Power consumption of Tetouan city prediction

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Dataset

5.921

2017-01-01 00:40:00

75.7

Data was collected by a public service operator, Supervisory Control and Data Acquisition system (SCADA) and has information on power consumption and environmental factors every 10 minutes for the period between 2017-01-01 and 2017-12-31.

Dataset doesn't contain any missing values.

0.081

	Temperature	Humidity	Wind Speed	general diffuse flows	diffuse flows	Zone 1 Power Consumption	Zone 2 Power Consumption	Zone 3 Power Consumption
DateTime								
2017-01-01 00:00:00	6.559	73.8	0.083	0.051	0.119	34055.69620	16128.87538	20240.96386
2017-01-01 00:10:00	6.414	74.5	0.083	0.070	0.085	29814.68354	19375.07599	20131.08434
2017-01-01 00:20:00	6.313	74.5	0.080	0.062	0.100	29128.10127	19006.68693	19668.43373
2017-01-01 00:30:00	6.121	75.0	0.083	0.091	0.096	28228.86076	18361.09422	18899.27711

0.085

0.048

27335.69620

17872.34043

18442.40964

Additional features

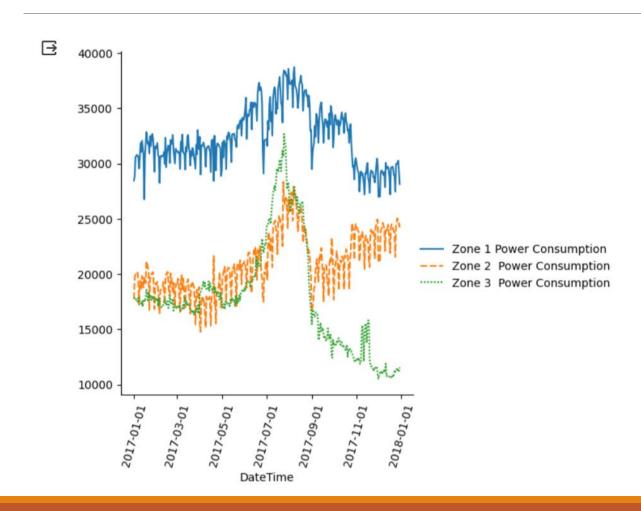
Under the suspicion there may emerge regularities (people sleeping, working etc.) in data, we created additional categorical features

- Time of the Day
- Day of the week

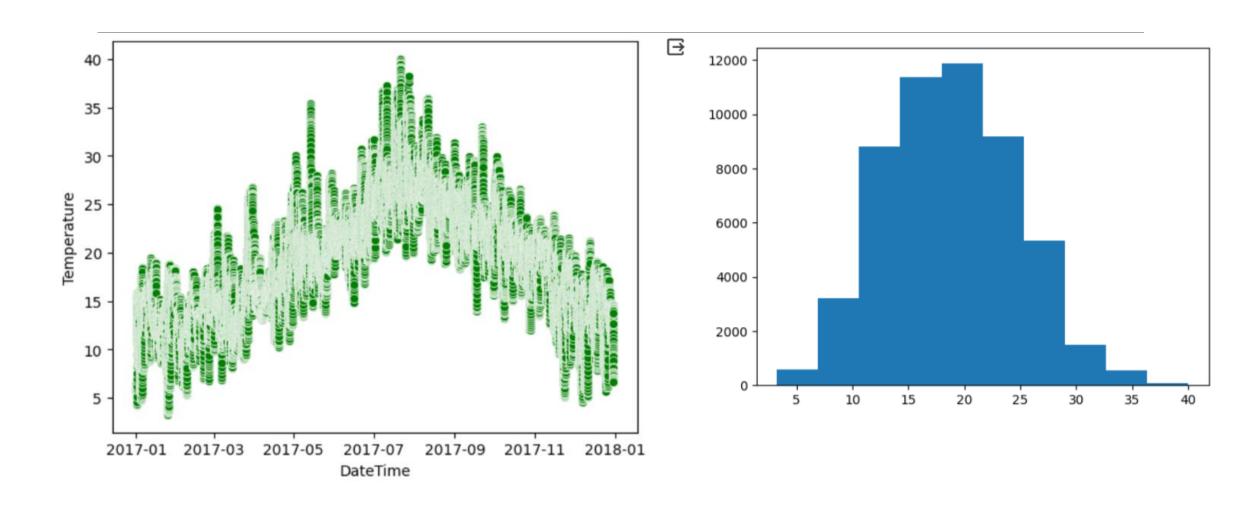
We used OHE for these features.

Power consumption in Tetouan

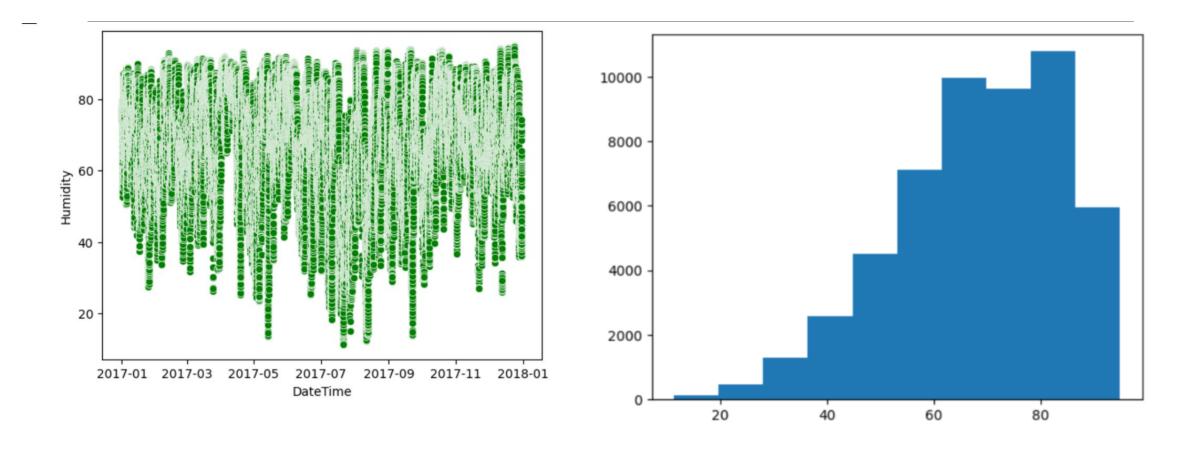
Distribution network is powered by 3 zone stations: Quads, Boussafou and Smir.



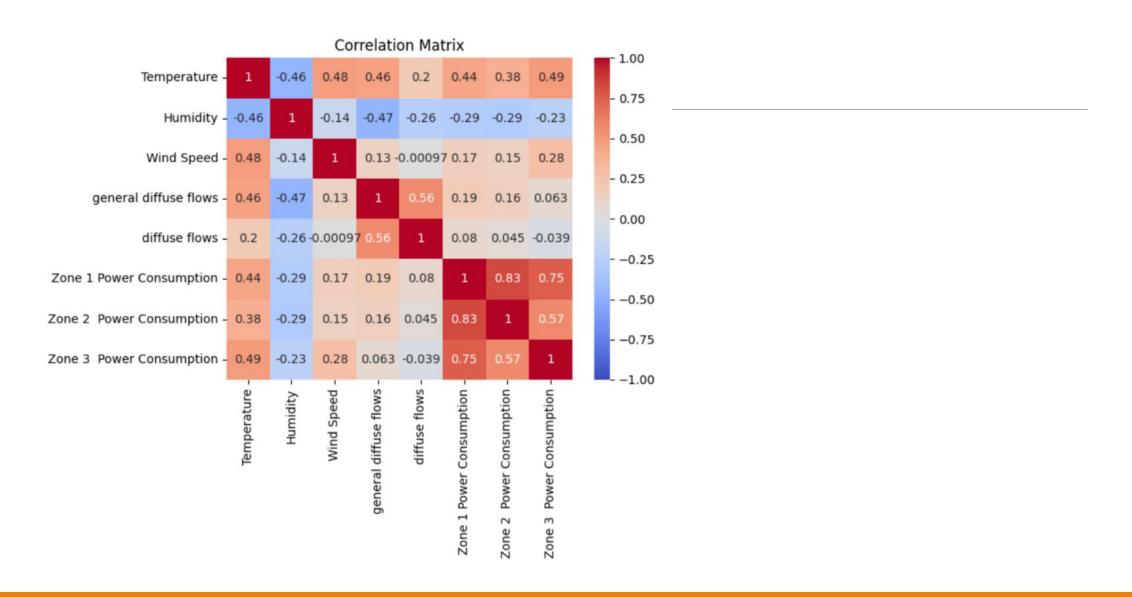
Temperature in Tetouan



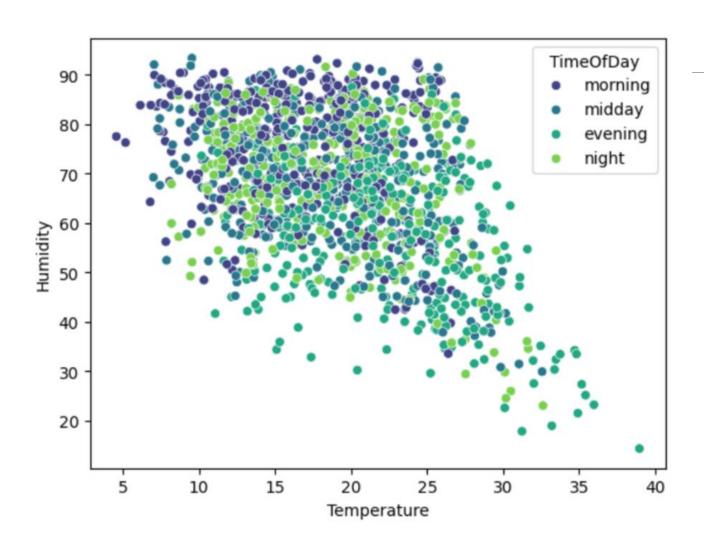
Humidity in Tetouan



Correlation between features



Humidity, Temperature Correlation



Findings

Power consumption in each zone varies throughout the year, and each location should be considered independently.

Energy consumption tends to increase with higher temperature levels.

Positive and negative correlations exist between humidity, temperature, and diffuse flows.

Energy usage typically increases in hours 8-16 and 17-22.

Over the week it also typically decreases on Sundays.

Pre-model preparations

A key think was to split the date column to separated columns representing the minute, the hour, the day of the month, the month the and year.

```
dr_first_zone_x['day_of_month'] = pd.to_datetime(dr_first_zone_x['DateTime']).dt.day
dr_first_zone_x['year'] = pd.to_datetime(dr_first_zone_x['DateTime']).dt.year
dr_first_zone_x['month'] = pd.to_datetime(dr_first_zone_x['DateTime']).dt.month
dr_first_zone_x['hour'] = pd.to_datetime(dr_first_zone_x['DateTime']).dt.hour
dr_first_zone_x['minute'] = pd.to_datetime(dr_first_zone_x['DateTime']).dt.minute
```

It was essential because every model that we have used needed a numerical value, not categorical one.

```
Also to make outputs more clear we normalized y value .
```

```
columns_to_normalize = ['DateTime_abs_normalized', 'Temperature', 'Humidity']
for col in columns_to_normalize:
    dr_first_zone_x[col] = scaler.fit_transform(dr_first_zone_x[col].values.reshape(-1, 1)).flatten()
```

Model candidates

Taking into consideration previous research we found three models :

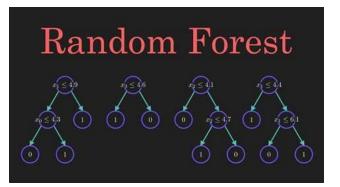
- XGBoost



- RandomForest

-Tensorflow





XGBoost

Zone 1:

MSE: 0.000611

MAE: 0.017678

MAP: 4.44%

Zone 2:

MSE:0.000679

MAE: 0.019102

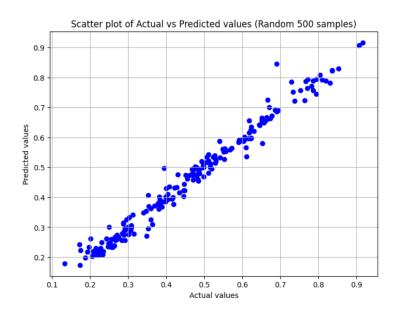
MAP: 5.93%

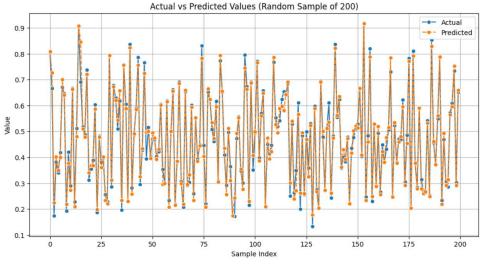
Zone 3:

MSE: 0.000188

MAE: 0.009692

MAP: 4.62%





RandomForest

Zone 1:

MSE: 0.000473

MAE: 0.013868

MAP: 3.5%

Zone 2:

MSE: 0.000469

MAE: 0.013826

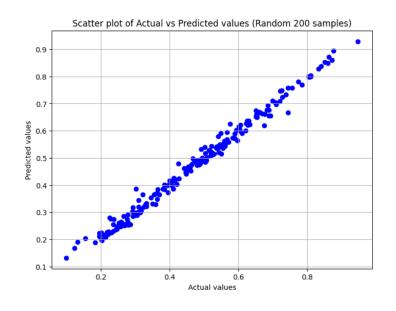
MAP: 4.3%

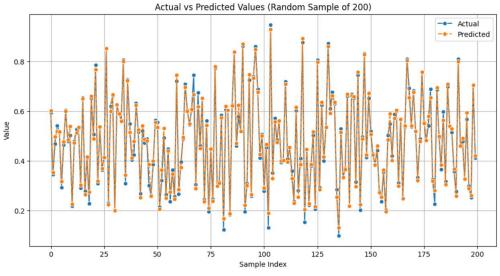
Zone 3:

MSE: 0.000119

MAE: 0.006957

MAP: 3.28%





Tensorflow

Zone 1:

MSE: 0.001768

MAE: 0.031303

MAP: 7.9%

Zone 2:

MSE: 0.002373

MAE: 0.037234

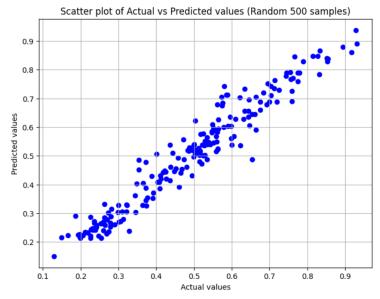
MAP: 11%

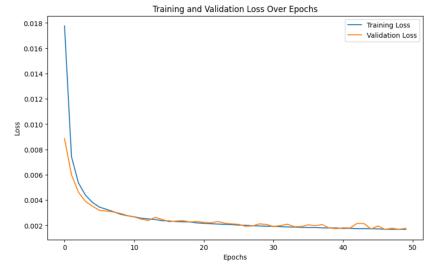
Zone 3:

MSE: 0.00574

MAE: 0.017973

MAP: 9.74%





Total performance

Mesures	XGBoost	RandomForest	Tensorflow
Mean MSE:	0.000492	0.000354	0.003290
Mean MAE:	0.015491	0.111550	0.028837
Mean MAP:	4.99%	3.69%	9.55%

Final resoults on test data

Mesures	ZONE 1	ZONE 2	ZONE 3
MSE	0.000469	0.000502	0.000125
MAE	0.014027	0.014062	0.006953
MAP	3.45%	4.58%	3.12%

Thank you for your time