

Probabilistic characterization and forecasting of waveform distortions in distribution networks

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Contents

1. Introduction

2. Statistical Characterization of Supraharmonics

- Theoretical background
- Numerical applications

3. Waveform distortion level forecasting

- Theoretical background
- Numerical applications

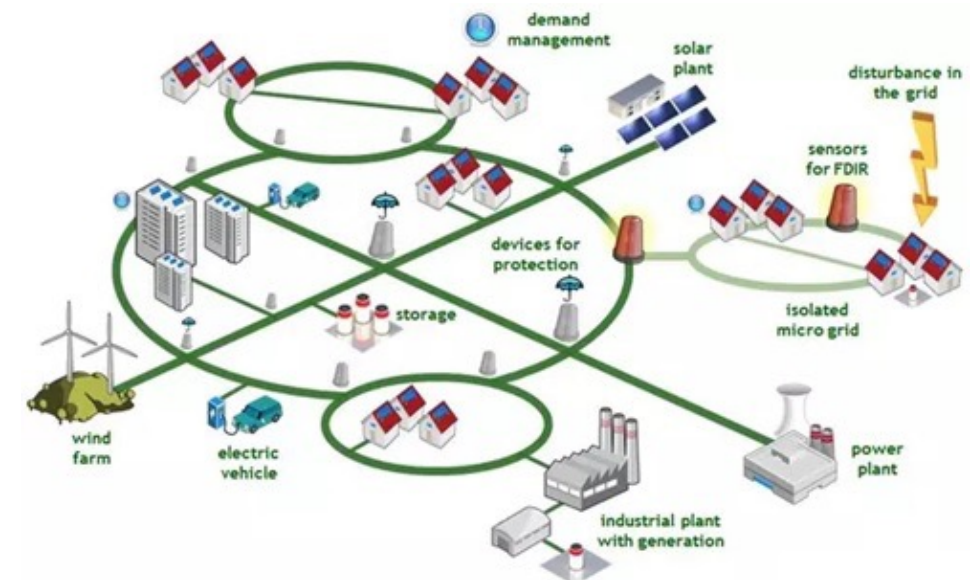
4. Conclusions and future researches

Introduction

Power systems are undergoing a smart transition **toward** more **sustainability and efficiency** that passes through the widespread installation of distributed generation, energy storage systems, and high-efficiency loads.

These changes **impacts on Power Quality (PQ) disturbances** with harmful effects on power system.

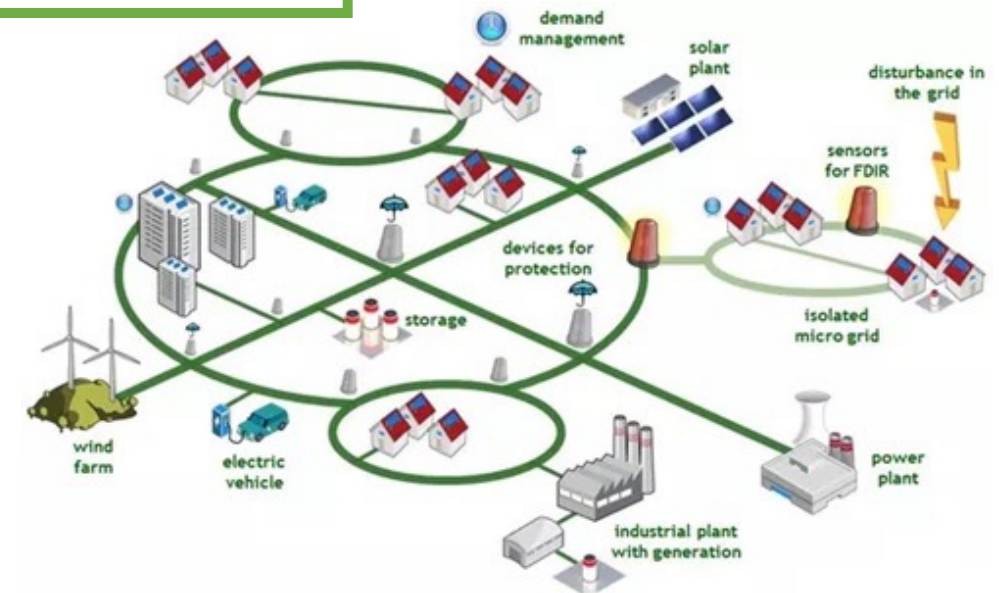
Planning engineers and system operators are deeply interested in developing **new methodologies** able to provide a support to limit this impact.



Introduction

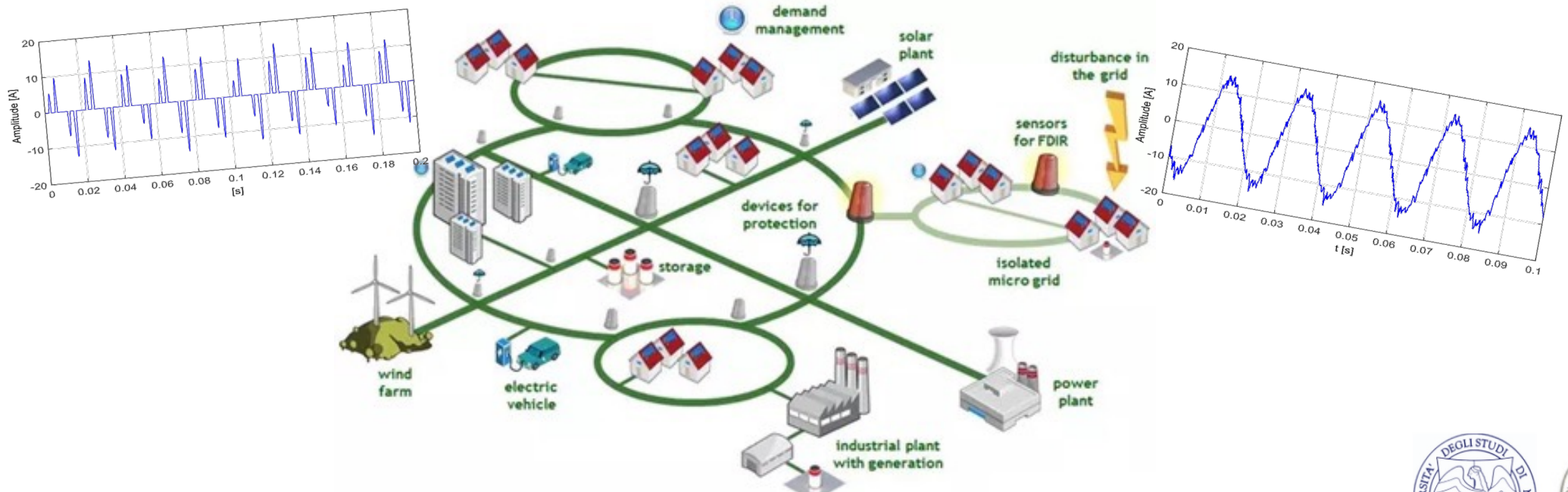
Our studies are focused on the development of probabilistic methodologies in the following topics:

- Statistical Characterization of **Supraharmonics**
- Waveform **distortion level forecasting**



Statistical Characterization of Supraharmonics

Smart Grids drive towards the use of high-frequency switching converters of distributed energy resources and high-efficiency end-user devices, that introduce waveform distortions with spectral components both below the traditional 2 kHz frequency limit and also significantly above this value, in a **range extended up to 150 kHz**.



Statistical Characterization of Supraharmonics

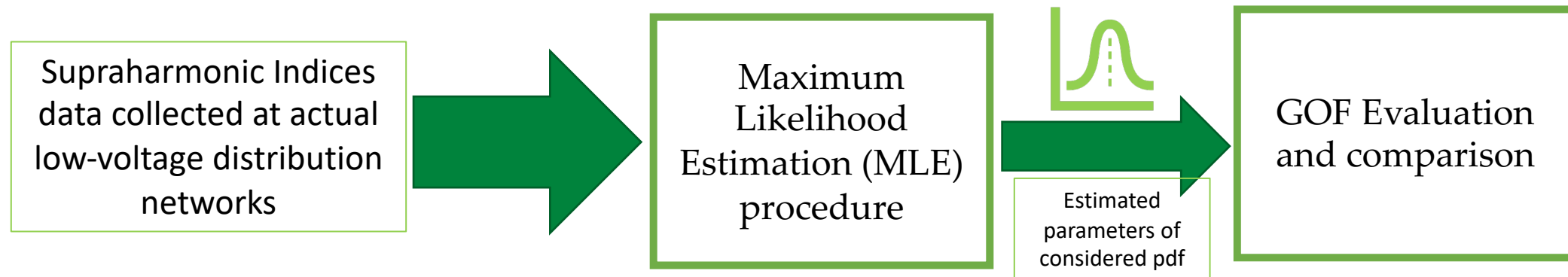
Theoretical background

- The components in the range 2-150 kHz, typically labelled as “supraharmonics” in the relevant literature, **have been studied much less than their low-frequency counterparts**
- Low frequency waveform distortion have consolidated regulation and Standards while supraharmonics **may follow time-varying patterns and are characterized by lack of regulation**. New methodologies are needed to define power quality indices and limits.
- Operators can take advantage from the **statistical characterization of supraharmonics**, e.g., for determining convenient power quality limits or to analyze the residual capacity of networks towards further installations of power electronic converters

Statistical Characterization of Supraharmonics

Theoretical background:

A MLE procedure is applied to estimate parameters for characterization of supraharmonics in low-voltage distribution networks at a global level (i.e., characterizing the **overall emissions levels** in the entire supraharmonic range) and at an **individual-component level** (i.e., characterizing the magnitude of individual supraharmonic components) using **several probabilistic distributions** compared in terms of Goodness of Fitting (GOF)



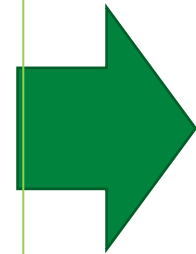
Statistical Characterization of Supraharmonics

Theoretical background

Supraharmonic indices measures data:

- Individual SH $Y_{k\Delta f}$
 $k \in \Omega: \{2\text{kHz} \leq k\Delta f \leq 150\text{kHz}\}$

- $$TSHD = \frac{\sqrt{\sum_{k \in \Omega} Y_{k\Delta f}^2}}{Y_{fr}} \cdot 10$$



MLE procedure to estimate parameters of:

Unimodal distributions

- Normal
- Log-normal
- Weibull
- Burr

Multimodal distribution

- Mixture of Normal



GOF evaluation:

- Adjusted Determination Coefficient (DC)
- Quantile-Quantile (Q-Q) plots

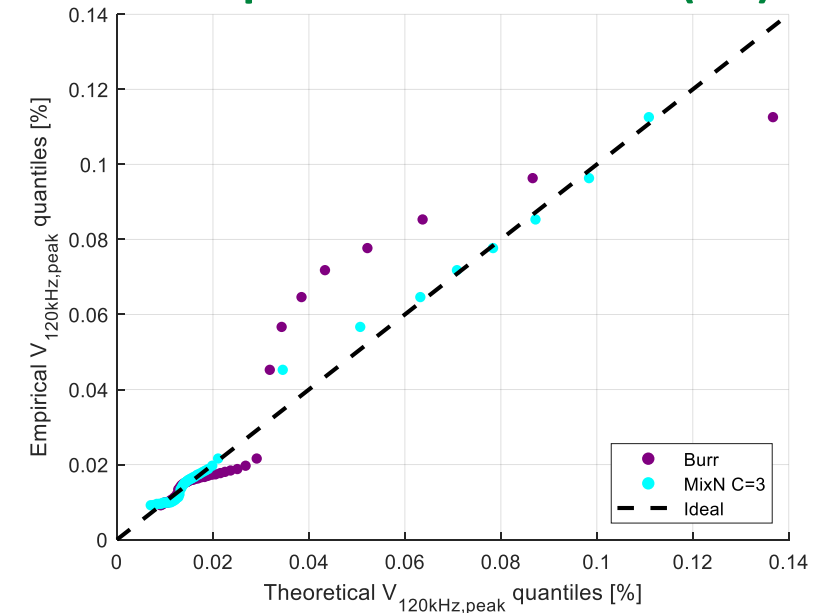
Statistical Characterization of Supraharmonics

Numerical applications: *Individual SH characterization*

Adjusted Determination Coefficient

Component frequency	Index	Individual component distribution					
		Norm	LogN	Weib	Burr	MixN $C = 2$	MixN $C = 3$
6 kHz	ADC (avg)	0.9147	0.9692	0.9154	0.9707	0.9723	0.9985
	ADC (peak)	0.4665	0.7893	0.7141	0.9426	0.9448	0.9448
26 kHz	ADC (avg)	0.9243	0.9591	0.9074	0.9863	0.9789	0.9910
	ADC (peak)	0.4409	0.6195	0.5927	0.7643	0.9720	0.9720
50 kHz	ADC (avg)	0.9141	0.9416	0.8997	0.9660	0.9849	0.9930
	ADC (peak)	0.4530	0.5984	0.5834	0.7192	0.9840	0.9840
120 kHz	ADC (avg)	0.9379	0.9364	0.9409	0.9408	0.9629	0.9636
	ADC (peak)	0.5683	0.8110	0.7380	0.9557	0.9560	0.9560

Q-Q plots of the 120-kHz voltage component at Alameda (CA)



- The MixN distributions provide the best pick in all the considered scenarios
- The Q-Q plots of the MixN distribution is closer to resemble the bisector line, compared to the Q-Q plots of the Burr distribution which cannot even be assimilated to a straight line

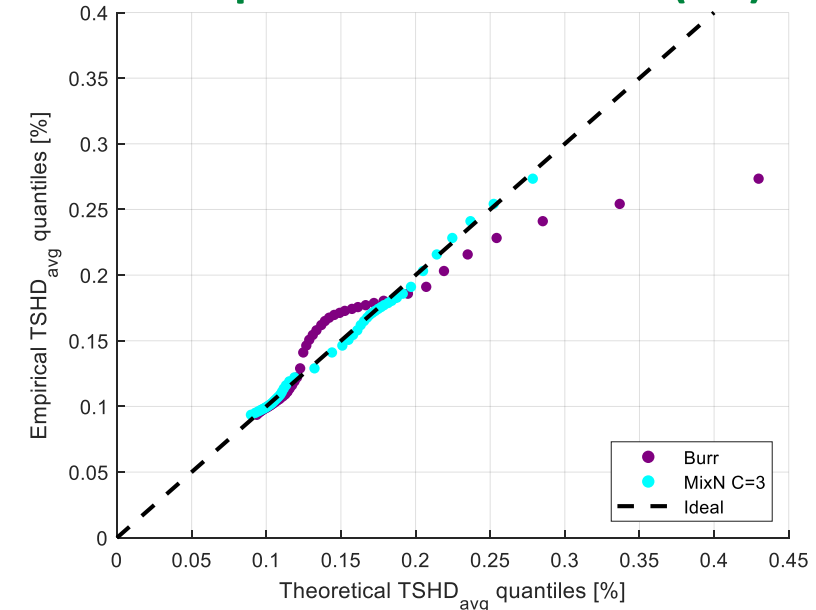
Statistical Characterization of Supraharmonics

Numerical applications: *TSHD* characterization

Adjusted Determination Coefficient

Location	Index	TSHD distribution					
		Norm	LogN	Weib	Burr	MixN $C = 2$	MixN $C = 3$
Austin	ADC (avg)	0.9913	0.9847	0.9787	0.9974	0.9999	0.9999
Delray Beach	ADC (avg)	0.9326	0.8770	0.9556	0.9556	0.9971	0.9998
Murphys	ADC (avg)	0.8469	0.8944	0.7542	0.9933	0.9971	0.9971
	ADC (peak)	0.8409	0.9174	0.7812	0.9957	0.9837	0.9987
Alameda	ADC (avg)	0.9329	0.9357	0.9402	0.9411	0.9880	0.9965
	ADC (peak)	0.4299	0.7281	0.6613	0.8820	0.9140	0.9140
Wohlen	ADC (avg)	0.9174	0.9418	0.9172	0.9792	0.9955	0.9999
	ADC (peak)	0.8794	0.9402	0.8694	0.9919	0.9854	0.9991
Rochford	ADC (avg)	0.7626	0.8643	0.8495	0.9082	0.9640	0.9958
	ADC (peak)	0.8037	0.8900	0.8789	0.9088	0.9707	0.9963
Amsterdam	ADC (avg)	0.9857	0.9640	0.9878	0.9878	0.9896	0.9988
	ADC (peak)	0.9873	0.9430	0.9532	0.9846	0.9929	0.9945
Skelleftea	ADC (avg)	0.9894	0.9949	0.9331	0.9988	0.9999	0.9999
	ADC (peak)	0.5604	0.9127	0.4604	0.9944	0.9982	0.9995

Q-Q plots of the 120-kHz voltage component at Alameda (CA)

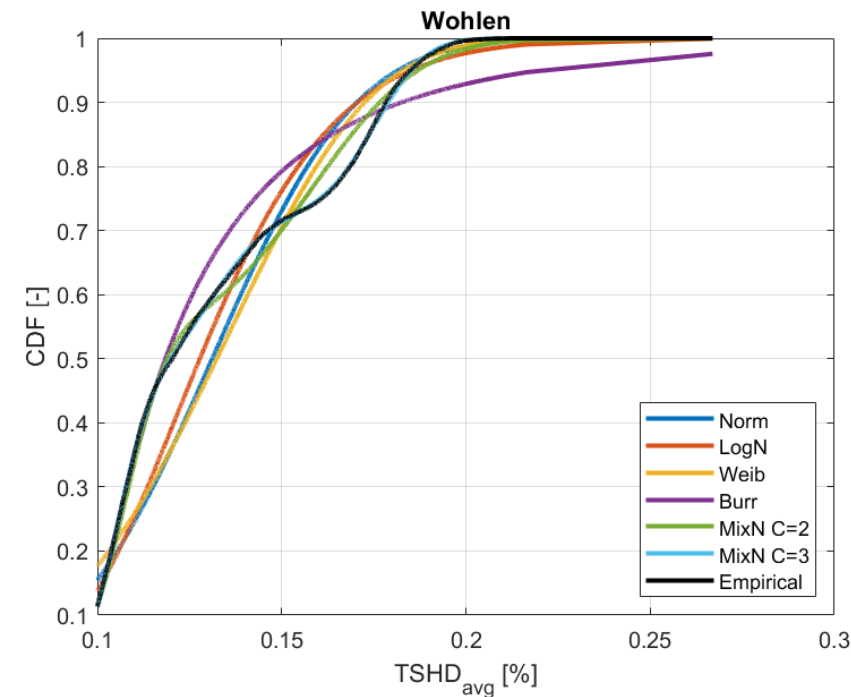
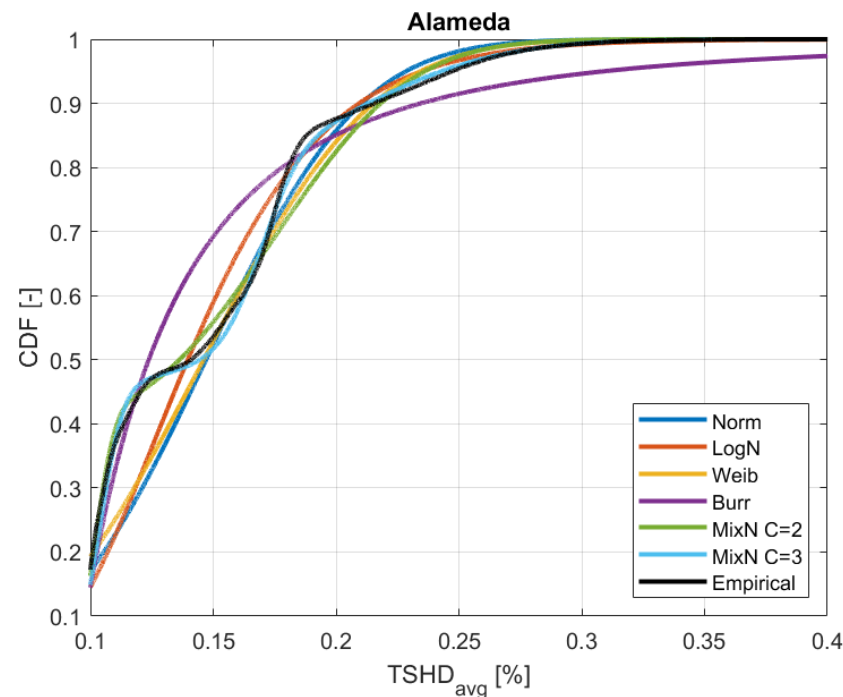


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Statistical Characterization of Supraharmonics

Numerical applications: *TSHD* characterization

Estimated Cumulative Distribution Functions (CDFs) in Alameda and Wohlen

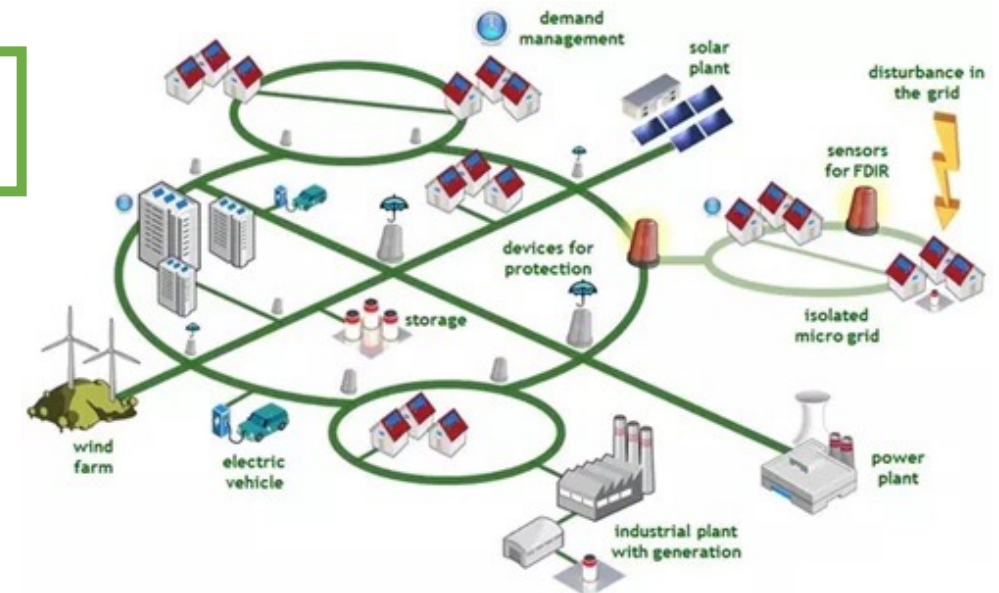


- The empirical CDF shapes of the TSHD data can be adequately modelled only through the multimodal MixN distribution. Particularly, the cdf of TSHD is captured only through a MixN with C=3 components

Introduction

Our studies are focused on the development of probabilistic methodologies in the following topics:

- Statistical Characterization of **Supraharmonics**
- Waveform **distortion level forecasting**



Waveform Distortion Level Forecasting

Theoretical background

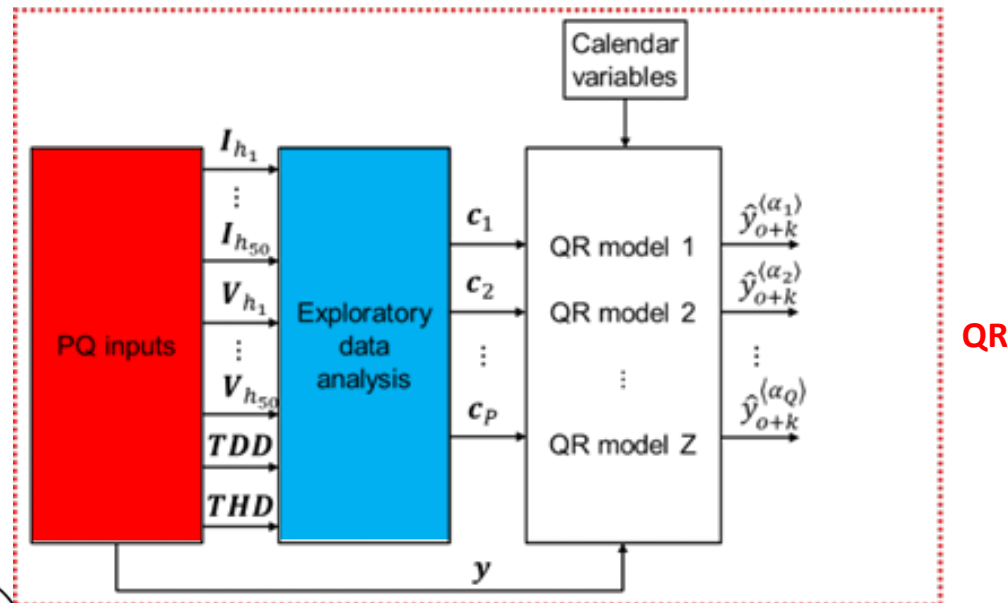
- **Forecasting methodologies** are widely used by planning engineers, system operators and customers who aim at solving several tasks in which the **decision must be taken before** the actual occurrence of the event (e.g., market bidding, optimal management of DERs, predictive maintenance,...)
- Historically, much of the effort on forecasting methodologies has been put on **energy, price and outages**, despite the potentialities of the exploitation of accurate predictions in other fields
- The **PQ disturbance forecasting problem** has only recently been addressed in the relevant literature, fostered by the finer diffusion of measurement devices. The availability of forecasts of voltage and current waveform distortions, in particular, can unlock:
 - the **inclusion of PQ indices constraints in the optimal scheduling strategies** of smart grids and microgrids, taking preventive measures to keep the PQ levels below contractual or Standard limits;
 - the **inclusion of the harmonics effect in the prediction of dynamic cable/line/transformer rating**;
 - new **ways to plan installations** based on the expected distortions;
 - ...

Waveform Distortion Level Forecasting

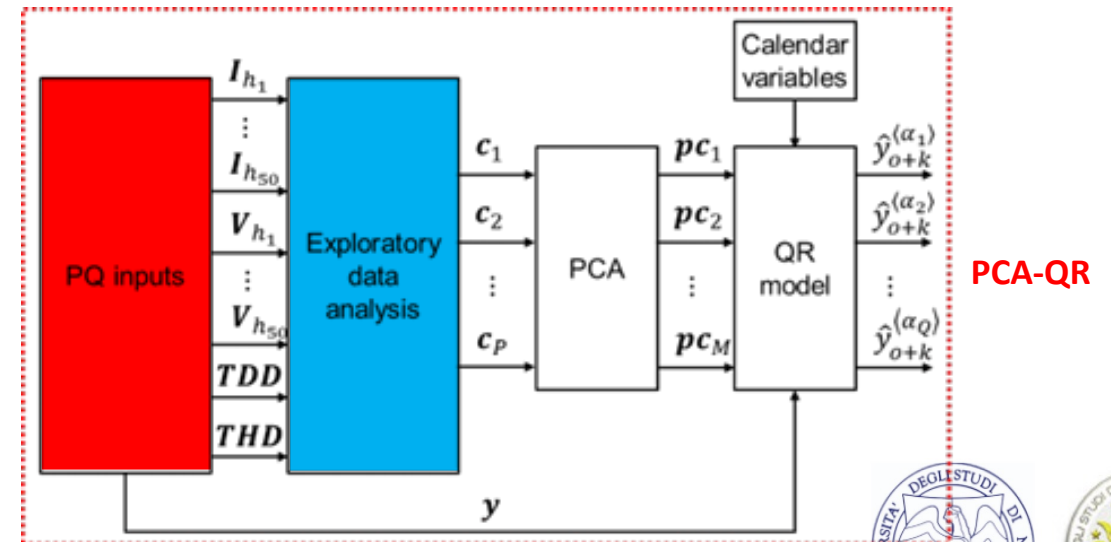
Theoretical background

The forecasting methodology exploits PQ **input data** (current harmonics $I_{h_1}, \dots, I_{h_{50}}$, voltage harmonics $V_{h_1}, \dots, V_{h_{50}}$, the **TDD** and the **THD**) to predict an individual harmonic component or a PQ index.

Having 102x3 inputs may constitute an **unnecessarily large forecasting problem**. To reduce the dimensionality of the problem, the inputs undergo an **exploratory data analysis** to discard the uninformative variables and keep only the P most informative candidate predictors c_1, c_2, \dots, c_P



QR



PCA-QR

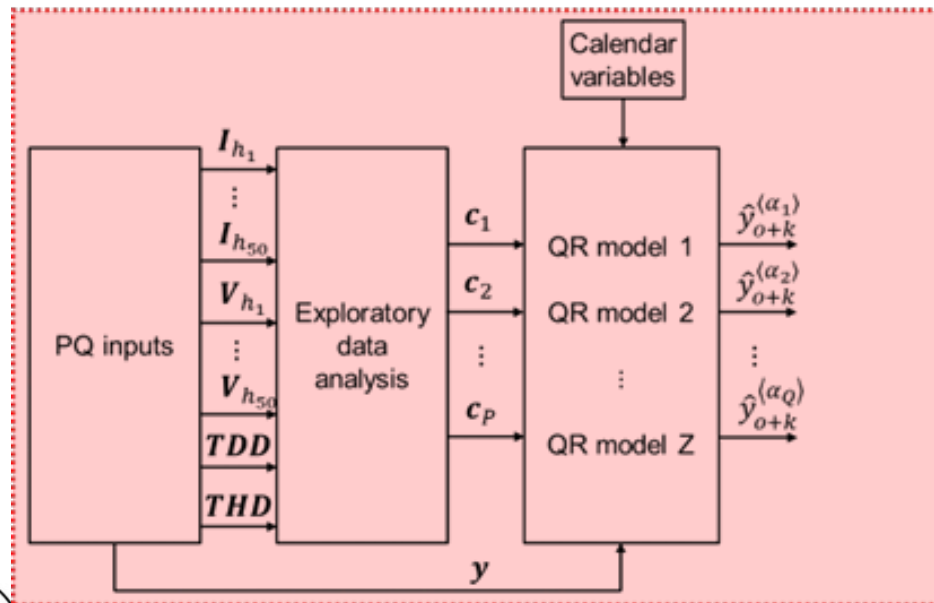
Waveform Distortion Level Forecasting

Theoretical background

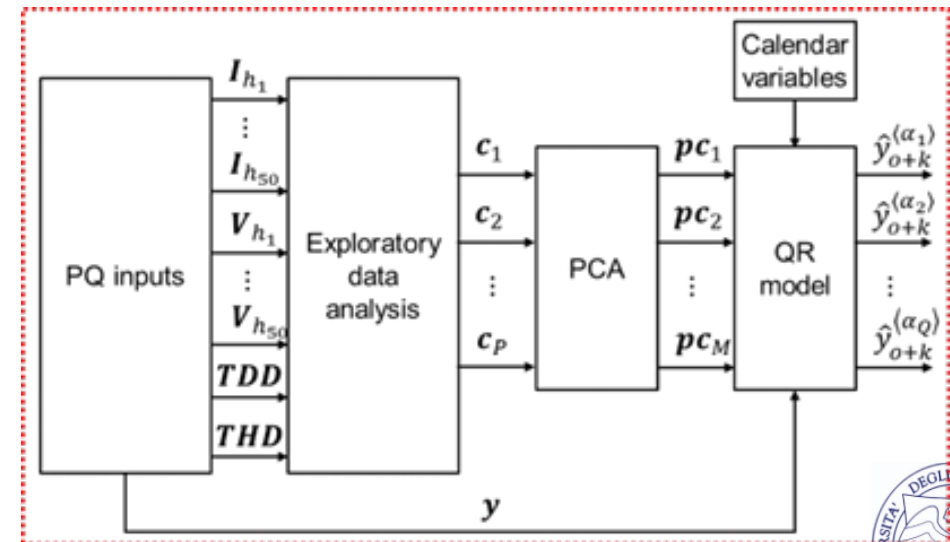
Two alternative approaches are developed for the eventual model selection:

QR: the candidate predictors are permuted in a validation procedure as inputs of Z QR models, allowing selecting the final model as the one with the best performance in the validation window.

This approach is **computationally intensive**, but allows exploring a wide variety of combinations/permutations of predictor variables in the underlying forecasting model



QR



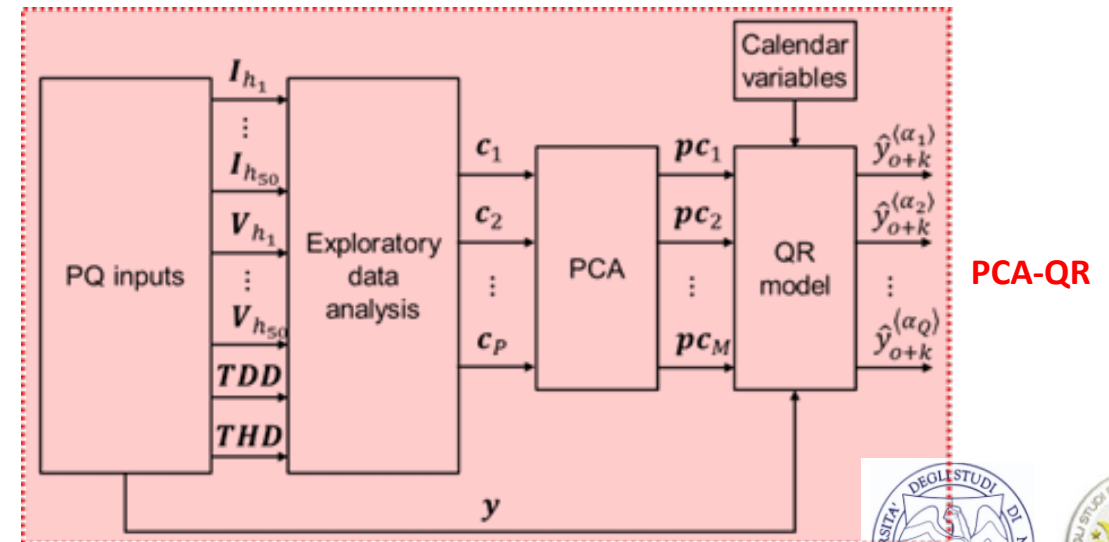
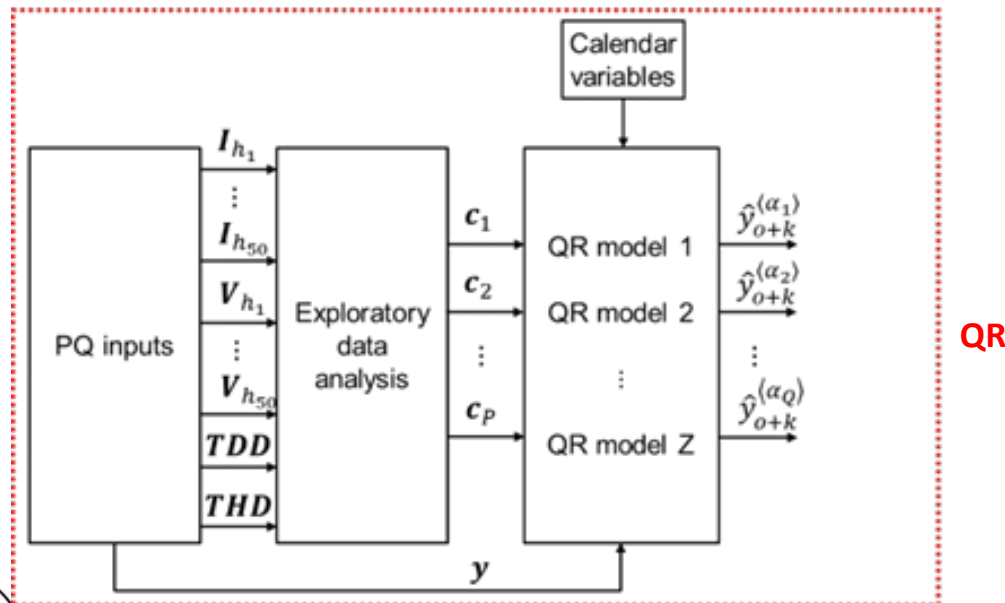
PCA-QR

Waveform Distortion Level Forecasting

Theoretical background

Two alternative approaches are developed for the eventual model selection:

PCA-QR: the candidate predictors are processed through the **Principal Component Analysis (PCA)** to extrapolate fewer ($M < P$) principal components pc_1, pc_2, \dots, pc_M , that are used as inputs of a QR model. This approach requires the implementation of the PCA, but is less computationally intensive than the QR as it does not require the permutation of input variables in the underlying forecasting model



Waveform Distortion Level Forecasting

Numerical applications:

- The input data are publicly available on the PQube Live World Map. They include **fifty current and voltage harmonics subgroups**, **Total Demand Distortion (TDD)** and **Total Harmonic Distortion (THD)** from March 11, 2019, through September 13, 2020, at an Alameda (US) installation
- We predict the THD, the TDD, and individual voltage or current harmonics on each phase (L1, L2 and L3) of the installation at **one-day-ahead and one-week-ahead horizons**.
- In all scenarios, each forecast is constituted by **99 predictive quantiles at coverages 0.01, 0.02, ..., 0.99**. The calendar variables are six dummy variables that model the day of the week
- **Proposed methods are compared to two benchmarks**: one that includes all the individual harmonics as predictors of the QR model (AH-QR) and one based on a naïve seasonal persistence model (SPM)
- **Pinball Score (PS) and Absolute Coverage Error (ACE)** respectively evaluate the overall skill and the reliability of the probabilistic predictions

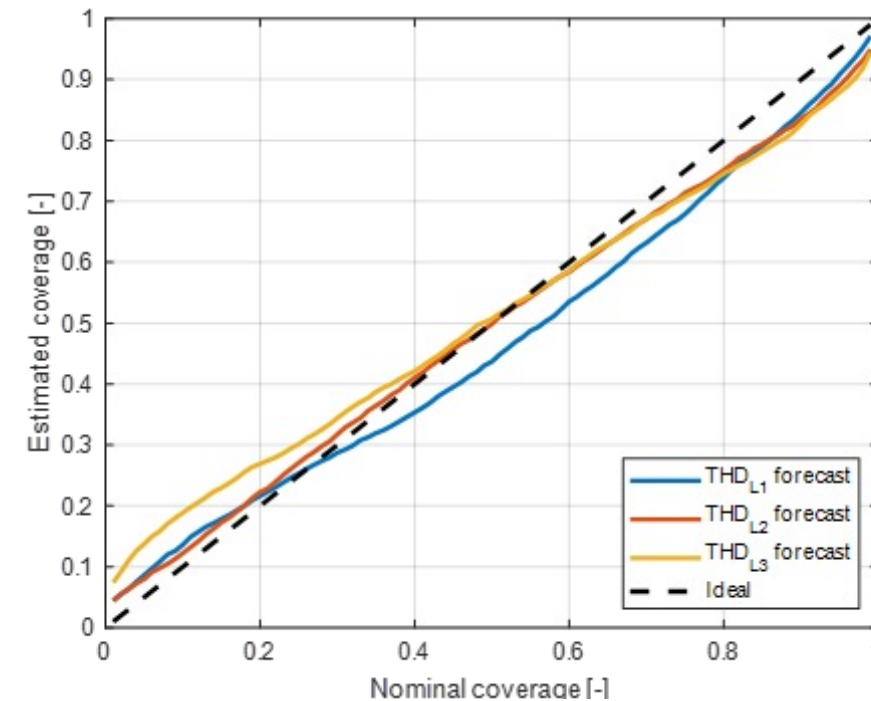
Waveform Distortion Level Forecasting

Numerical applications: *day-ahead prediction*

Pinball score

PQ target variable	Model	Error index					
		PS [%]			ACE [%]		
		<i>L1</i>	<i>L2</i>	<i>L3</i>	<i>L1</i>	<i>L2</i>	<i>L3</i>
THD	QR	0.0158	0.0176	0.0185	2.94	2.20	3.29
	PCA-QR	0.0166	0.0176	0.0200	1.56	2.69	1.69
	AH-QR	0.0250	0.0247	0.0267	19.83	15.62	16.23
	SPM	0.0282	0.0318	0.0314	-	-	-
TDD	QR	0.3070	0.0473	0.0547	8.77	11.74	15.96
	PCA-QR	0.2803	0.0466	0.0510	0.85	4.29	1.74
	AH-QR	0.2664	0.0446	0.0498	3.01	4.97	1.89
	SPM	0.5049	0.0825	0.0975	-	-	-
3 rd harmonic	QR	0.2936	0.0602	0.0648	5.77	6.24	7.14
	PCA-QR	0.2740	0.0629	0.0674	1.34	4.51	5.94
	AH-QR	0.2625	0.0574	0.0680	1.65	1.63	4.44
	SPM	0.4999	0.1016	0.1205	-	-	-

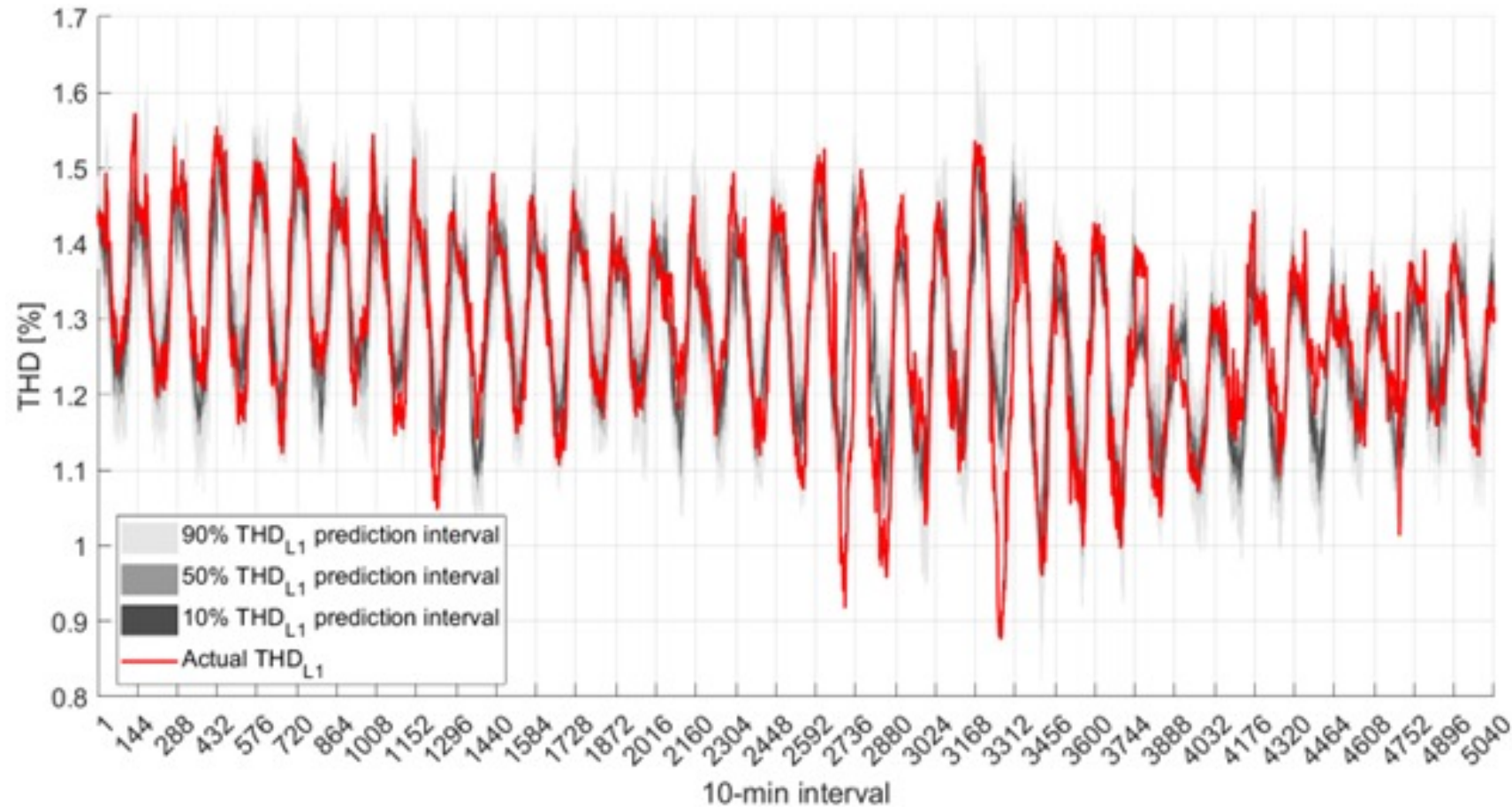
Reliability diagrams of PCA-QR THD forecast



- The QR outperforms other methods in THD forecasting for both PS and ACE indices, whereas, concerning the TDD forecasts, AH-QR provides the best results in terms of PS and PCA-QR in terms of ACE.
- The PS improvement of QR with respect to SPM benchmark ranges from 36% (THD_{L3}) to 47% (TDD_{L3})
- Reliability of Forecasts on phase L1 are slightly under-dispersed compared to those on phases L2 and L3

Waveform Distortion Level Forecasting

Numerical applications: *day-ahead prediction*



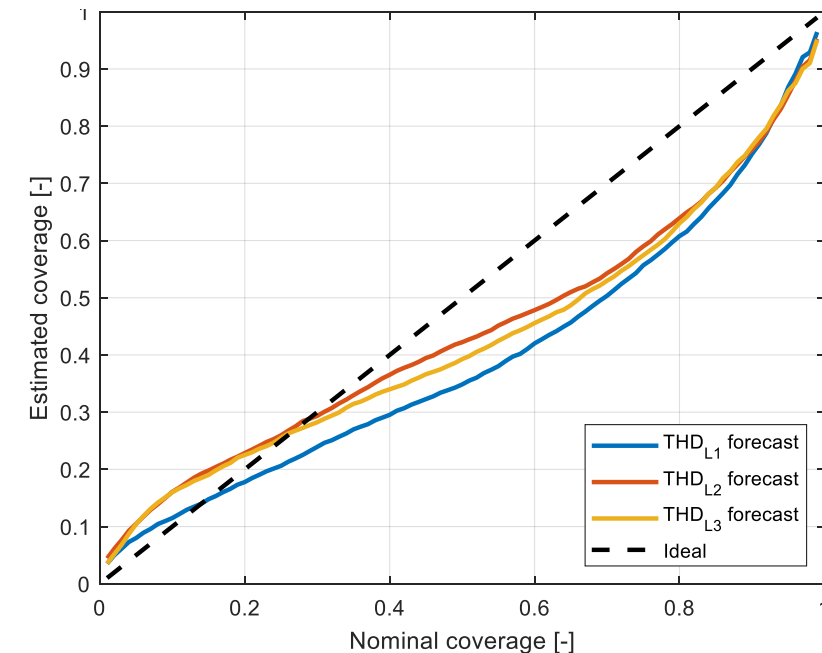
Waveform Distortion Level Forecasting

Numerical applications: *one week-ahead predictions*

Pinball score

PQ target variable	Model	Error index					
		PS [%]			ACE [%]		
		<i>L1</i>	<i>L2</i>	<i>L3</i>	<i>L1</i>	<i>L2</i>	<i>L3</i>
THD	QR	0.0248	0.0279	0.0290	11.13	8.40	9.35
	PCA-QR	0.0555	0.0529	0.0597	25.92	20.71	25.95
	AH-QR	0.0450	0.0384	0.0480	33.67	27.03	32.19
	SPM	0.0562	0.0651	0.0549	-	-	-
TDD	QR	0.3581	0.0537	0.0691	4.06	17.11	21.44
	PCA-QR	0.3457	0.0599	0.0702	2.69	14.62	15.03
	AH-QR	0.3200	0.0552	0.0707	1.72	8.97	11.86
	SPM	0.4708	0.0873	0.1065	-	-	-
3 rd harmonic	QR	0.3569	0.0685	0.0833	3.26	8.79	19.07
	PCA-QR	0.3442	0.0753	0.0853	2.58	7.84	18.74
	AH-QR	0.3213	0.0733	0.1029	2.10	8.00	25.62
	SPM	0.4712	0.1043	0.1157	-	-	-

Reliability diagrams of PCA-QR THD forecast



- QR outperforms other methods in THD forecasting for both PS and ACE indices
- The PS improvement of QR with respect to SPM benchmark ranges from 23% (TDD_{L1}) to 57% (THD_{L1})
- Reliability of some predictions is poor in some cases, as suggested by the great values of the ACE index; this may be caused by the small amount of data that compose the input datasets

Conclusions and future researches

Statistical Characterization of Supraharmonics

- A methodology for statistical characterization of supraharmonics was presented
- Among the considered distributions, the MixN distribution showed the best fitting results in characterizing both the overall supraharmonic content (through the TSHD) and individual supraharmonic components
- Future research on this topic may follow several paths, such as:
 - the development of more appropriate probability distributions to model supraharmonics
 - the exploitation of the statistical characterization to generate scenarios and to implement probabilistic analysis with a specific focus on supraharmonic emissions (e.g., within probabilistic harmonic power flow studies)

Conclusions and future researches

Waveform Distortion Level Forecasting

- A waveform distortion level forecasting problem by individuating a methodology to develop predictions, exploiting and properly selecting the input data coming from the measurement systems was presented
- The methodology uses QR models for THD, TDD and subgroup harmonic day-ahead and week predictions. Numerical experiments based on actual public data confirm that the proposal is suitable for probabilistic forecasting. However, results also evidenced shortcomings in the reliability of the predictions for longer forecast horizons.
- Future works on this topic will address:
 - other PQ disturbances, also considering that other predictor variable can require other pre-processing approaches.
 - More advanced techniques to maintain the calibration of forecasts at longer horizons

**Thank you very
much
for your attention!**
