PREVISÃO DA VELOCIDADE DO VENTO A CURTO PRAZO USANDO REDES NEURAIS ARTIFICIAIS EM MUCURI, BAHIA

Configuração

Realizando imports necessários.

In [1]:

```
import os
import math
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import tabulate
import tensorflow as tf

from datetime import datetime
from IPython.display import SVG, HTML, display
from keras import backend as K
from keras.callbacks import LambdaCallback, ModelCheckpoint
from keras.layers import Dense
from keras.models import Sequential
from keras.optimizers import SGD, Adam, RMSprop
from keras.utils import model_to_dot
from keras_lr_finder import LRFinder
from scipy.stats import pearsonr
from sklearn.metrics import r2_score
from sklearn.preprocessing import MinMaxScaler
```

```
Using TensorFlow backend.
```

Definição do modelo.

In [2]:

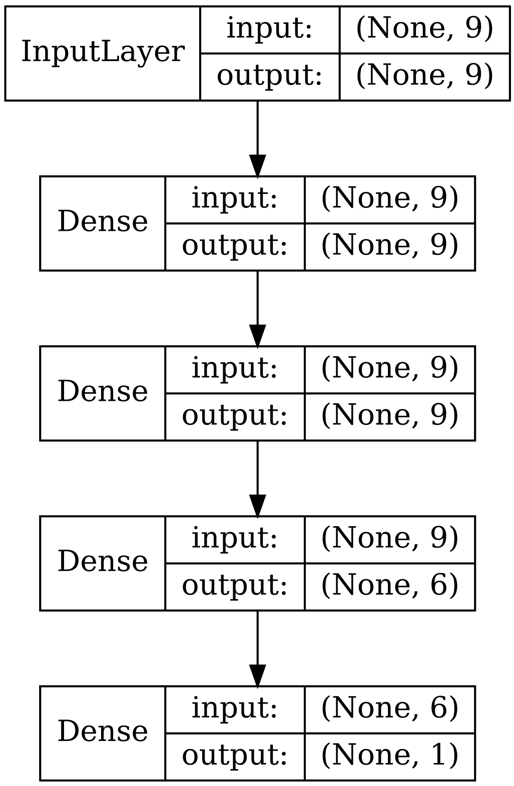
```
class MucuriModel:
    def __init__(self, lr=0.01):

        self.model = None
        self.best_loss = 1e9

        self._build_model(lr)

    def _build_model(self, lr):

        if self.model is None:
            self.model = Sequential()
            self.model.add(Dense(9, input_shape=(9,)))
            self.model.add(Dense(9, activation="tanh"))
            self.model.add(Dense(6, activation="tanh"))
            self.model.add(Dense(1, activation="linear"))
            self.model.compile(
                loss="mean_squared_error",
                optimizer=RMSprop(lr=lr), #Adam(lr=0.1),
                metrics=["mse", "mae"],
            )

    def train(self, X, Y, X_test=None, Y_test=None, epochs=65, verbose=0):

        assert self.model is not None

        checkpoint_callback = ModelCheckpoint(
            filepath="./weights.hdf5", save_best_only=True, monitor="mse"
        )

        return self.model.fit(
            X,
            Y,
            validation_data=(X_test, Y_test)
            if X_test is not None and Y_test is not None
            else None,
            verbose=verbose,
            epochs=epochs,
            callbacks=[checkpoint_callback],
        )

    def predict(self, data):

        assert self.model is not None

        return self.model.predict(data)
```

Foi utilizada a configuração 5 para a construção desse modelo, conforme especificado no paper. A quantidade de épocas foi definida por padrão como 65, no entanto essa quantidade pode ser ajustada. A função de loss foi definida como a de `mean squared error` e as métricas MSE, MAE e r2 são usadas para a avaliação da performance. O otimizador Adam foi utilizado, configurado com o `learning rate` de 0.01.

In [3]:

```
models = {
    "one_hour": MucuriModel(lr=0.01),
    "three_hours": MucuriModel(lr=0.01),
    "six_hours": MucuriModel(lr=0.01),
    "twelve_hours": MucuriModel(lr=0.02),
}

SVG(model_to_dot(models["one_hour"].model, show_shapes=True, show_layer_names=False).create(prog='dot', format='s
vg'))
```

Out[3]:



Leitura e normalização dos dados

Lendo o arquivo que contém os dados a serem analisados.

In [4]:

```
_file = pd.ExcelFile("./Mucuri_novo_semNaN_torre150m.xlsx")
df = _file.parse("Dados anemo")
```

Carregando os dados de treino e teste, ordenando as colunas da seguinte maneira:

> pressão, umid, temp, dir_1, v_anemo2, hora, ano, mês, dia

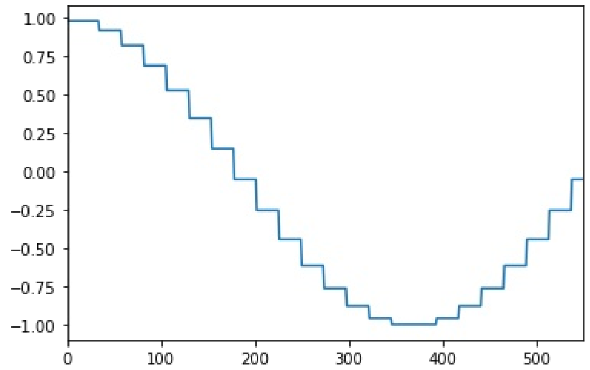
As informações referentes às datas (i.e. ano, mês e dia) foram colocadas por último, já que a sua repetição na massa de dados dificulta a convergência do modelo.

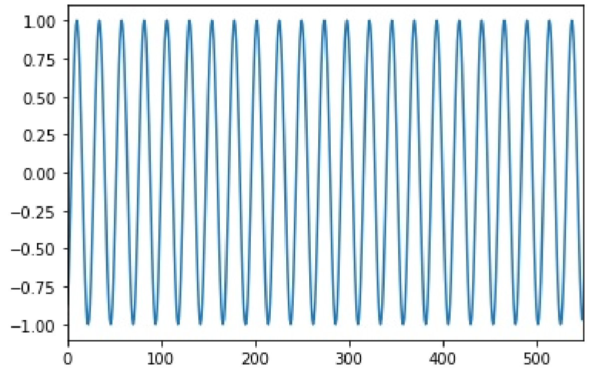
In [5]:

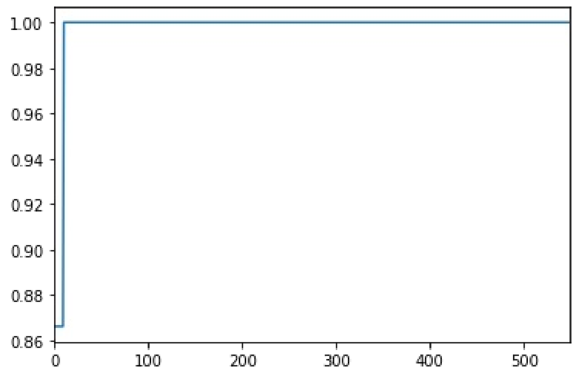
```
train_data_1 = df[pd.to_datetime(df["Data"]) <= datetime(year=2015, month=12, day=22)]
train_data_2 = df[
    (pd.to_datetime(df["Data"]) == datetime(year=2015, month=12, day=23))
    & (df["hora"] <= 11)
]

X_train_data = pd.concat([train_data_1, train_data_2]).drop("Data", axis=1)

cols = X_train_data.columns.tolist()
cols = cols[::-1]

X_train_data = X_train_data[cols]
```

In [6]:

```
X_train_data["mês_cos"] = np.cos(2 * np.pi * X_train_data["mês"] / 12)
X_train_data["dia_cos"] = np.cos(2 * np.pi * X_train_data["dia"] / 31)
X_train_data["hora_cos"] = np.cos(2 * np.pi * X_train_data["hora"] / 24)

X_train_data.drop("dia", axis=1, inplace=True)
X_train_data.drop("hora", axis=1, inplace=True)
X_train_data.drop("mês", axis=1, inplace=True)

X_train_data["dia_cos"].plot()
plt.show()
X_train_data["hora_cos"].plot()
plt.show()
X_train_data["mês_cos"].plot()
plt.show()
X_train_data
```







Out[6]:

	pressão	umid	temp	dir_1	v_anemo2	ano	mês_cos	dia_cos	hora_cos
0	1020.422601	72.930636	27.516129	75.105481	13.012139	2015	0.866025	0.979530	-8.660254e-01
1	1020.394348	75.212121	27.238095	68.334332	12.726087	2015	0.866025	0.979530	-7.071068e-01
2	1020.508333	75.741379	27.105263	64.457865	12.081111	2015	0.866025	0.979530	-5.000000e-01
3	1020.611000	75.302632	26.305556	53.842100	11.647222	2015	0.866025	0.979530	-2.588190e-01
4	1020.866500	76.592593	25.464286	53.945279	11.064444	2015	0.866025	0.979530	-1.836970e-16
...	...	...	...	...	...	...	...	...	...
545	1015.316167	86.600000	22.637795	67.426924	2.912222	2015	1.000000	-0.050649	-2.588190e-01
546	1015.975667	82.110390	22.455696	84.999251	3.958333	2015	1.000000	-0.050649	-5.000000e-01
547	1016.323667	79.801205	22.602410	107.133454	5.216667	2015	1.000000	-0.050649	-7.071068e-01
548	1016.071500	80.907407	22.203252	110.979895	6.506667	2015	1.000000	-0.050649	-8.660254e-01
549	1014.882833	84.761111	22.024096	107.805201	7.690000	2015	1.000000	-0.050649	-9.659258e-01

550 rows × 9 columns

In [7]:

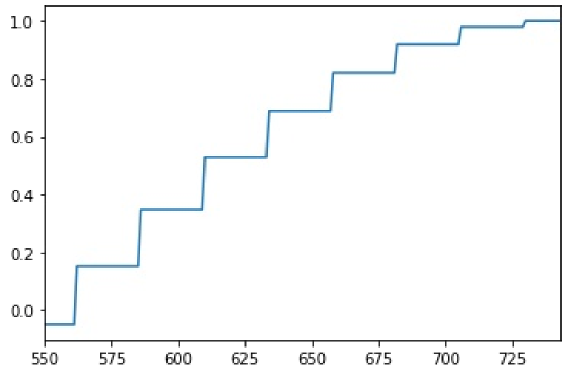
```
X_train = {
    "one_hour": None,
    "three_hours": None,
    "six_hours": None,
    "twelve_hours": None,
}
Y_train = {
    "one_hour": None,
    "three_hours": None,
    "six_hours": None,
    "twelve_hours": None,
}
```

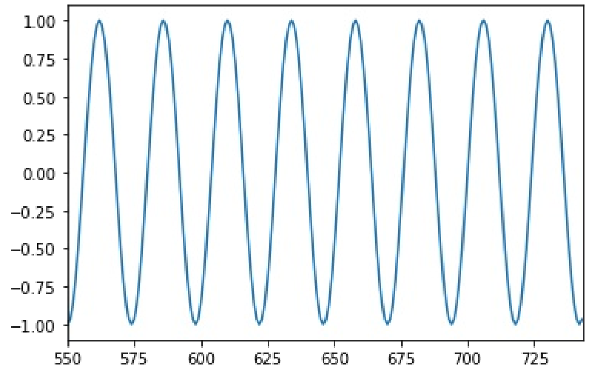
In [8]:

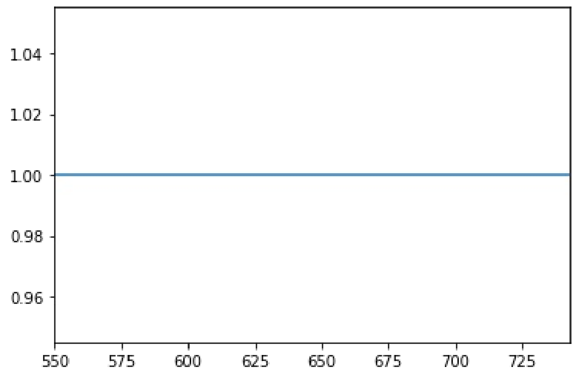
```
test_data_1 = df[
    (pd.to_datetime(df["Data"]) == datetime(year=2015, month=12, day=23))
    & (df["hora"] >= 12)
]
test_data_2 = df[
    (pd.to_datetime(df["Data"]) >= datetime(year=2015, month=12, day=24))
    & (pd.to_datetime(df["Data"]) <= datetime(year=2015, month=12, day=30))
]
test_data_3 = df[
    (pd.to_datetime(df["Data"]) == datetime(year=2015, month=12, day=31))
    & (df["hora"] <= 13)
]

X_test_data = pd.concat([test_data_1, test_data_2, test_data_3])

X_test_data = X_test_data.drop("Data", axis=1)

cols = X_test_data.columns.tolist()
cols = cols[::-1]

X_test_data = X_test_data[cols]
```

In [9]:

```
X_test_data["mês_cos"] = np.cos(2 * np.pi * X_test_data["mês"] / 12)
X_test_data["dia_cos"] = np.cos(2 * np.pi * X_test_data["dia"] / 31)
X_test_data["hora_cos"] = np.cos(2 * np.pi * X_test_data["hora"] / 24)

X_test_data.drop("dia", axis=1, inplace=True)
X_test_data.drop("hora", axis=1, inplace=True)
X_test_data.drop("mês", axis=1, inplace=True)

X_test_data["dia_cos"].plot()
plt.show()
X_test_data["hora_cos"].plot()
plt.show()
X_test_data["mês_cos"].plot()
plt.show()
X_test_data
```







Out[9]:

	pressão	umid	temp	dir_1	v_anemo2	ano	mês_cos	dia_cos	hora_cos
550	1014.845833	87.861111	21.516779	77.442821	12.242778	2015	1.0	-0.050649	-1.000000
551	1014.793333	73.338889	23.075269	73.171002	9.268333	2015	1.0	-0.050649	-0.965926
552	1014.085333	78.533333	22.545455	96.238878	8.734444	2015	1.0	-0.050649	-0.866025
553	1013.541500	83.722222	21.459770	110.156291	9.662222	2015	1.0	-0.050649	-0.707107
554	1013.563333	84.691275	22.133803	97.686662	8.620556	2015	1.0	-0.050649	-0.500000
...	...	...	...	...	...	...	...	...	...
739	1018.871167	90.612500	25.545455	88.967009	7.370556	2015	1.0	1.000000	-0.707107
740	1018.303667	91.142857	23.558442	89.474475	10.400556	2015	1.0	1.000000	-0.866025
741	1017.004667	90.567376	23.369863	89.119129	12.400556	2015	1.0	1.000000	-0.965926
742	1016.574167	88.645833	23.240741	85.945816	13.944444	2015	1.0	1.000000	-1.000000
743	1016.205167	87.005556	23.875000	82.373032	14.821111	2015	1.0	1.000000	-0.965926

194 rows × 9 columns

In [10]:

```
X_test = {
    "one_hour": None,
    "three_hours": None,
    "six_hours": None,
    "twelve_hours": None,
}
Y_test = {
    "one_hour": None,
    "three_hours": None,
    "six_hours": None,
    "twelve_hours": None,
}
```

Preparando dados para previsão em intervalos de uma hora.

In [11]:

```
X_train_one_hr = X_train_data.copy()

Y_train_one_hr = X_train_one_hr.v_anemo2.shift(-1)
Y_train_one_hr.drop(Y_train_one_hr.tail(1).index, inplace=True)
X_train_one_hr.drop(X_train_one_hr.tail(1).index, inplace=True)

X_train["one_hour"] = X_train_one_hr
Y_train["one_hour"] = Y_train_one_hr
```

In [12]:

```
X_test_one_hr = X_test_data.copy()

Y_test_one_hr = X_test_one_hr.v_anemo2.shift(-1)
Y_test_one_hr.drop(Y_test_one_hr.tail(1).index, inplace=True)
X_test_one_hr.drop(X_test_one_hr.tail(1).index, inplace=True)

X_test["one_hour"] = X_test_one_hr
Y_test["one_hour"] = Y_test_one_hr
```

Preparando dados para previsão em intervalos de três horas.

In [13]:

```
X_train_three_hr = X_train_data.copy()

Y_train_three_hr = X_train_three_hr.v_anemo2.shift(-3)
Y_train_three_hr.drop(Y_train_three_hr.tail(3).index, inplace=True)
X_train_three_hr.drop(X_train_three_hr.tail(3).index, inplace=True)

X_train["three_hours"] = X_train_three_hr
Y_train["three_hours"] = Y_train_three_hr
```

In [14]:

```
X_test_three_hr = X_test_data.copy()

Y_test_three_hr = X_test_three_hr.v_anemo2.shift(-3)
Y_test_three_hr.drop(Y_test_three_hr.tail(3).index, inplace=True)
X_test_three_hr.drop(X_test_three_hr.tail(3).index, inplace=True)

X_test["three_hours"] = X_test_three_hr
Y_test["three_hours"] = Y_test_three_hr
```

Preparando dados para previsão em intervalos de seis horas.

In [15]:

```
X_train_six_hr = X_train_data.copy()

Y_train_six_hr = X_train_six_hr.v_anemo2.shift(-6)
Y_train_six_hr.drop(Y_train_six_hr.tail(6).index, inplace=True)
X_train_six_hr.drop(X_train_six_hr.tail(6).index, inplace=True)

X_train["six_hours"] = X_train_six_hr
Y_train["six_hours"] = Y_train_six_hr
```

In [16]:

```
X_test_six_hr = X_test_data.copy()

Y_test_six_hr = X_test_six_hr.v_anemo2.shift(-6)
Y_test_six_hr.drop(Y_test_six_hr.tail(6).index, inplace=True)
X_test_six_hr.drop(X_test_six_hr.tail(6).index, inplace=True)

X_test["six_hours"] = X_test_six_hr
Y_test["six_hours"] = Y_test_six_hr
```

Preparando dados para previsão em intervalos de doze horas.

In [17]:

```
X_train_twelve_hr = X_train_data.copy()

Y_train_twelve_hr = X_train_twelve_hr.v_anemo2.shift(-12)
Y_train_twelve_hr.drop(Y_train_twelve_hr.tail(12).index, inplace=True)
X_train_twelve_hr.drop(X_train_twelve_hr.tail(12).index, inplace=True)

X_train["twelve_hours"] = X_train_twelve_hr
Y_train["twelve_hours"] = Y_train_twelve_hr
```

In [18]:

```
X_test_twelve_hr = X_test_data.copy()

Y_test_twelve_hr = X_test_twelve_hr.v_anemo2.shift(-12)
Y_test_twelve_hr.drop(Y_test_twelve_hr.tail(12).index, inplace=True)
X_test_twelve_hr.drop(X_test_twelve_hr.tail(12).index, inplace=True)

X_test["twelve_hours"] = X_test_twelve_hr
Y_test["twelve_hours"] = Y_test_twelve_hr
```

Realizando a normalização com `minmax` .

In [19]:

```
for key in X_train.keys():
    scaler = MinMaxScaler()
    X_train[key] = scaler.fit_transform(X_train[key].values)
    X_test[key] = scaler.fit_transform(X_test[key].values)
```

Treino

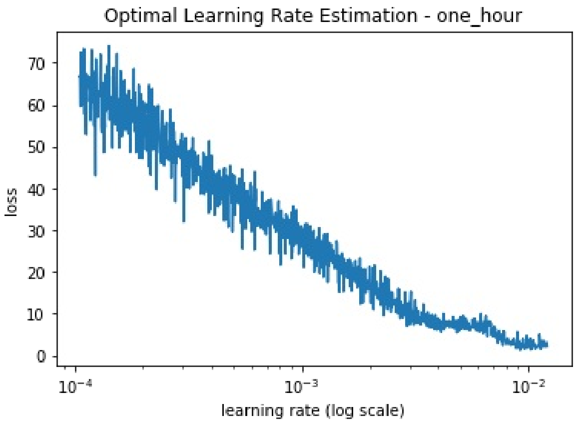
Realizando o processo de treino do modelo, incluindo dados de validação.

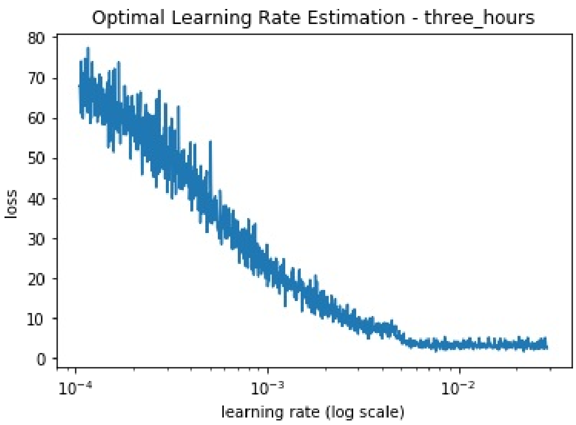
In [20]:

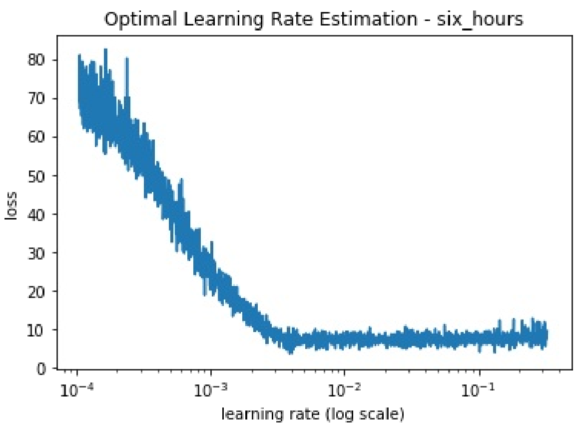
```
%%capture

lr_finders = {
    "one_hour": None,
    "three_hours": None,
    "six_hours": None,
    "twelve_hours": None,
}

for key in lr_finders.keys():
    lr_finders[key] = LRFinder(models[key].model)
    lr_finders[key].find(X_train[key], Y_train[key], start_lr=0.0001, end_lr=20.0, epochs=300)
```

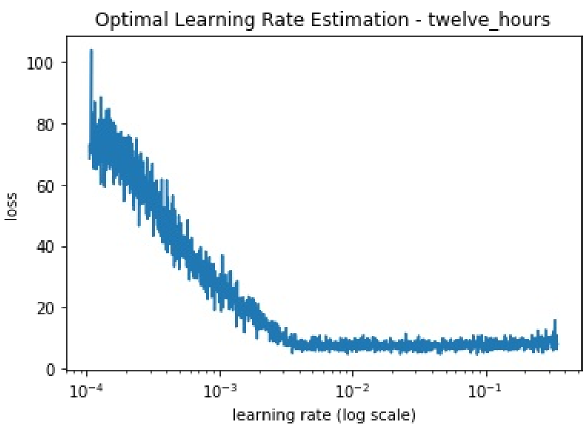
In [21]:

```
for key in lr_finders.keys():
    lr_finders[key].plot_loss()
    plt.title(f"Optimal Learning Rate Estimation - {key}")
    plt.show()
```


Optimal Learning Rate Estimation - one_hour
loss
learning rate (log scale)


Optimal Learning Rate Estimation - three_hours
loss
learning rate (log scale)


Optimal Learning Rate Estimation - six_hours
loss
learning rate (log scale)


Optimal Learning Rate Estimation - twelve_hours
loss
learning rate (log scale)

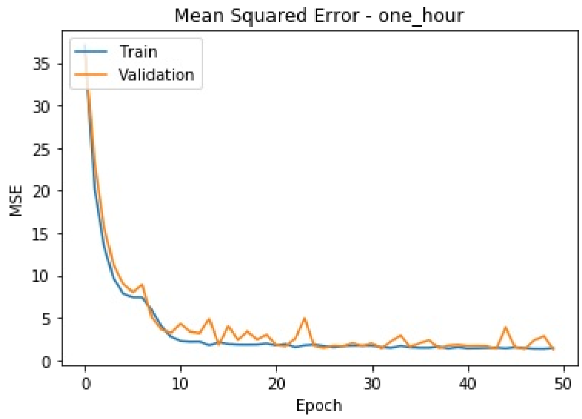
In [22]:

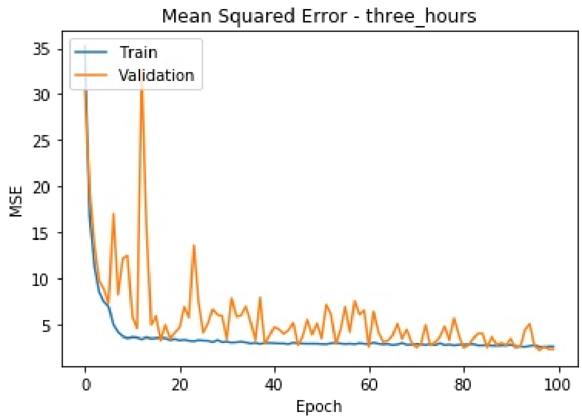
```
training_history = {
    "one_hour": None,
    "three_hours": None,
    "six_hours": None,
    "twelve_hours": None,
}

verbose = 0

training_history["one_hour"] = models["one_hour"].train(
    X_train["one_hour"], Y_train["one_hour"].values, X_test["one_hour"], Y_test["one_hour"].values,
    epochs=50, verbose=verbose
)

training_history["three_hours"] = models["three_hours"].train(
    X_train["three_hours"], Y_train["three_hours"].values, X_test["three_hours"], Y_test["three_hours"].values,
    epochs=100, verbose=verbose
)

training_history["six_hours"] = models["six_hours"].train(
    X_train["six_hours"], Y_train["six_hours"].values, X_test["six_hours"], Y_test["six_hours"].values,
    epochs=100, verbose=verbose
)

training_history["twelve_hours"] = models["twelve_hours"].train(
    X_train["twelve_hours"], Y_train["twelve_hours"].values, X_test["twelve_hours"], Y_test["twelve_hours"].value
s,
    epochs=140, verbose=verbose
)
```

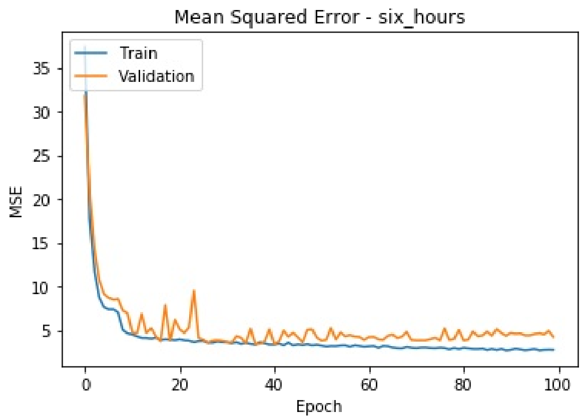
Avaliação

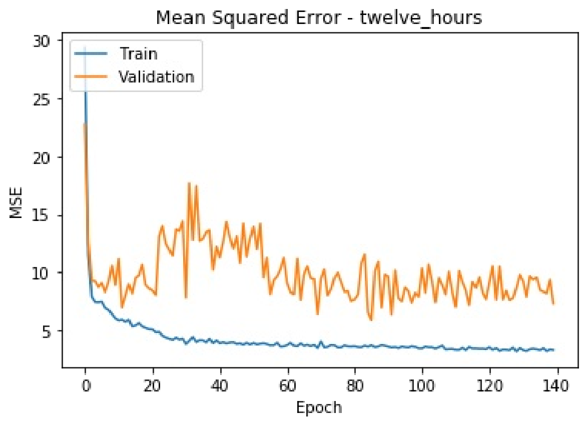
In [23]:

```
for key in training_history.keys():
    plt.plot(training_history[key].history["mse"])
    plt.plot(training_history[key].history["val_mse"])
    plt.title(f"Mean Squared Error - {key}")
    plt.ylabel("MSE")
    plt.xlabel("Epoch")
    plt.legend(["Train", "Validation"], loc="upper left")
    plt.show()
```


Mean Squared Error - one_hour
Train
Validation
MSE
0 5 10 15 20 25 30 35
0 10 20 30 40 50
Epoch

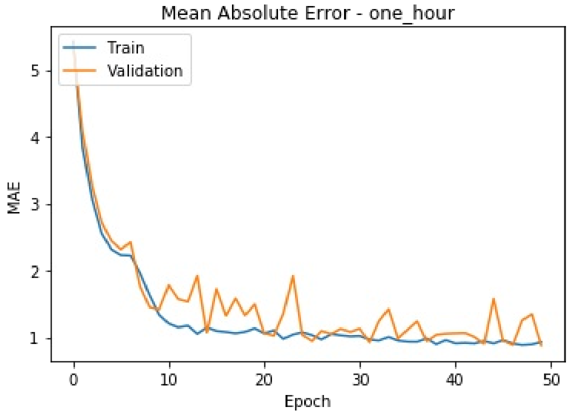

Mean Squared Error - three_hours
Train
Validation
MSE
5 10 15 20 25 30 35
0 20 40 60 80 100
Epoch

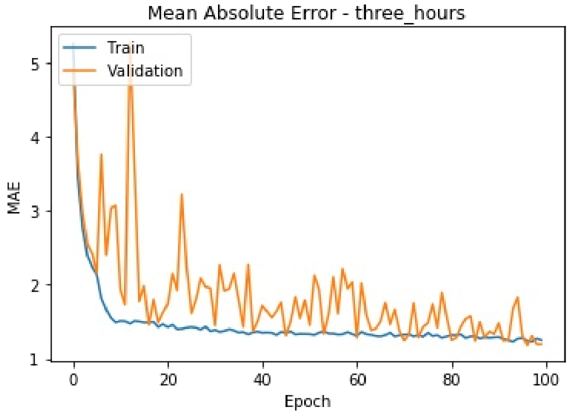

Mean Squared Error - six_hours
Train
Validation
MSE
5 10 15 20 25 30 35
0 20 40 60 80 100
Epoch

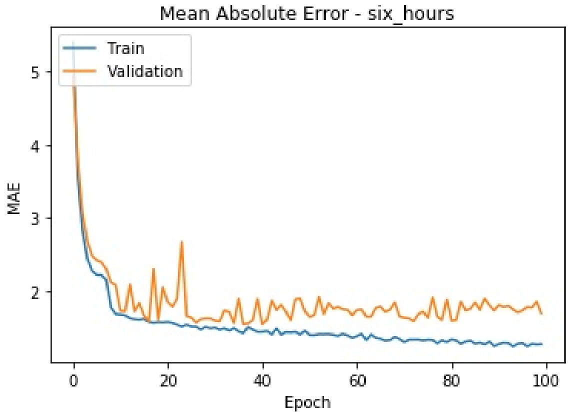

Mean Squared Error - twelve_hours
Train
Validation
MSE
5 10 15 20 25 30
0 20 40 60 80 100 120 140
Epoch

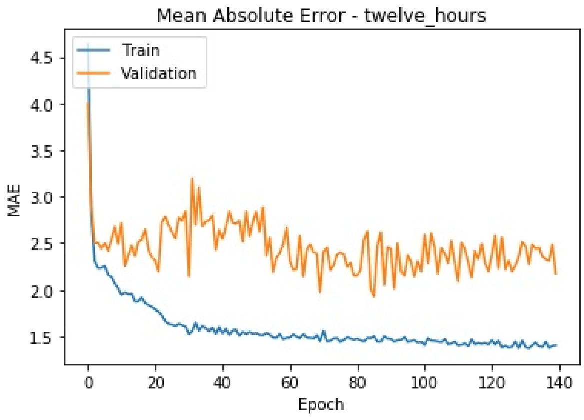
In [24]:

```
for key in training_history.keys():
    plt.plot(training_history[key].history["mae"])
    plt.plot(training_history[key].history["val_mae"])
    plt.title(f"Mean Absolute Error - {key}")
    plt.ylabel("MAE")
    plt.xlabel("Epoch")
    plt.legend(["Train", "Validation"], loc="upper left")
    plt.show()
```



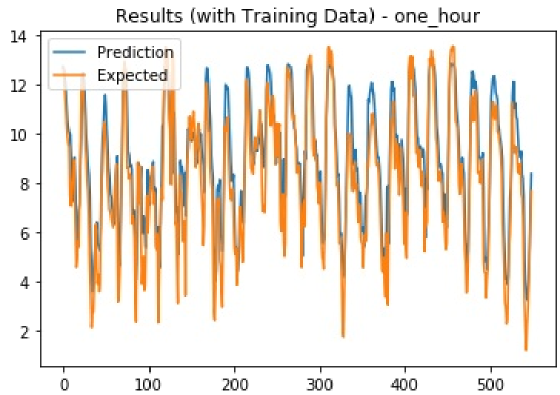


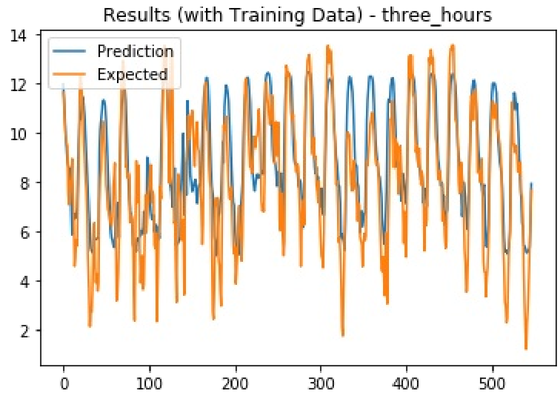


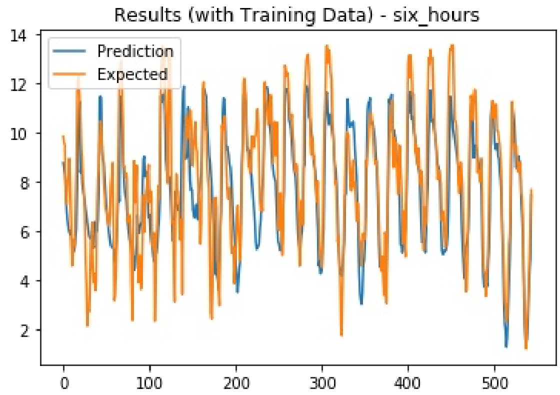


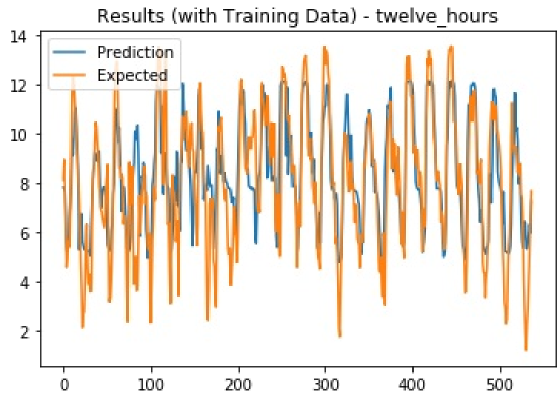
In [25]:

```
for key in models.keys():
    predictions = [models[key].predict([[value]])[0][0] for value in X_train[key]]

    training_history[key].history["r_train"] = pearsonr(Y_train[key].values, predictions)
    training_history[key].history["r2_train"] = r2_score(Y_train[key].values, predictions)

    plt.plot(predictions)
    plt.plot(Y_train[key].values)
    plt.title(f"Results (with Training Data) - {key}")
    plt.legend(["Prediction", "Expected"], loc="upper left")
    plt.show()
```



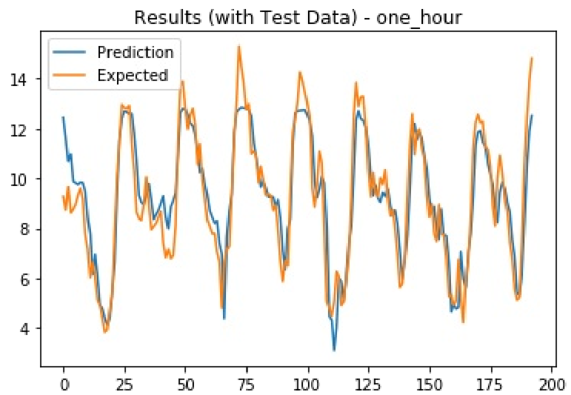


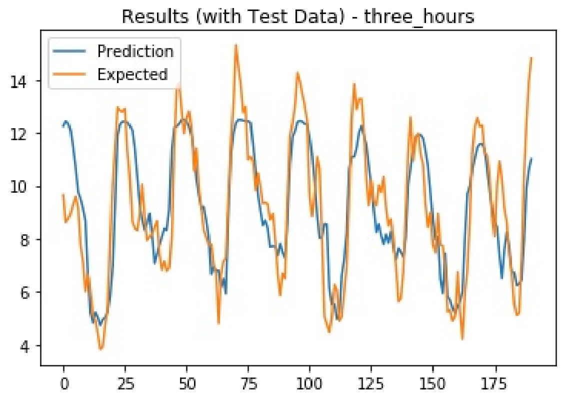


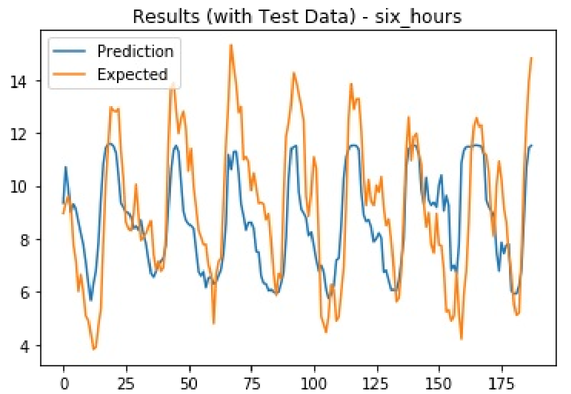


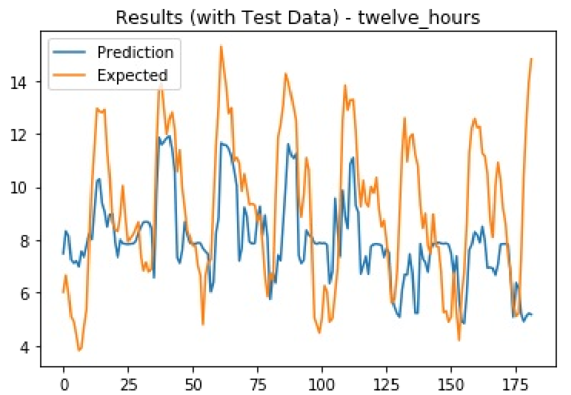
In [26]:

```
for key in models.keys():
    predictions = [models[key].predict([[value]])[0][0] for value in X_test[key]]

    training_history[key].history["r_test"] = pearsonr(Y_test[key].values, predictions)
    training_history[key].history["r2_test"] = r2_score(Y_test[key].values, predictions)

    plt.plot(predictions)
    plt.plot(Y_test[key].values)
    plt.title(f"Results (with Test Data) - {key}")
    plt.legend(["Prediction", "Expected"], loc="upper left")
    plt.show()
```









In [34]:

```
table = [
    ["",],
    ["MSE training",],
    ["MSE validation",],
    ["MAE training",],
    ["MAE validation",],
    ["R training",],
    ["R test",],
    ["R2 training",],
    ["R2 test",],
]

for key in training_history.keys():

    table[0].append(key.upper())
    table[1].append(min(training_history[key].history['mse']))
    table[2].append(min(training_history[key].history['val_mse']))
    table[3].append(min(training_history[key].history['mae']))
    table[4].append(min(training_history[key].history['val_mae']))
    table[5].append(training_history[key].history['r_train'][0])
    table[6].append(training_history[key].history['r_test'][0])
    table[7].append(training_history[key].history['r2_train'])
    table[8].append(training_history[key].history['r2_test'])

display(HTML(tabulate.tabulate(table, tablefmt="html", headers="firstrow")))
```

	ONE_HOUR	THREE_HOURS	SIX_HOURS	TWELVE_HOURS
MSE training	1.30741	2.49377	2.6675	3.18985
MSE validation	1.24375	2.12991	3.40777	5.89503
MAE training	0.885233	1.23072	1.24026	1.36796
MAE validation	0.878765	1.17989	1.54448	1.92687
R training	0.916688	0.803834	0.800636	0.778498
R test	0.911785	0.832431	0.683147	0.49366
R2 training	0.755382	0.58934	0.601747	0.600191
R2 test	0.829036	0.692227	0.429346	0.0459581