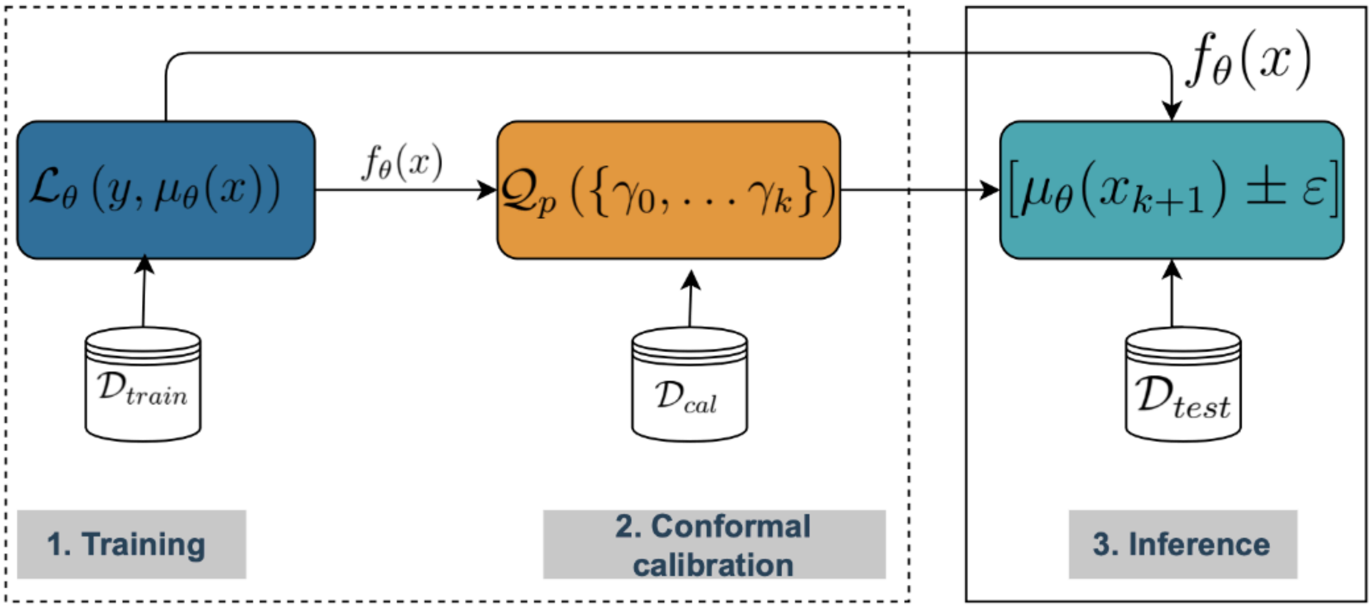
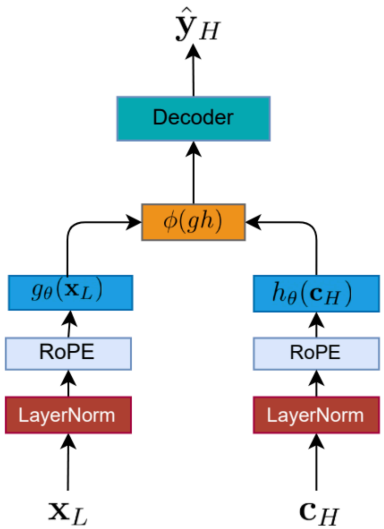
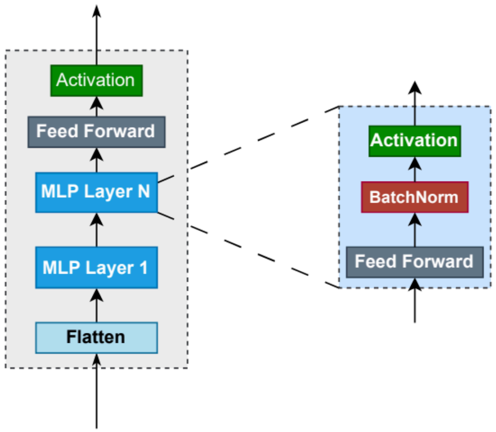


Fig. 1: Overview of conformalised-MLPF.

Efficiency through Simplicity: MLP-based Approach for Net-Load Forecasting with Uncertainty Estimates in Low-Voltage Distribution Networks Faustine, Anthony, Pereira, Lucas, and Nuno J Nunes. IEEE Transactions on Power Systems 2024.

1. Training MLPF





MLPF *effectively capture the complex relationship between historical power features and future covariates.*

$$\mathcal{L}_\theta(\mathbf{y}_H, \hat{\mathbf{y}}_H) = \frac{1}{H}\sum_{t=1}^{H} \lambda(y_t - \hat{y}_t)^2 + (1-\lambda)|y_t - \hat{y}_t|$$

PyPi: https://pypi.org/project/mlpforecast/

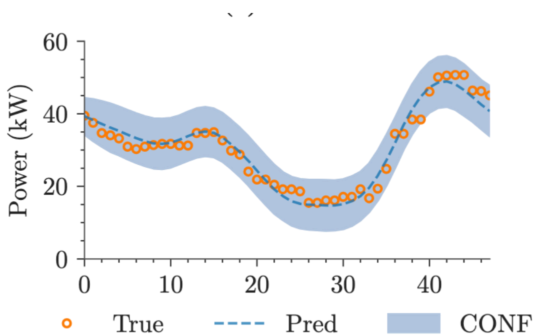
2. Conformal calibration

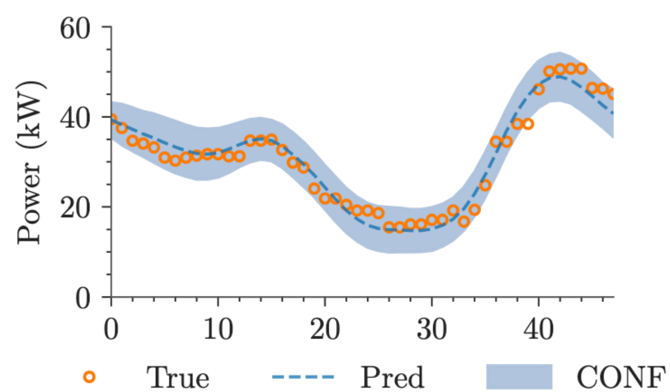
For each data point k in the calibration data: Group the obtained H forecasts to generate a vector of non-conformity scores.

$$\gamma_H^k = \{\gamma_{t+1}, \ldots, \gamma_{t+H}\}$$

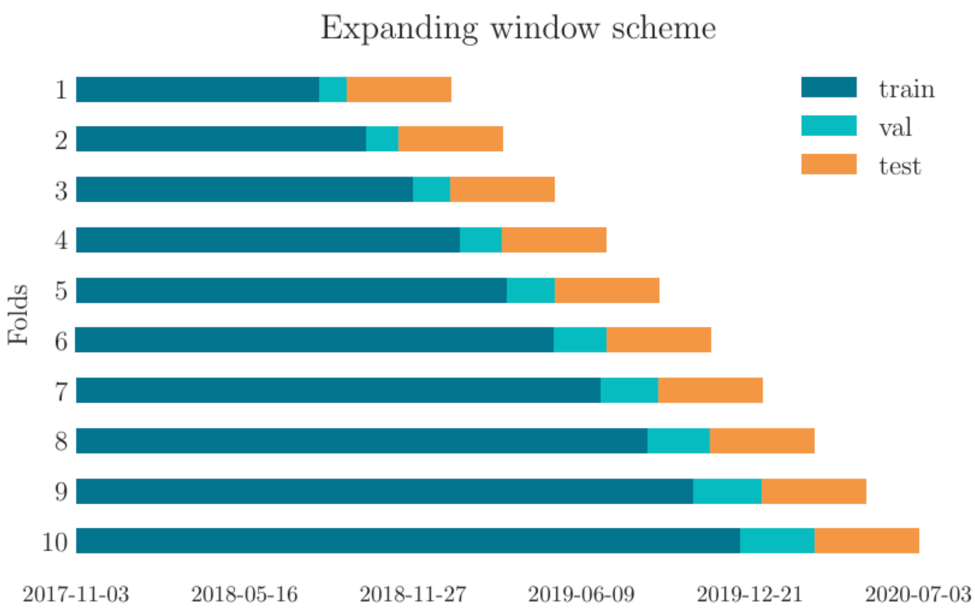
Two non-conformity score are considered

$$\gamma_{sgn}(x_k) = |y_h^k - \mu_\theta(x_k)_h| \qquad \gamma_{sgn}(x_k) = y_h^k - \mu_\theta(x_k)_h$$



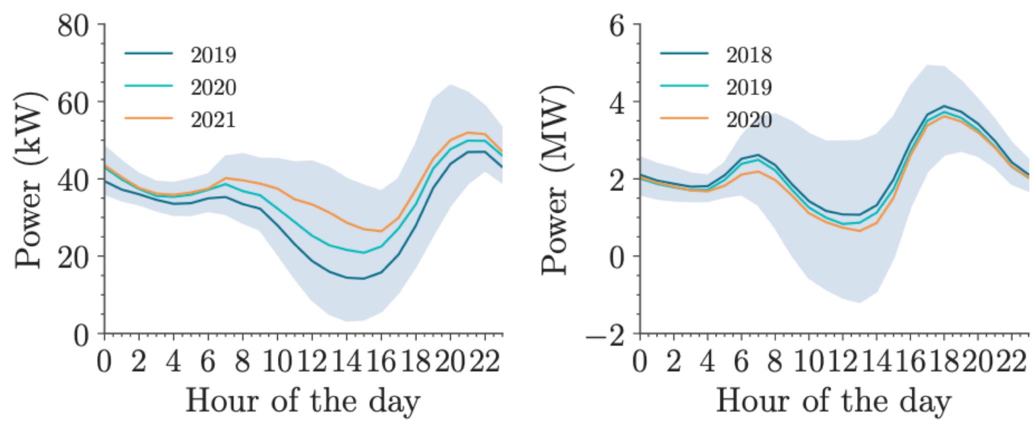


Experiment: Evaluation and Dataset



Datasets

- Madeira LowVoltage distribution substation dataset in Portugal (**MLVS-PT**)
- The Stentaway substation dataset in Plymouth-UK (**SPS-UK**)



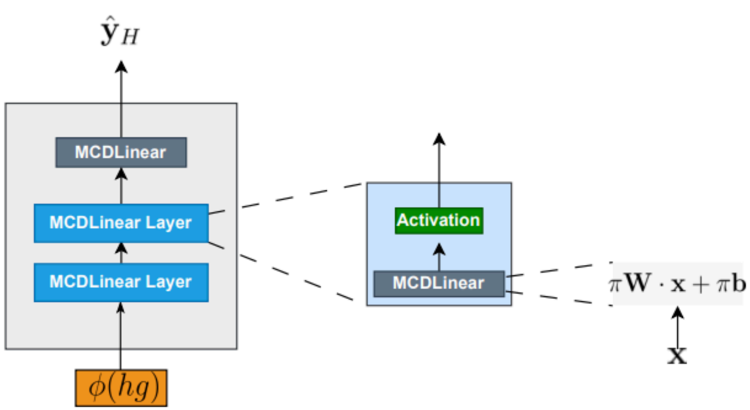
(a) MLVS-PT (b) SPS-UK

Experiment: Benchmark & Metrics

Benchmarks:
1. Quantile Regression with

$$q = \left\{\frac{\alpha}{2}, 0.1, 0.2, \ldots, 0.9, 1 - \frac{\alpha}{2}\right\}$$

2. Monte-Carlo Dropout



(b) Monte Carlo Dropout MLPF (MLPF-MCD)

Metrics

- **PICP:** Predictive Interval Coverage Probability

$$\mathrm{PICP} = \frac{1}{H}\sum_{t=1}^{H}\begin{cases} 0, & \notin [\mathcal{C}_t^U, \mathcal{C}_t^L] \\ 1, & y_t \in [\mathcal{C}_t^U, \mathcal{C}_t^L] \end{cases}$$

- **NMPI**: Normalized Median Prediction Interval width

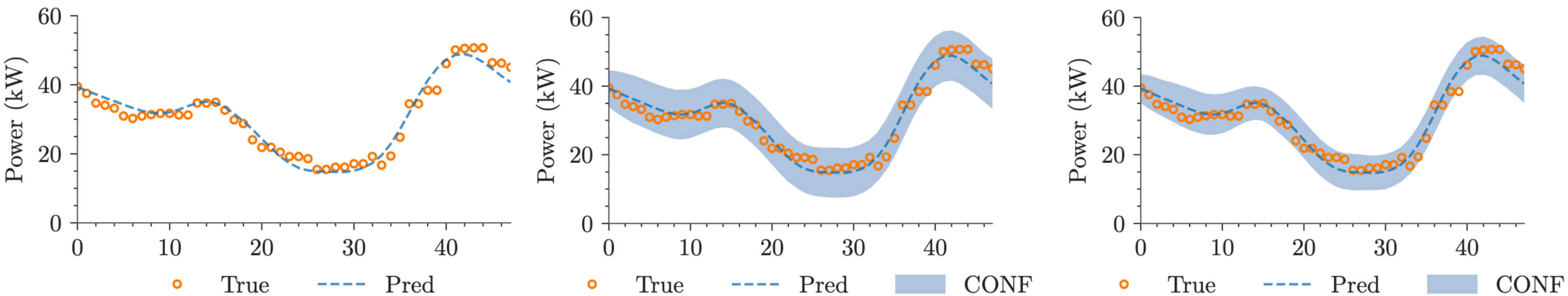
$$\mathrm{NMPI} = \frac{1}{R}\mathrm{median}(\mathcal{C}_d)$$

- **CWE**

$$\mathrm{CWE} = 2 \cdot \frac{\gamma_{nmpi} \cdot \gamma_{pcip}}{\gamma_{picp} + \gamma_{nmpi}}$$

Results: Non-conformity scores

Dataset	Model	PICP	NMPI	CWE
MLVS-PT	MLPF-SCPR	0.85 ± 0.13	0.29 ± 0.05	0.81 ± 0.10
	MLPF-SCPS	0.79 ± 0.15	0.23 ± 0.04	0.80 ± 0.15
SPS-UK	MLPF-SCPR	0.91 ± 0.10	0.48 ± 0.15	0.70 ± 0.17
	MLPF-SCPS	0.74 ± 0.18	0.22 ± 0.07	0.68 ± 0.25



(d) Deterministic (e) Abs-res (f) Sign-res

Results: ProbForecast Benchmark

TABLE I: Experiment 2

Dataset	Model	NRMSE	PICP	NMPI	CWE
MLVS-PT	MLP-MCD	0.13	0.72	0.22	0.75
	MLP-QR	0.09	**0.84**	**0.26**	**0.82**
	Conformal-MLPF	0.09	**0.84**	0.28	0.79
SPS-UK	MLP-MCD	0.19	0.82	0.36	0.75
	MLP-QR	0.13	0.96	0.32	0.83
	Conformal-MLPF	0.13	0.78	**0.24**	0.74

☑ *Conformal-MLPF performed competitively on par with the well-established QR without imposing any restrictive assumptions about the underlying data distribution.*

Conclusion

- **Conformal-MLPF**: Efficient, CP-based neural network for net-load forecasting.
- **No restrictive assumptions**: Competitive performance with QR, outperforms MCD.
- **Sign-based non-conformity**: Balances interval coverage and width effectively

SCP: Fixed intervals may lead to marginal coverage. Future work: explore adaptive CP techniques.

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>92K
Employees around the world

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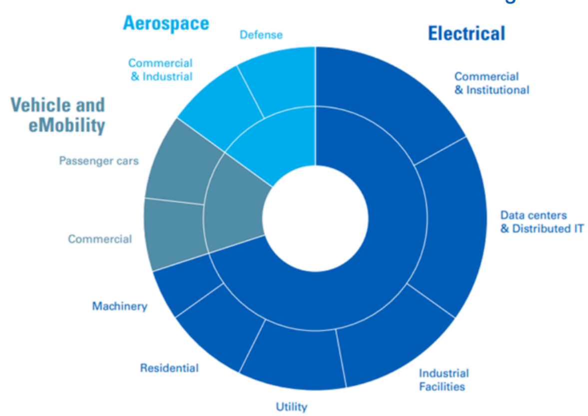
Market Segments



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