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Panel Session on Probabilistic Energy Forecasting

PROBABILISTIC INDUSTRIAL LOAD FORECASTING

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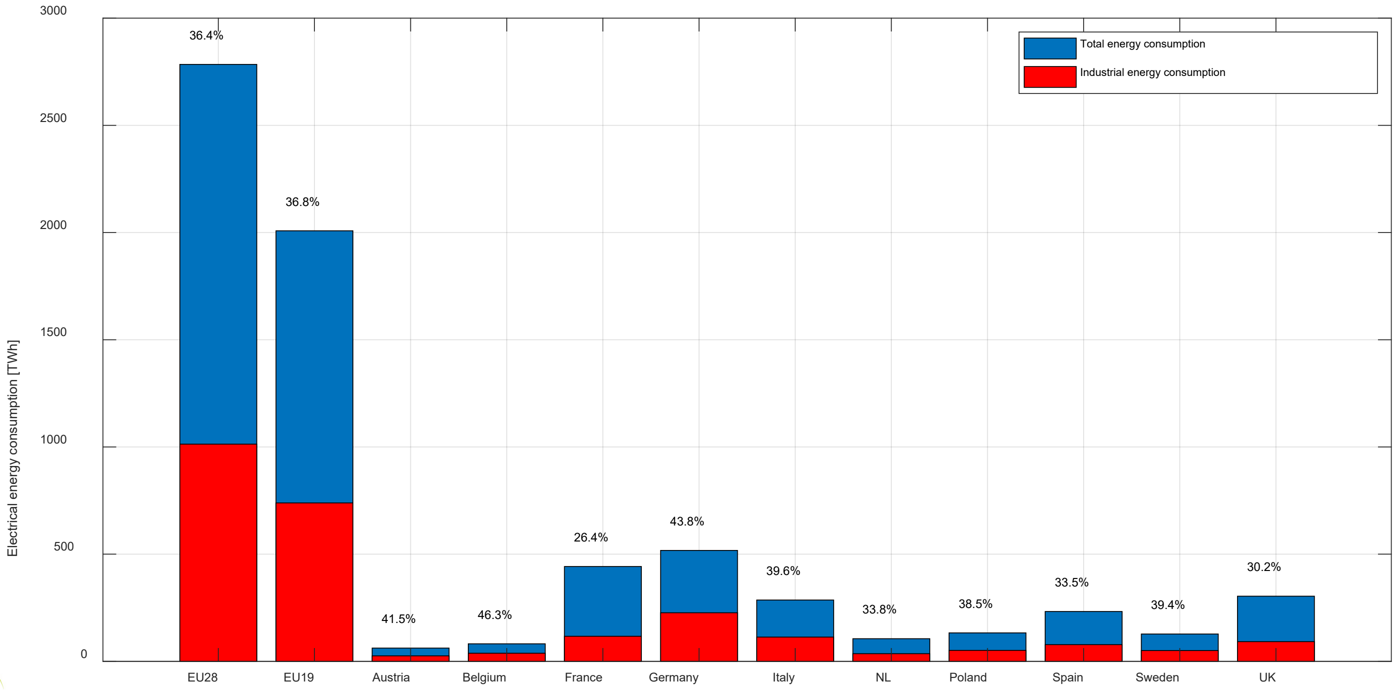
Contents

Introduction

Industrial load is a big share of the total electrical load



Ref. Eurostat
Data for 2016

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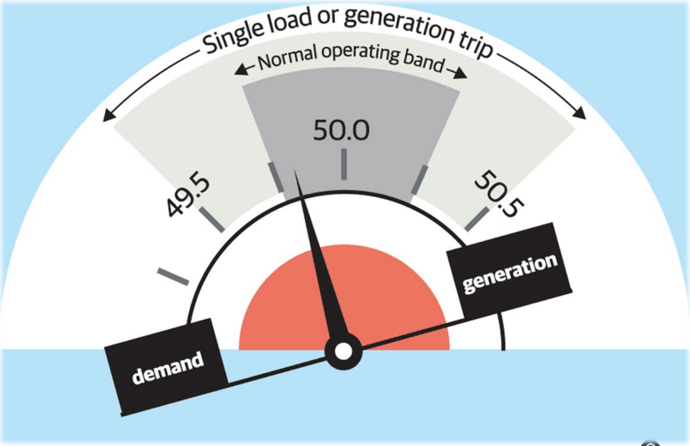
Introduction

Much of the industrial load is non-controllable and characterized by an intrinsic randomness due to human behavior, non-schedulable activities, and contingencies

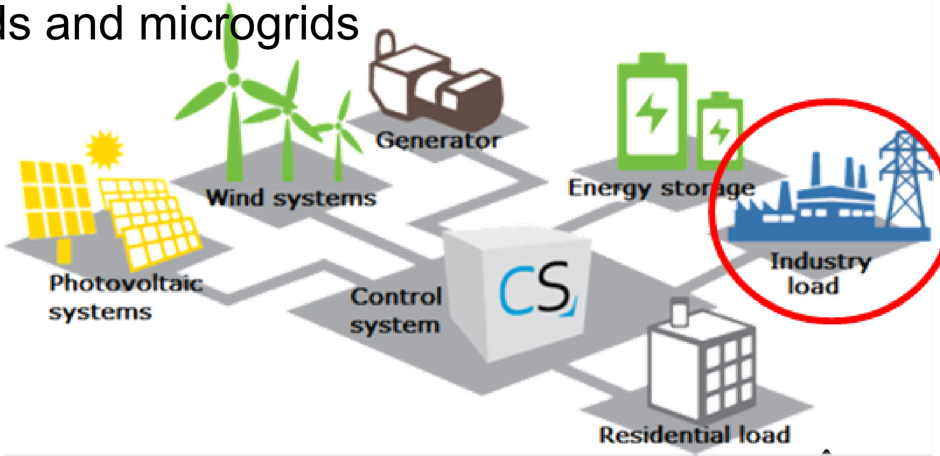
Forecasts of industrial load allow:
TSO and DSO for dispatching energy and for acquiring energy reserves



Introduction

Much of the industrial load is non-controllable and characterized by an intrinsic randomness due to human behavior, non-schedulable activities, and contingencies

Forecasts of industrial load allow:
Ownership of the industrial system for bidding on markets and for managing DERs and equipment in industrial smart grids and microgrids



Introduction

Traditional (regional) load forecasting

Seasonality, calendar events, and weather are common features in modeling and forecasting load

Industrial load forecasting

Traditional load forecasting methods may not adapt well to industrial load, due to the different nature and peculiar characteristics of industrial sites

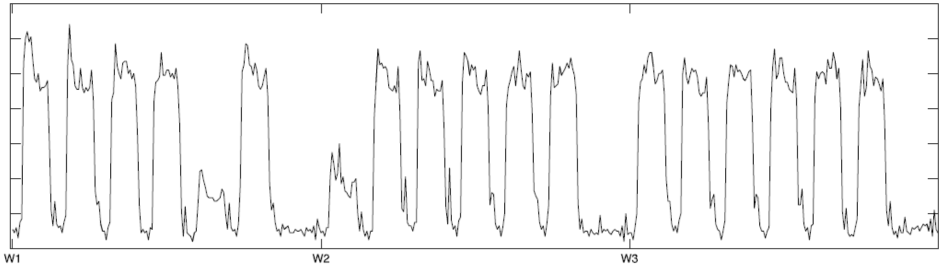
Major challenges: individuation of work regimes, low dependency on ambient temperature, and low-level load aggregation!!

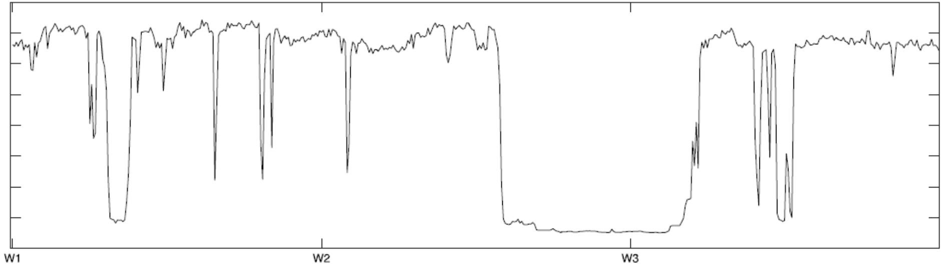
Introduction

Challenge 1: Individuation of work regimes

Some industrial load follow regime-switching profile patterns due to turn-on and turn-off of large machines. This determines heteroscedasticity, i.e., conditional variance cannot be assumed constant throughout the entire sample

Forecasting models based on assumptions upon low variability of conditional residuals might be inappropriate to fit industrial load



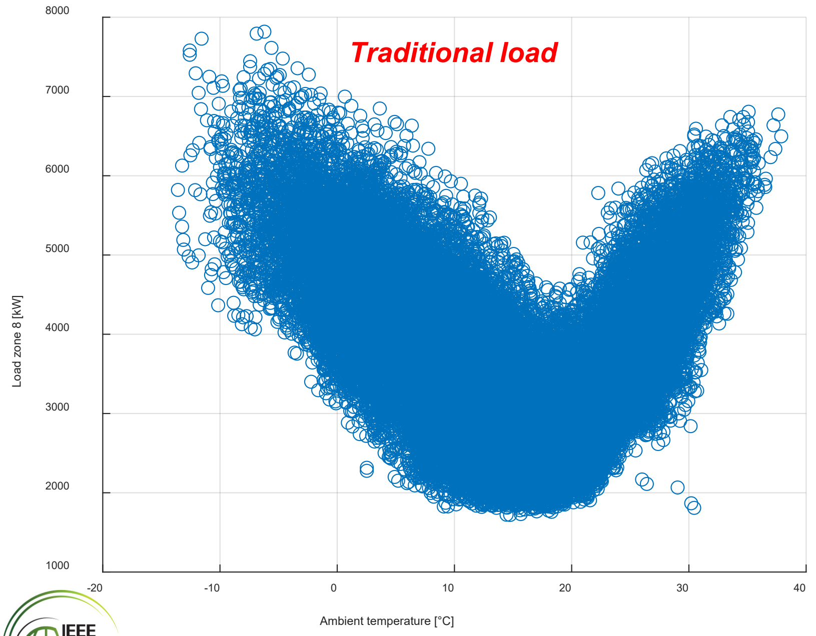


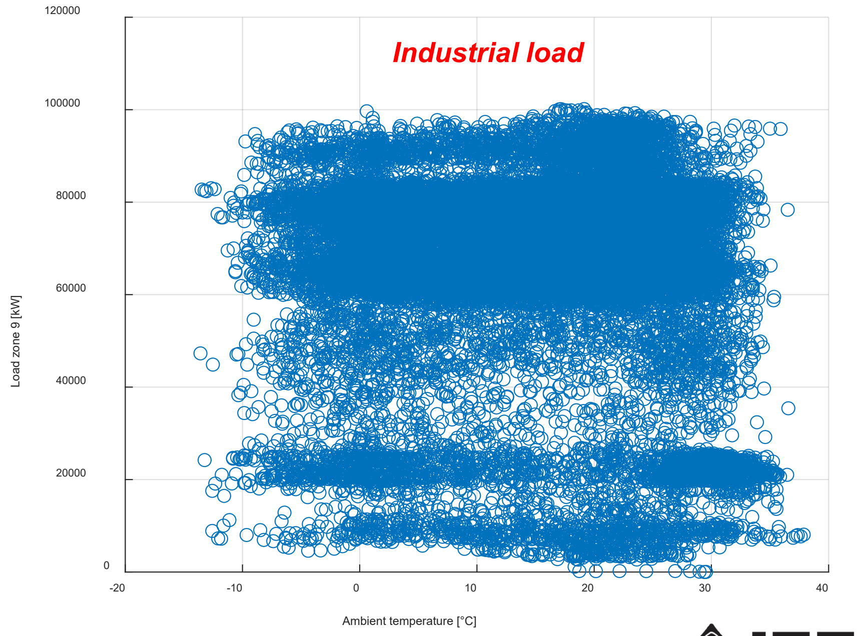
Berk K, Hoffmann A, Muller A. "Probabilistic forecasting of industrial electricity load with regime switching behavior," Int. J. Forec., vol. 34, 2018

Introduction

Challenge 2: Low dependency on ambient temperature

GEFCom2012 data



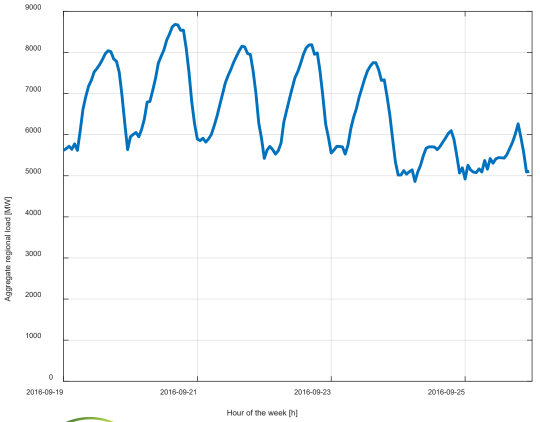


Introduction

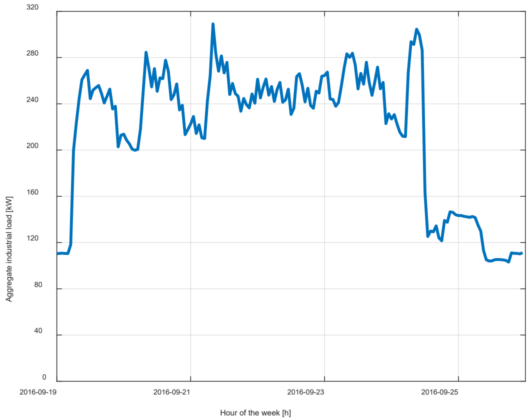
Challenge 3: Low-level load aggregation

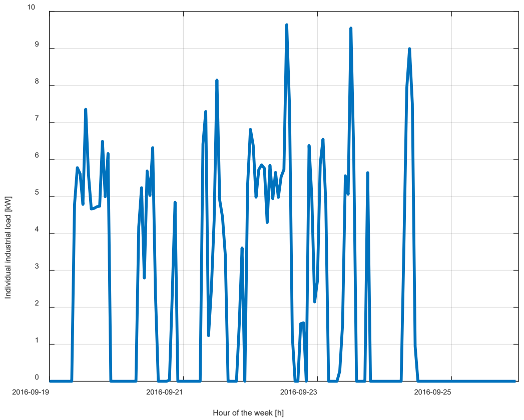
Compared to load at regional or national level of aggregation, industrial load follow patterns that are much less smooth. At individual industrial-load level, patterns might also be intermittent, due to the need for manual usage by operators

ISO NE data



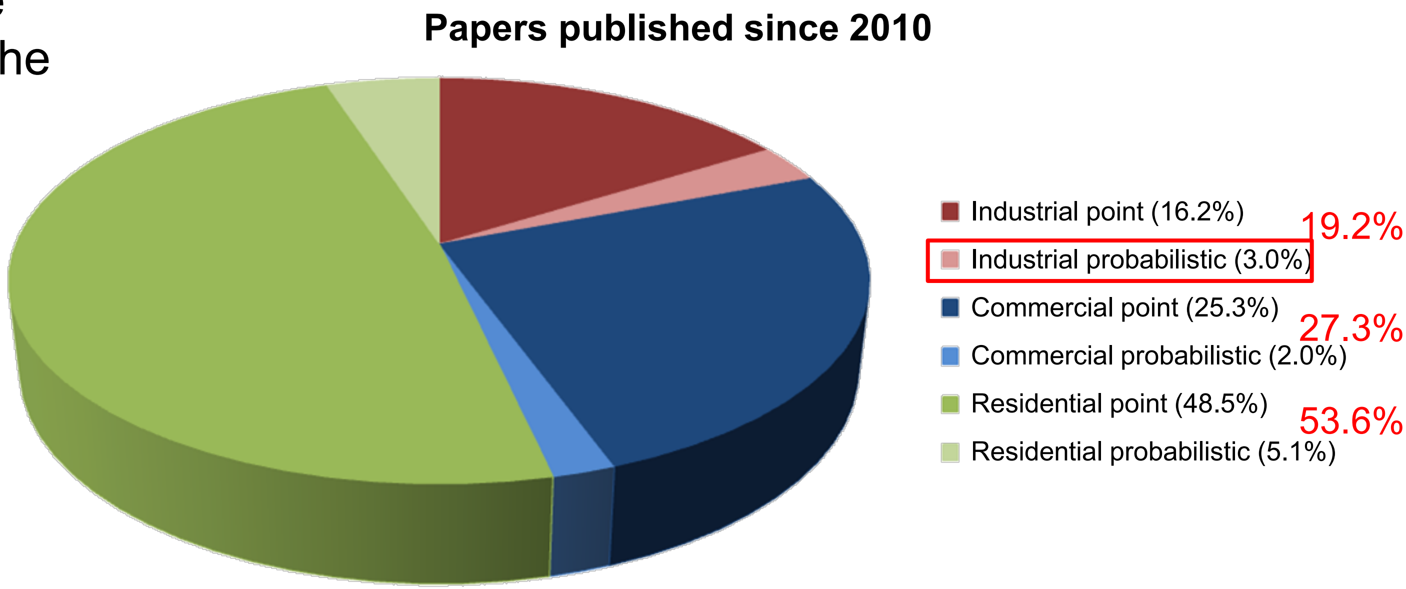
Data of an Italian industrial site





Methodologies

Despite allocating the most of the share of the total aggregate load, industrial load forecasting is not as popular as residential or commercial load forecasting



Methodologies

Relevant Probabilistic Industrial Load Forecasting (PILF) methodologies:

- Sparse Heteroscedastic Gaussian Process
- Regime-switching Markov Chains with time series
- Quantile Regression Forest with electric predictors
- Multivariate Quantile Regression on individual forecasts

Example of an application of PILF:

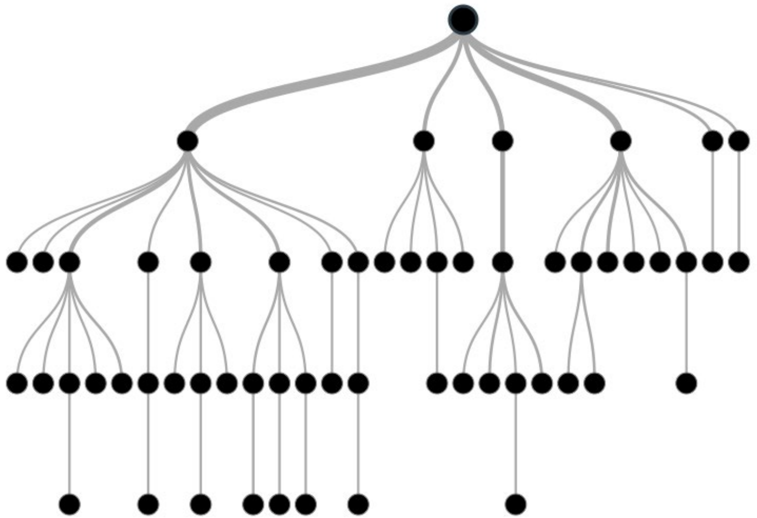
- Management of a distribution transformer by dynamic transformer rating

Methodologies

Quantile Regression Forest (QRF)

Challenge 1:

Work regimes -> QRF models allow clustering similar observations in specific leaves



Bracale A, Carpinelli G, De Falco P. "Comparing univariate and multivariate methods for probabilistic industrial load forecasting," in Proc. of EFEA2018, Rome, 24-26 September 2018

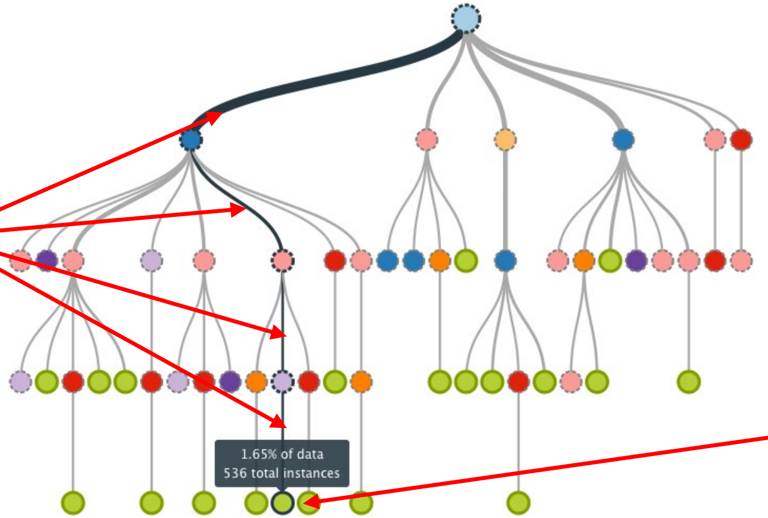
Methodologies

Quantile Regression Forest (QRF)

Challenge 1:

Work regimes -> QRF models allow clustering similar observations in specific leaves

Path determined by split on predictors



Leaf containing past observations

Bracale A, Carpinelli G, De Falco P. "Comparing univariate and multivariate methods for probabilistic industrial load forecasting," in Proc. of EFEA2018, Rome, 24-26 September 2018

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Methodologies

Quantile Regression Forest (QRF) with electric predictors

Challenge 2:

Low dependency on ambient temperature -> Exploit “new” variables that are informative for the target variable!

Active and reactive power are mutually informative in industrial frameworks

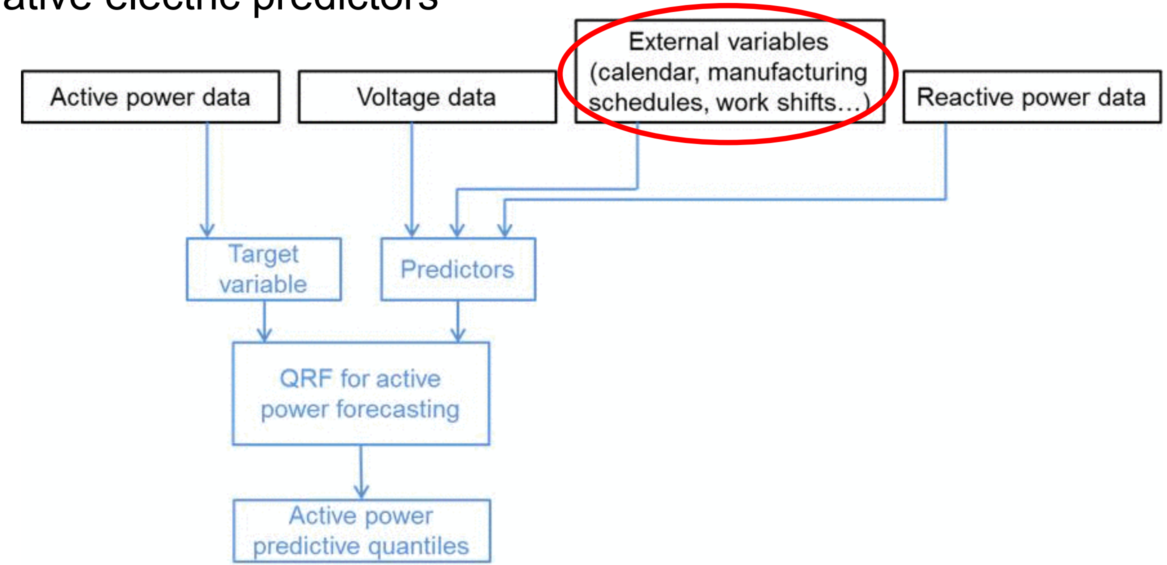
Other electric variables (e.g., voltage), together with calendar variables and information on manufacturing schedules and work shifts within the industrial site might be informative for predicting the load (and even for individuating work regimes!!!)

Bracale A, Caramia P, De Falco P, Hong T. “Short-term industrial reactive power forecasting,” Int. J. Electr. Power Energy Systems, vol. 107, 2019

Methodologies

Quantile Regression Forest (QRF) with electric predictors

Active and **reactive power** are individually forecasted by QRF in a univariate approach, exploiting informative electric predictors



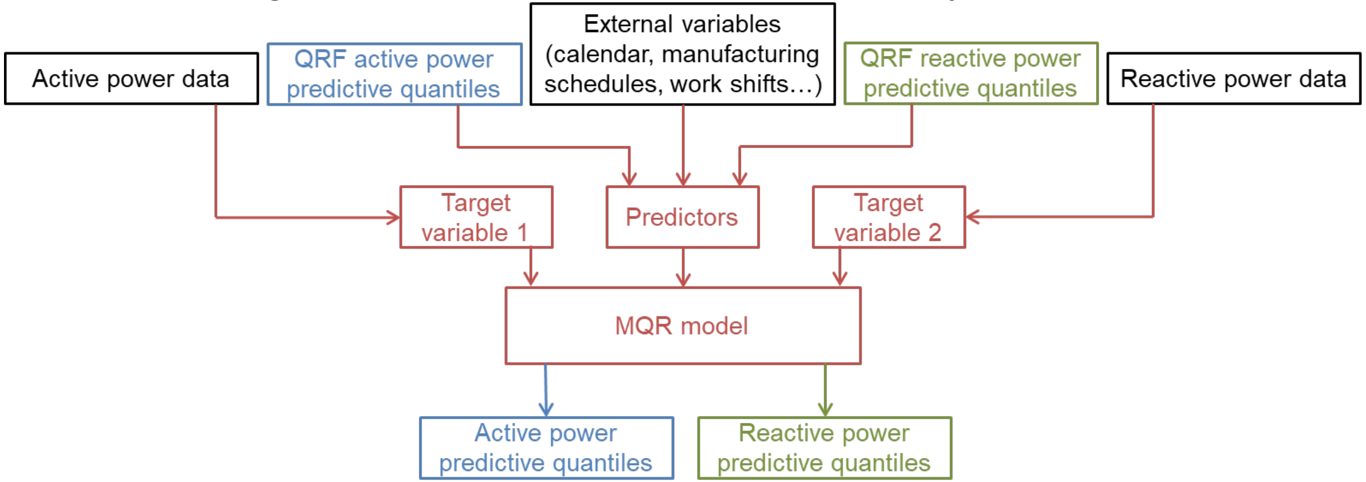
Bracale A, Carpinelli G, De Falco P. "Comparing univariate and multivariate methods for probabilistic industrial load forecasting," in Proc. of EFEA2018, Rome, 24-26 September 2018

Methodologies

Multivariate Quantile Regression (MQR) on individual forecasts

Challenge 3:

Low-level aggregation -> Active and reactive power are mutually informative at low-level aggregation, so a multivariate scheme may increase the skill of forecast



Bracale A, Caramia P, De Falco P, Hong T. "A multivariate approach to probabilistic industrial load forecasting," submitted to Int. J. Electr. Power Energy Systems

Methodologies

Multivariate Quantile Regression (MQR) on individual forecasts

Challenge 3:

Low-level aggregation -> Active and reactive power are mutually informative at low-level aggregation, so a multivariate scheme may increase the skill of forecast

Models can be re-trained as new observations become available, in order to catch dynamic variation of industrial load pattern on the basis of recent outcomes

Multivariate approaches are computationally intensive, but MQR models are easily re-estimated as new observations become available, since the underlying optimization problem (Pinball Score minimization during the training stage) can be set in a linear programming form

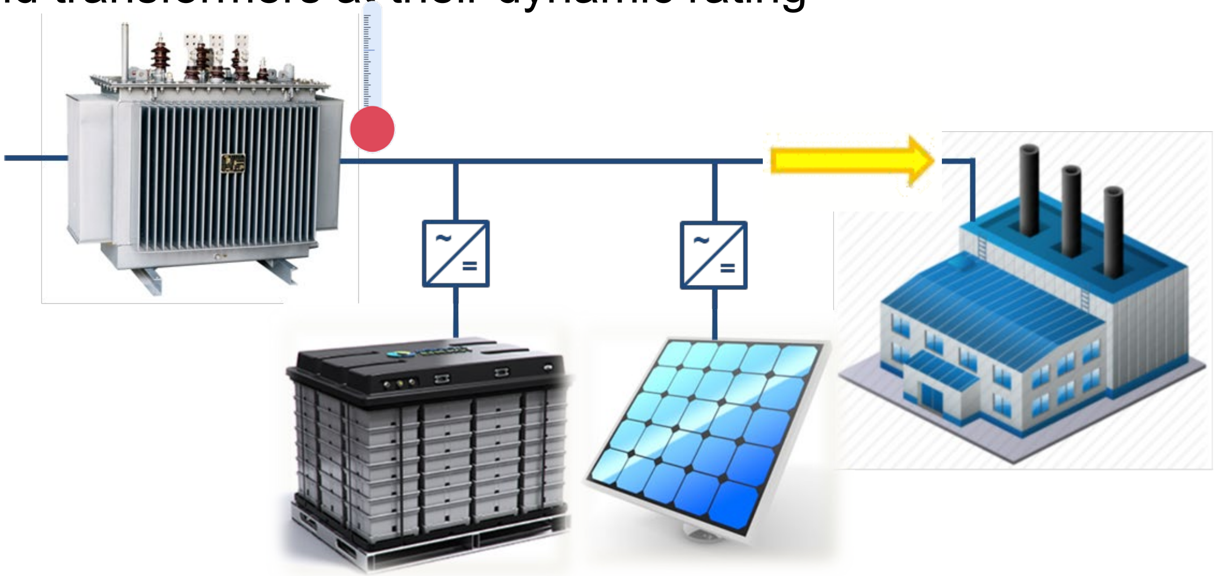
Bracale A, Caramia P, De Falco P, Hong T. "A multivariate approach to probabilistic industrial load forecasting," submitted to Int. J. Electr. Power Energy Systems

Methodologies

Application of PILF: dynamic transformer rating

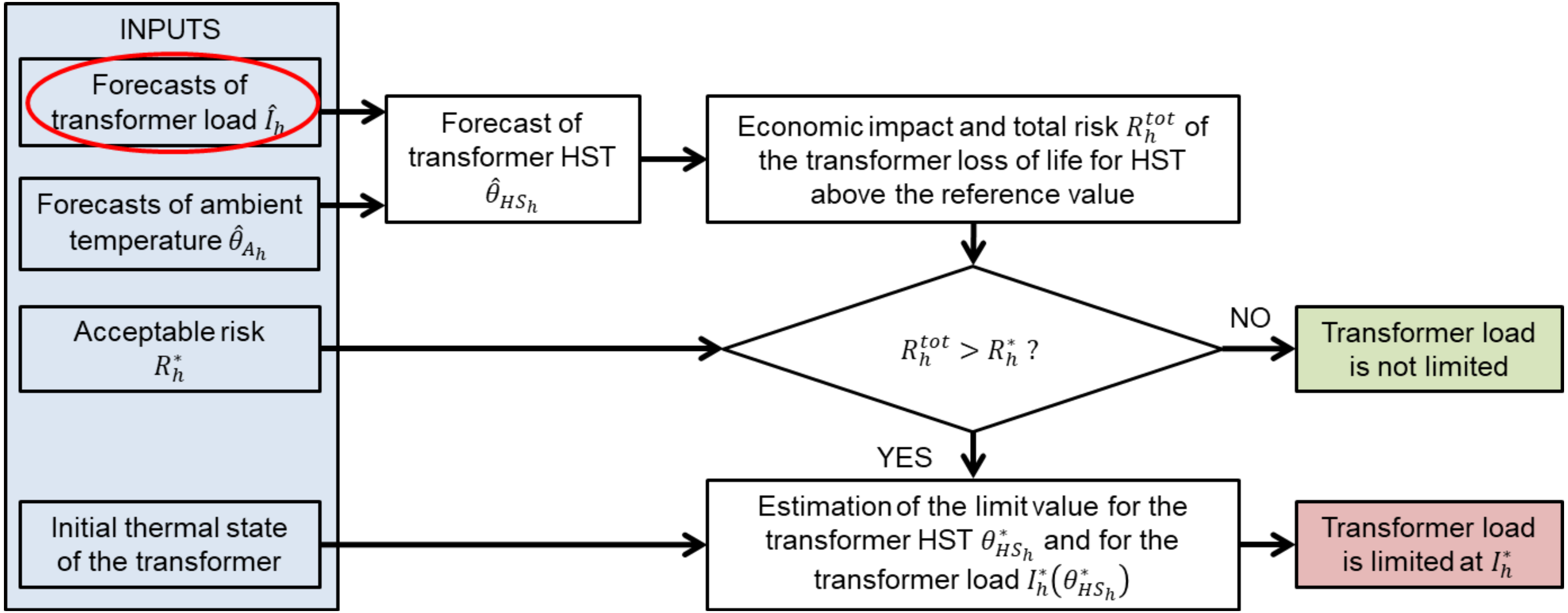
In an industrial microgrid, forecasts of the industrial load may be used to manage DERs and to operate lines and transformers at their dynamic rating

Dynamic Transformer Rating (DTR) allows exploiting the interface transformer at its best, by avoiding the Hottest-Spot Temperature (HST) going beyond dangerous levels



Methodologies

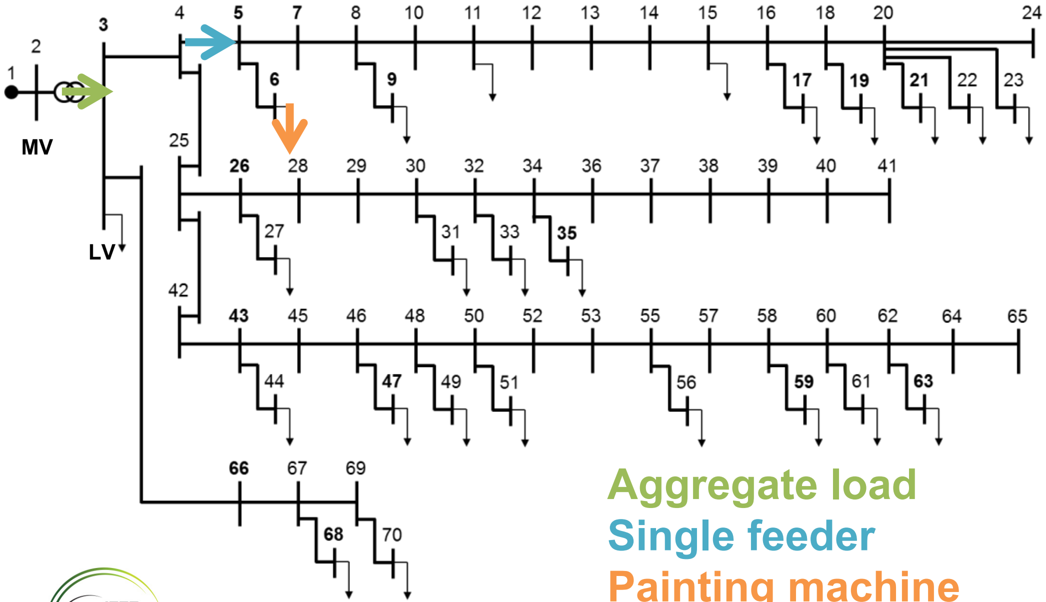
Application of PILF: dynamic transformer rating



Bracale A, Carpinelli G, De Falco P. "Probabilistic risk-based management of distribution transformers by dynamic transformer rating," Int. J. Electr. Power Energy Systems, vol. 113, 2019

Numerical applications

Experiments are carried out on an Italian industrial site dedicated to power transformer manufacturing



Aggregate load
Single feeder
Painting machine

Numerical applications

1-hour forecasts

99 predictive quantiles are provided for each target time horizon

Pinball Score (PS) and Coverage Error (CE) are shown to assess the performance

MODEL	AGGREGATE LOAD				SINGLE FEEDER				PAINTING MACHINE			
	Active power		Reactive power		Active power		Reactive power		Active power		Reactive power	
	PS [kW]	CE [%]	PS [kVAr]	CE [%]	PS [kW]	CE [%]	PS [kVAr]	CE [%]	PS [kW]	CE [%]	PS [kVAr]	CE [%]
QRF	522.76	2.77	371.85	2.12	266.57	2.43	197.58	4.81	46.47	5.47	40.71	2.48
MQR	511.68	3.91	347.91	2.98	250.25	2.96	192.74	2.51	43.46	1.81	39.02	4.22
PM	606.08	-	423.81	-	314.80	-	233.60	-	61.48	-	50.95	-

-15.5% -18% -20.5% -17.5% -29.4% -23.5%

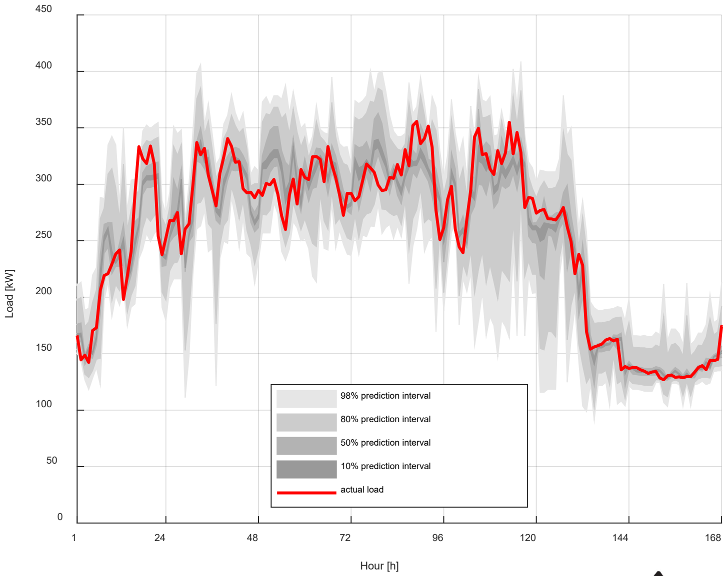
Numerical applications

1-hour forecasts

99 predictive quantiles are provided for each target time horizon

Pinball Score (PS) and Coverage Error (CE) are shown to assess the performance

MODEL	AGGREGATE LOAD			
	Active power		Reactive power	
	PS [kW]	CE [%]	PS [kVAr]	CE [%]
QRF	522.76	2.77	371.85	2.12
MQR	511.68	3.91	347.91	2.98
PM	606.08	-	423.81	-



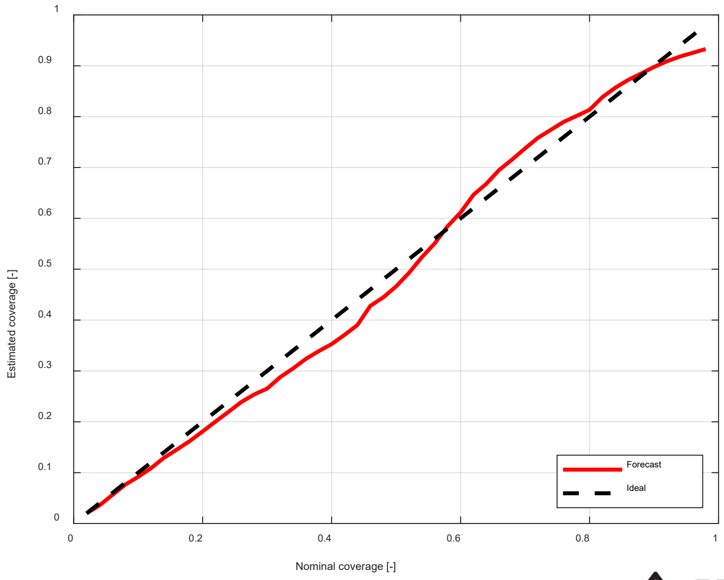
Numerical applications

1-hour forecasts

99 predictive quantiles are provided for each target time horizon

Pinball Score (PS) and Coverage Error (CE) are shown to assess the performance

MODEL	AGGREGATE LOAD			
	Active power		Reactive power	
	PS [kW]	CE [%]	PS [kVAr]	CE [%]
QRF	522.76	2.77	371.85	2.12
MQR	511.68	3.91	347.91	2.98
PM	606.08	-	423.81	-



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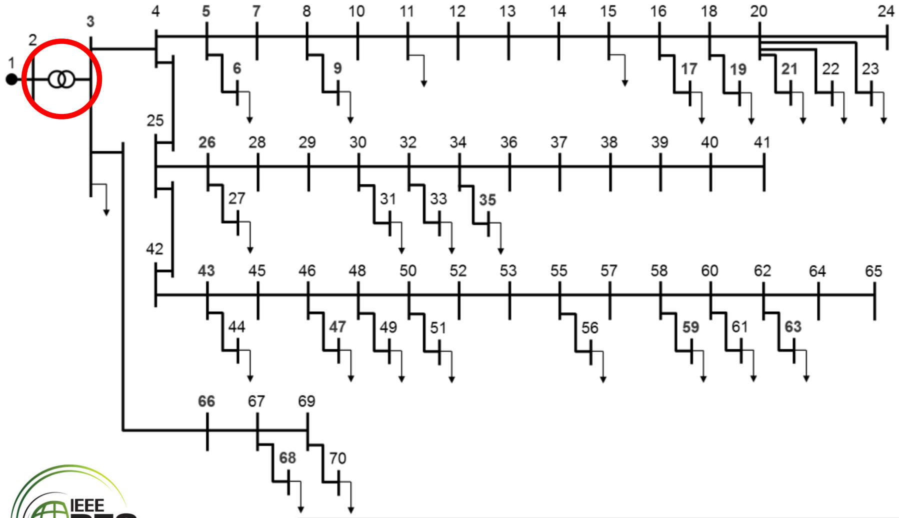
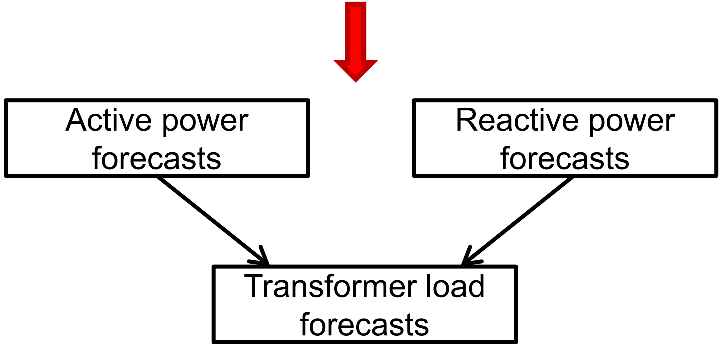
Numerical applications

Application: dynamic transformer rating

Forecasts of the aggregate industrial load can be used to operate the feeding transformer at its dynamic rating

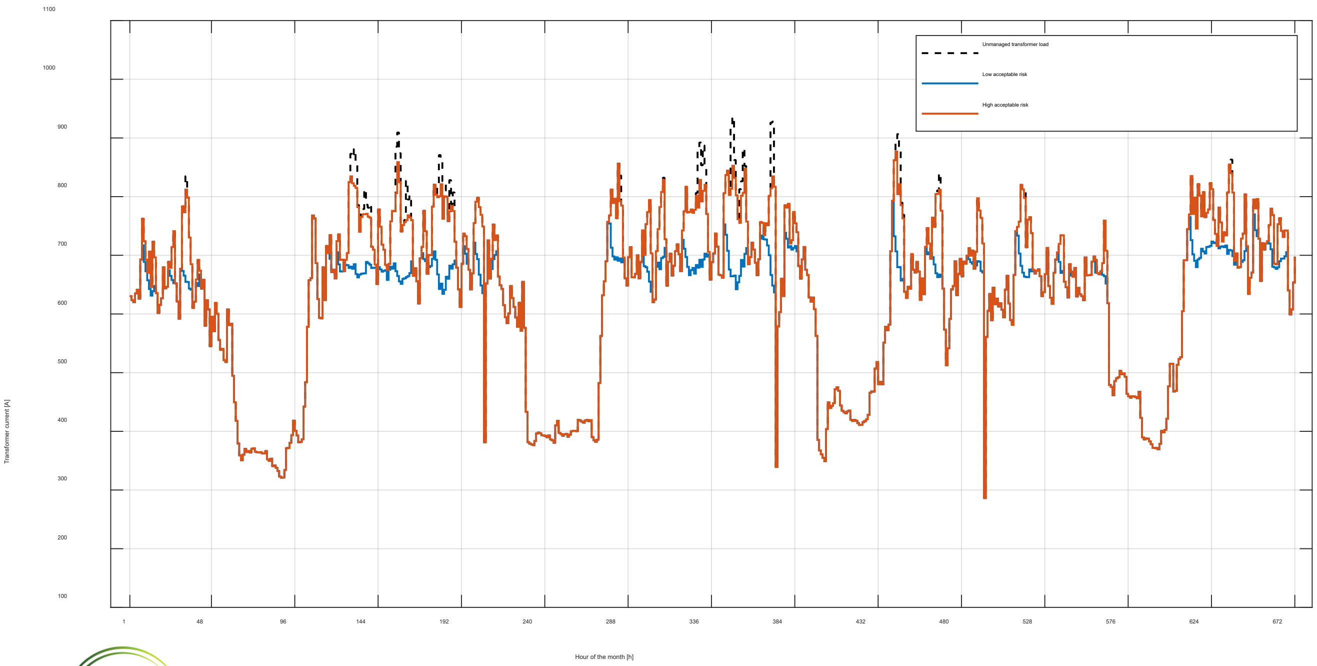


MODEL	AGGREGATE LOAD			
	Active power		Reactive power	
	PS [kW]	CE [%]	PS [kVAr]	CE [%]
QRF	522.76	2.77	371.85	2.12



Numerical applications

Application: dynamic transformer rating

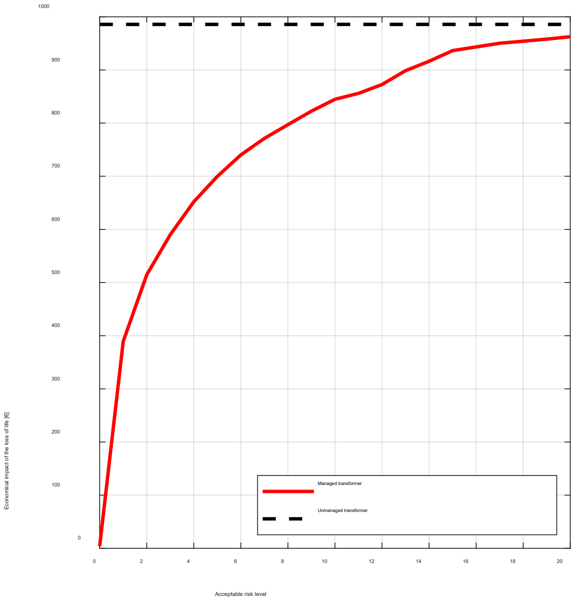


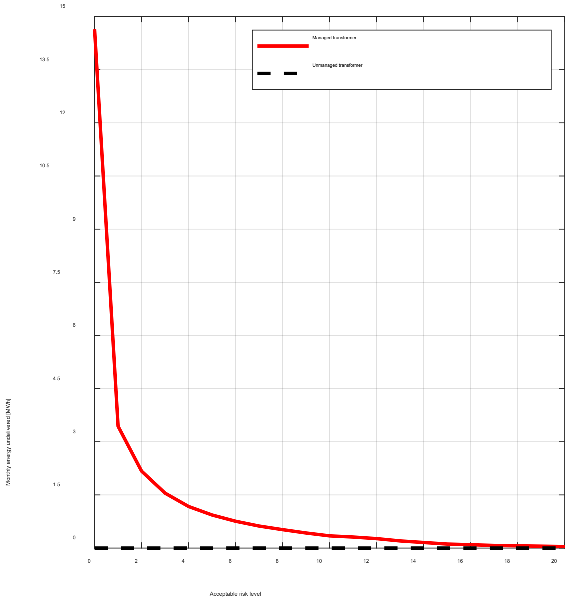
Winter month
February 2018

Load and ambient temperature forecasts obtained by QRFs

Numerical applications

Application: dynamic transformer rating





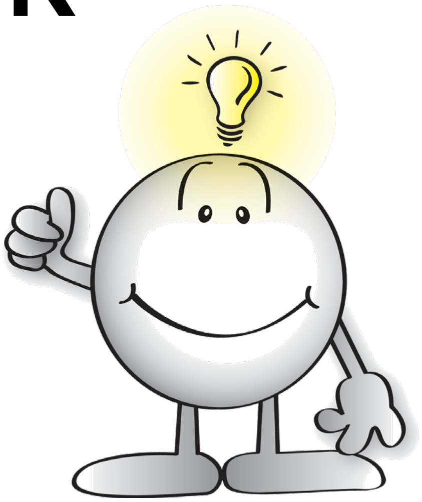
$C_{tot}^{(m)}$: economic impact with QRF forecasts
$C_{tot}^{(id)}$: economic impact with ideal forecasts
$C_{tot}^{(u)}$: economic impact of unmanaged transformer
$En_{tot}^{(m)}$: energy not delivered with QRF forecasts
$En_{tot}^{(id)}$: energy not delivered with ideal forecasts

$k_r = 1$	Positive outcomes	Negative outcomes
Positive predictions	182	44
Negative predictions	29	417
ACC [-]	0.891	
$C_{tot}^{(m)}$ [€]	389.33	
$C_{tot}^{(id)}$ [€]	110.11	
$C_{tot}^{(u)}$ [€]	985.59	
$En_{tot}^{(m)}$ [MWh]	3.44	
$En_{tot}^{(id)}$ [MWh]	8.80	

Conclusions

- Even if most of the electrical energy is consumed by industries, industrial load forecasting is often overlooked, specially within probabilistic frameworks
- In order to reach excellence, PILF methodologies must account for individuation of work regimes, for low dependency on ambient temperature, and for low-level aggregation
- Univariate and multivariate methods have been applied with success to an Italian industrial load, exploiting information provided by electrical and industrial-process-related predictors. Improvements are in the range 15-30%
- Applications of PILF to DTR show potentialities in managing components at their maximum capability

THANK YOU FOR YOUR ATTENTION!!!



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