# Passion_v5

July 16, 2020

## 1 Welcome to Passion!

Passion is a model that can detection anomaly using different methods (Both supervised and unsupervised)

1. The goal for this project is to study the difference between different anomnaly detection model, and to find the state of art method for detecting anomaly in real world data
2. Evaluate the results based on this :real server data+ https://www.kaggle.com/sohier/30-years-of-european-wind-generation + https://github.com/numenta/NAB
3. Also use real data generated from server.
4. The model has the following fuctions:

   a. Visualize the input data. Help the user to find critical features within the inputs.
   b. Give user options to choose different models that are suitable for different circumstances.
   c. Evaluate the performance based on the rules in this link https://github.com/numenta/NAB
   d. Save model. Easy to be appplied to other dataset.

5. This is the very beginning of the process. Still need to do a lot of works!

## 2 What's new in version 5

1. Add Attention based model
2. Add ATTLSTM + FCN
3. still need to think about how to apply the attention mechanism and encoder decoder.
4. Add loss+validation loss plot

In [1]:
```
# import packages


from matplotlib.pylab import rc
import torch
from scipy.stats import chisquare
from scipy.stats import pearsonr
import pickle
import pandas as pd
import datetime
```

```
import matplotlib
import tensorflow as tf
import sklearn
import math
import matplotlib.pyplot as plt
import xgboost
from xgboost import XGBClassifier
from xgboost import plot_importance
import numpy as np
from sklearn.model_selection import train_test_split
import sklearn
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
import copy
import scipy
import datetime
import time
import os
from sklearn.model_selection import KFold
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.covariance import EllipticEnvelope
from sklearn.ensemble import IsolationForest
from sklearn.svm import OneClassSVM
import gc

plot_path = "plots/"
```

In [2]:
```
# Real server data

root_path = "Data/Ant_202007/"


cif = pd.read_json(root_path+'cif.json', orient='index')
paycore = pd.read_json(root_path+'paycore.json', orient='index')
paydecision = pd.read_json(root_path+'paydecision.json', orient='index')
paydecision2 = pd.read_json(root_path+'paydecision2.json', orient='index')
paydecision3 = pd.read_json(root_path+'paydecision3.json', orient='index')

df = pd.DataFrame()
df["time_stamp"] = cif.index
df["cif"] = cif[0].values
df["paycore"] = paycore[0].values
df["paydecision"] = paydecision[0].values
df["paydecision2"] = paydecision2[0].values
df["paydecision3"] = paydecision3[0].values
```

```
    # Optional
    if False:
        df.to_csv(root_path+"fusion.csv")


    # convert time stamp
    df['time_stamp'] = pd.to_datetime(df['time_stamp'])
    names_array = np.array(df.keys()[1:],dtype="str")
    os.listdir(root_path)
```

Out[2]:
```
['.ipynb_checkpoints',
 'cif.json',
 'fusion.csv',
 'paycore.json',
 'paydecision.json',
 'paydecision2.json',
 'paydecision3.json']
```

In [3]:
```
if False:

    # calculate previous hour high low:
    # convert to seconds
    temp = df['time_stamp'] - min(df['time_stamp'])
    temp = temp.dt.total_seconds().astype(int)
    df["hours"] = temp//3600

    h_max = max(df["hours"])+1

    for n in range(len(names_array)):
        df[names_array[n]+"_open"] = df[names_array[n]]
        df[names_array[n]+"_close"] = df[names_array[n]]
        df[names_array[n]+"_max"] = df[names_array[n]]
        df[names_array[n]+"_min"] = df[names_array[n]]

    for j in range(1,h_max):
        mask_j = df["hours"]==j-1
        max_val = df[mask_j][names_array].max(axis=0).values
        min_val = df[mask_j][names_array].max(axis=0).values
        open_val = df[mask_j][names_array].values[0,:]
        close_val = df[mask_j][names_array].values[-1,:]
        mask_i = df["hours"]==j
        r = df[mask_i][names_array].shape[0]
        df.loc[mask_i,[r+"_open" for r in names_array]] = np.tile(open_val,(r,1))
        df.loc[mask_i,[r+"_close" for r in names_array]] = np.tile(close_val,(r,1))

        df.loc[mask_i,[r+"_max" for r in names_array]] = np.tile(max_val,(r,1))
        df.loc[mask_i,[r+"_min" for r in names_array]] = np.tile(min_val,(r,1))
```

In [5]:
```python
def scaled_dot_product_attention(q, k, v, mask):
    matmul_qk = tf.matmul(q, k, transpose_b=True)  # (..., seq_len_q, seq_len_k)

    # scale matmul_qk
    dk = tf.cast(tf.shape(k)[-1], tf.float32)
    scaled_attention_logits = matmul_qk / tf.math.sqrt(dk)

    # add the mask to the scaled tensor.
    if mask is not None:
        scaled_attention_logits += (mask * -1e9)

    # softmax is normalized on the last axis (seq_len_k) so that the scores
    # add up to 1.
    attention_weights = tf.nn.softmax(scaled_attention_logits, axis=-1)  # (..., seq_l

    output = tf.matmul(attention_weights, v)  # (..., seq_len_q, depth_v)

    return output, attention_weights
```

In [10]:
```python
# Attention:
# Multi-head Attention:
class MultiHeadAttention(tf.keras.layers.Layer):
    def __init__(self, d_model, num_heads):

        # Always use Super to inheriatte and avoid extra code.
        super(MultiHeadAttention, self).__init__()
        self.num_heads = num_heads
        self.d_model = d_model
        # sanity check:
        assert d_model % self.num_heads == 0
        self.depth = d_model // self.num_heads
        # Q K W:
        self.wq = tf.keras.layers.Dense(d_model)
        self.wk = tf.keras.layers.Dense(d_model)
        self.wv = tf.keras.layers.Dense(d_model)

        self.dense = tf.keras.layers.Dense(d_model)
    def split_heads(self, x, batch_size):
        # Transpose the result such that the shape is (batch_size, num_heads, seq_len
        x = tf.reshape(x, (batch_size, -1, self.num_heads, self.depth))
        return tf.transpose(x, perm=[0, 2, 1, 3])
    def call(self, v, k, q, mask):
        batch_size = tf.shape(q)[0]
        q = self.wq(q)  # (batch_size, seq_len, d_model)
```

```
        k = self.wk(k)  # (batch_size, seq_len, d_model)
        v = self.wv(v)  # (batch_size, seq_len, d_model)

        q = self.split_heads(q, batch_size)  # (batch_size, num_heads, seq_len_q, dep
        k = self.split_heads(k, batch_size)  # (batch_size, num_heads, seq_len_k, dep
        v = self.split_heads(v, batch_size)  # (batch_size, num_heads, seq_len_v, dep

        # scaled_attention.shape == (batch_size, num_heads, seq_len_q, depth)
        # attention_weights.shape == (batch_size, num_heads, seq_len_q, seq_len_k)

        scaled_attention, attention_weights = scaled_dot_product_attention(q, k, v, ma
        # https://www.tensorflow.org/api_docs/python/tf/transpose : perm
        scaled_attention = tf.transpose(scaled_attention, perm=[0, 2, 1, 3])  # (batc
        concat_attention = tf.reshape(scaled_attention,
                                  (batch_size, -1, self.d_model))  # (batch_size, seq
        output = self.dense(concat_attention)  # (batch_size, seq_len_q, d_model)
        return output, attention_weights



# check our Multi-head attention:

# change d to smaller
n_d_model=16


temp_mha = MultiHeadAttention(d_model=n_d_model, num_heads=8)
y = tf.random.uniform((1, 60, n_d_model))  # (batch_size, encoder_sequence, d_model)
out, attn = temp_mha(y, k=y, q=y, mask=None)
out.shape, attn.shape

"""
# Point wise feed forward network consists of two fully-connected layers with a ReLU
def point_wise_feed_forward_network(d_model, dff):
    # Two FC layers:
    return tf.keras.Sequential([
      tf.keras.layers.Dense(dff, activation='relu'),  # (batch_size, seq_len, dff)
      tf.keras.layers.Dense(d_model)  # (batch_size, seq_len, d_model)
  ])
sample_ffn = point_wise_feed_forward_network(512, 2048)
sample_ffn(tf.random.uniform((64, 50, 512))).shape




"""
```

Out[10]: "\n# Point wise feed forward network consists of two fully-connected layers with a Rel

In [24]:
```
# Variable-length int sequences.
query_input = tf.keras.Input(shape=(None,), dtype='int32')
value_input = tf.keras.Input(shape=(None,), dtype='int32')

max_tokens = 1440
# encoding
dimension = 200

# Embedding lookup.
token_embedding = tf.keras.layers.Embedding(max_tokens, dimension)
# Query embeddings of shape [batch_size, Tq, dimension].
query_embeddings = token_embedding(query_input)
# Value embeddings of shape [batch_size, Tv, dimension].
value_embeddings = token_embedding(value_input)

# CNN layer.
cnn_layer = tf.keras.layers.Conv1D(
    filters=100,
    kernel_size=4,
    # Use 'same' padding so outputs have the same shape as inputs.
    padding='same')
# Query encoding of shape [batch_size, Tq, filters].
query_seq_encoding = cnn_layer(query_embeddings)
# Value encoding of shape [batch_size, Tv, filters].
value_seq_encoding = cnn_layer(value_embeddings)

# Query-value attention of shape [batch_size, Tq, filters].
query_value_attention_seq = tf.keras.layers.Attention()(
    [query_seq_encoding, value_seq_encoding])

# Reduce over the sequence axis to produce encodings of shape
# [batch_size, filters].
query_encoding = tf.keras.layers.GlobalAveragePooling1D()(
    query_seq_encoding)
query_value_attention = tf.keras.layers.GlobalAveragePooling1D()(
    query_value_attention_seq)

# Concatenate query and document encodings to produce a DNN input layer.
input_layer = tf.keras.layers.Concatenate()(
    [query_encoding, query_value_attention])
```

In [68]:
```
from keras.models import Model
from keras.layers import Input, Dense, LSTM, multiply, concatenate, Activation, Maskin
from keras.layers import Conv1D, BatchNormalization, GlobalAveragePooling1D, Permute,
```

In [58]:
```
NB_CLASS = 1
n_cell = 12
```

```
def generate_model(MAX_TIMESTEPS,MAX_NB_VARIABLES):
    ip = Input(shape=(MAX_TIMESTEPS,MAX_NB_VARIABLES))
    x = LSTM(20)(ip)
    attention = tf.keras.layers.Attention()
    x = attention([x,x])
    out = Dense(1)(x)
    model = Model(ip, out)
    return model

model = generate_model(1440,5)
model.compile(loss='mae', optimizer='adam')
```

In [59]:
```
model.summary()
```

```
Model: "model_2"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_13 (InputLayer)           [(None, 1440, 5)]    0
__________________________________________________________________________________________________
lstm_12 (LSTM)                  (None, 20)           2080        input_13[0][0]
__________________________________________________________________________________________________
attention_11 (Attention)        (None, 20)           0           lstm_12[0][0]
                                                                 lstm_12[0][0]
__________________________________________________________________________________________________
dense_23 (Dense)                (None, 1)            21          attention_11[0][0]
==================================================================================================
Total params: 2,101
Trainable params: 2,101
Non-trainable params: 0
__________________________________________________________________________________________________
```

In [115]:
```
# Attention LSTM simple model
delta_t = 1440
n_epoch=40
n_cell = 50
# predict 1 minute for now
N_output=1
N_input = 5
index_name= 0
```

In [116]:
```
# calculate previous hour high low:
# convert to seconds
temp = df['time_stamp'] - min(df['time_stamp'])
temp = temp.dt.total_seconds().astype(int)
df["hours"] = temp//3600

h_max = max(df["hours"])+1
```

```
for n in range(len(names_array)):
    df[names_array[n]+"_open"] = df[names_array[n]]
    df[names_array[n]+"_close"] = df[names_array[n]]
    df[names_array[n]+"_max"] = df[names_array[n]]
    df[names_array[n]+"_min"] = df[names_array[n]]

for j in range(1,h_max):
    mask_j = df["hours"]==j-1
    max_val = df[mask_j][names_array].max(axis=0).values
    min_val = df[mask_j][names_array].max(axis=0).values
    open_val = df[mask_j][names_array].values[0,:]
    close_val = df[mask_j][names_array].values[-1,:]
    mask_i = df["hours"]==j
    r = df[mask_i][names_array].shape[0]
    df.loc[mask_i,[r+"_open" for r in names_array]] = np.tile(open_val,(r,1))
    df.loc[mask_i,[r+"_close" for r in names_array]] = np.tile(close_val,(r,1))

    df.loc[mask_i,[r+"_max" for r in names_array]] = np.tile(max_val,(r,1))
    df.loc[mask_i,[r+"_min" for r in names_array]] = np.tile(min_val,(r,1))
```

In [117]:
```
df["minutes"]=df["time_stamp"].dt.hour*1440+df["time_stamp"].dt.hour*60+df["time_stam


checkpoint_path = "LSTM_ATT/cp.ckpt"
checkpoint_dir = os.path.dirname(checkpoint_path)

min_max_scaler = preprocessing.StandardScaler()

name_mod = [names_array[index_name],names_array[index_name]+"_open",names_array[inde

np_scaled = min_max_scaler.fit_transform(df[name_mod])

df_scaled = pd.DataFrame(np_scaled,columns=name_mod)


X = np.zeros((df_scaled.shape[0]-delta_t,delta_t,5),dtype=float)
y = df_scaled[names_array[index_name]][delta_t:]

for i in range(len(y)):
    if i%10000==0:
        print("Prepare data %.2f percent"%(100*i/len(y)))
    X[i,:,:] = df_scaled[i:i+delta_t][name_mod].values

# split train test:
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=Tru
```

```
Prepare data 0.00 percent
Prepare data 24.80 percent
Prepare data 49.60 percent
Prepare data 74.40 percent
Prepare data 99.20 percent
```

In [118]:
```python
# model:

NB_CLASS = N_output

def squeeze_excite_block(input):

    filters = input._shape[-1] # channel_axis = -1 for TF

    se = GlobalAveragePooling1D()(input)
    se = Reshape((1, filters))(se)
    se = Dense(filters // 16,  activation='relu', kernel_initializer='he_normal', use
    se = Dense(filters, activation='sigmoid', kernel_initializer='he_normal', use_bia
    se = multiply([input, se])
    return se

def generate_model(MAX_TIMESTEPS,MAX_NB_VARIABLES):
    ip = Input(shape=(MAX_TIMESTEPS,MAX_NB_VARIABLES))
    # split into x and y two channels

    x = Masking()(ip)
    x = LSTM(n_cell)(x)
    # Add attention here:
    attention = tf.keras.layers.Attention()
    x = attention([x,x])

    x = Dropout(0.8)(x)

    y = Permute((2, 1))(ip)
    y = Conv1D(128, 8, padding='same', kernel_initializer='he_uniform')(y)
    y = BatchNormalization()(y)
    y = Activation('relu')(y)
    y = squeeze_excite_block(y)

    y = Conv1D(256, 5, padding='same', kernel_initializer='he_uniform')(y)
    y = BatchNormalization()(y)
    y = Activation('relu')(y)
    y = squeeze_excite_block(y)

    y = Conv1D(128, 3, padding='same', kernel_initializer='he_uniform')(y)
    y = BatchNormalization()(y)
    y = Activation('relu')(y)
```

```
        y = GlobalAveragePooling1D()(y)
        # combine
        x = concatenate([x, y])

        #out = Dense(NB_CLASS, activation='softmax')(x)
        # For regression model use MAE
        out = Dense(N_output)(x)

        model = Model(ip, out)
        model.summary()

        # add load model code here to fine-tune

        return model
```

In [119]:
```
model = generate_model(delta_t,5)

model.compile(loss='mae', optimizer='adam')
#model.summary()

callback = tf.keras.callbacks.ModelCheckpoint(filepath=checkpoint_path,
                                              save_weights_only=True,
                                              verbose=1)
```

```
WARNING:tensorflow:Tensor._shape is private, use Tensor.shape instead. Tensor._shape will even
WARNING:tensorflow:Tensor._shape is private, use Tensor.shape instead. Tensor._shape will even
Model: "model_12"
________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
================================================================================================
input_29 (InputLayer)           [(None, 1440, 5)]    0
________________________________________________________________________________________________
permute_14 (Permute)            (None, 5, 1440)      0           input_29[0][0]
________________________________________________________________________________________________
conv1d_50 (Conv1D)              (None, 5, 128)       1474688     permute_14[0][0]
________________________________________________________________________________________________
batch_normalization_36 (BatchNo (None, 5, 128)       512         conv1d_50[0][0]
________________________________________________________________________________________________
activation_36 (Activation)      (None, 5, 128)       0           batch_normalization_36[0][0]
________________________________________________________________________________________________
global_average_pooling1d_49 (Gl (None, 128)          0           activation_36[0][0]
________________________________________________________________________________________________
reshape_24 (Reshape)            (None, 1, 128)       0           global_average_pooling1d_49[0
________________________________________________________________________________________________
dense_82 (Dense)                (None, 1, 8)         1024        reshape_24[0][0]
________________________________________________________________________________________________
dense_83 (Dense)                (None, 1, 128)       1024        dense_82[0][0]
```

```
__________________________________________________________________________________________________
multiply_24 (Multiply)          (None, 5, 128)       0           activation_36[0][0]
                                                                 dense_83[0][0]
__________________________________________________________________________________________________
conv1d_51 (Conv1D)              (None, 5, 256)       164096      multiply_24[0][0]
__________________________________________________________________________________________________
batch_normalization_37 (BatchNo (None, 5, 256)       1024        conv1d_51[0][0]
__________________________________________________________________________________________________
activation_37 (Activation)      (None, 5, 256)       0           batch_normalization_37[0][0]
__________________________________________________________________________________________________
global_average_pooling1d_50 (Gl (None, 256)          0           activation_37[0][0]
__________________________________________________________________________________________________
reshape_25 (Reshape)            (None, 1, 256)       0           global_average_pooling1d_50[0
__________________________________________________________________________________________________
dense_84 (Dense)                (None, 1, 16)        4096        reshape_25[0][0]
__________________________________________________________________________________________________
dense_85 (Dense)                (None, 1, 256)       4096        dense_84[0][0]
__________________________________________________________________________________________________
multiply_25 (Multiply)          (None, 5, 256)       0           activation_37[0][0]
                                                                 dense_85[0][0]
__________________________________________________________________________________________________
masking_15 (Masking)            (None, 1440, 5)      0           input_29[0][0]
__________________________________________________________________________________________________
conv1d_52 (Conv1D)              (None, 5, 128)       98432       multiply_25[0][0]
__________________________________________________________________________________________________
lstm_15 (LSTM)                  (None, 50)           11200       masking_15[0][0]
__________________________________________________________________________________________________
batch_normalization_38 (BatchNo (None, 5, 128)       512         conv1d_52[0][0]
__________________________________________________________________________________________________
attention_27 (Attention)        (None, 50)           0           lstm_15[0][0]
                                                                 lstm_15[0][0]
__________________________________________________________________________________________________
activation_38 (Activation)      (None, 5, 128)       0           batch_normalization_38[0][0]
__________________________________________________________________________________________________
dropout_13 (Dropout)            (None, 50)           0           attention_27[0][0]
__________________________________________________________________________________________________
global_average_pooling1d_51 (Gl (None, 128)          0           activation_38[0][0]
__________________________________________________________________________________________________
concatenate_13 (Concatenate)    (None, 178)          0           dropout_13[0][0]
                                                                 global_average_pooling1d_51[0
__________________________________________________________________________________________________
dense_86 (Dense)                (None, 1)            179         concatenate_13[0][0]
==================================================================================================
Total params: 1,760,883
Trainable params: 1,759,859
Non-trainable params: 1,024
__________________________________________________________________________________________________
```

In [120]: # Let's do it!

```
history = model.fit(X_train, y_train, epochs=n_epoch, batch_size=64, validation_data=
```

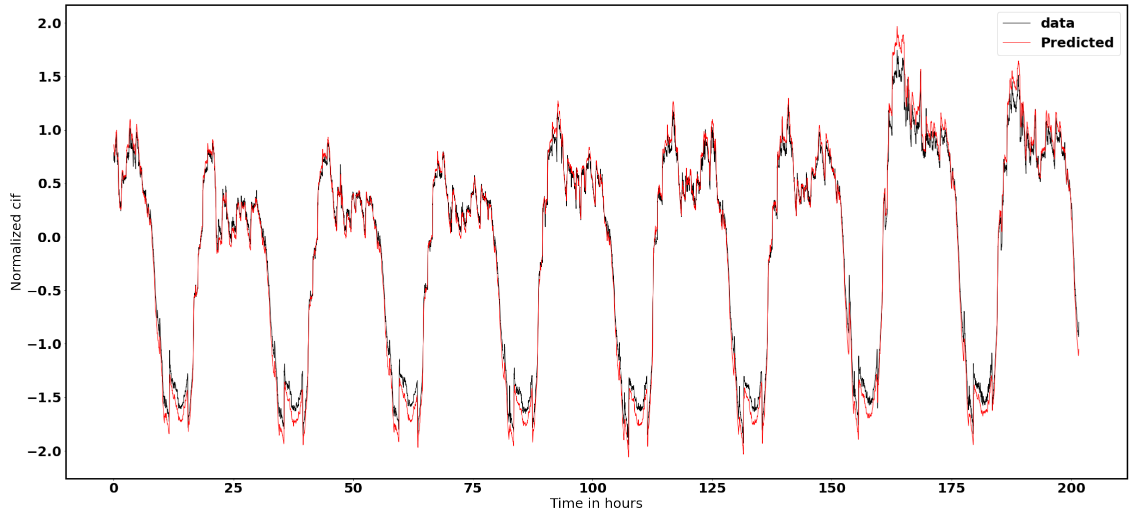
```
Epoch 1/40
441/441 [==============================] - ETA: 0s - loss: 0.1608
Epoch 00001: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 93ms/step - loss: 0.1608 - val_loss: 0.1030
Epoch 2/40
441/441 [==============================] - ETA: 0s - loss: 0.1066
Epoch 00002: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 93ms/step - loss: 0.1066 - val_loss: 0.1015
Epoch 3/40
441/441 [==============================] - ETA: 0s - loss: 0.0927
Epoch 00003: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0927 - val_loss: 0.0712
Epoch 4/40
441/441 [==============================] - ETA: 0s - loss: 0.0845
Epoch 00004: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0845 - val_loss: 0.0694
Epoch 5/40
441/441 [==============================] - ETA: 0s - loss: 0.0763
Epoch 00005: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 93ms/step - loss: 0.0763 - val_loss: 0.0829
Epoch 6/40
441/441 [==============================] - ETA: 0s - loss: 0.0720
Epoch 00006: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0720 - val_loss: 0.0670
Epoch 7/40
441/441 [==============================] - ETA: 0s - loss: 0.0657
Epoch 00007: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0657 - val_loss: 0.0774
Epoch 8/40
441/441 [==============================] - ETA: 0s - loss: 0.0637
Epoch 00008: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 93ms/step - loss: 0.0637 - val_loss: 0.0595
Epoch 9/40
441/441 [==============================] - ETA: 0s - loss: 0.0608
Epoch 00009: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0608 - val_loss: 0.0566
Epoch 10/40
441/441 [==============================] - ETA: 0s - loss: 0.0575
Epoch 00010: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 40s 92ms/step - loss: 0.0575 - val_loss: 0.0615
Epoch 11/40
441/441 [==============================] - ETA: 0s - loss: 0.0567
Epoch 00011: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 40s 92ms/step - loss: 0.0567 - val_loss: 0.0485
```

```
Epoch 12/40
441/441 [==============================] - ETA: 0s - loss: 0.0529
Epoch 00012: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0529 - val_loss: 0.0743
Epoch 13/40
441/441 [==============================] - ETA: 0s - loss: 0.0526
Epoch 00013: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 40s 92ms/step - loss: 0.0526 - val_loss: 0.0566
Epoch 14/40
441/441 [==============================] - ETA: 0s - loss: 0.0498
Epoch 00014: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 93ms/step - loss: 0.0498 - val_loss: 0.0445
Epoch 15/40
441/441 [==============================] - ETA: 0s - loss: 0.0485
Epoch 00015: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 93ms/step - loss: 0.0485 - val_loss: 0.0463
Epoch 16/40
441/441 [==============================] - ETA: 0s - loss: 0.0470
Epoch 00016: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0470 - val_loss: 0.0467
Epoch 17/40
441/441 [==============================] - ETA: 0s - loss: 0.0464
Epoch 00017: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0464 - val_loss: 0.0404
Epoch 18/40
441/441 [==============================] - ETA: 0s - loss: 0.0458
Epoch 00018: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0458 - val_loss: 0.0458
Epoch 19/40
441/441 [==============================] - ETA: 0s - loss: 0.0443
Epoch 00019: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 93ms/step - loss: 0.0443 - val_loss: 0.0488
Epoch 20/40
441/441 [==============================] - ETA: 0s - loss: 0.0436
Epoch 00020: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 93ms/step - loss: 0.0436 - val_loss: 0.0419
Epoch 21/40
441/441 [==============================] - ETA: 0s - loss: 0.0423
Epoch 00021: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 40s 92ms/step - loss: 0.0423 - val_loss: 0.0401
Epoch 22/40
441/441 [==============================] - ETA: 0s - loss: 0.0408
Epoch 00022: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0408 - val_loss: 0.0402
Epoch 23/40
441/441 [==============================] - ETA: 0s - loss: 0.0405
Epoch 00023: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0405 - val_loss: 0.0461
```

```
Epoch 24/40
441/441 [==============================] - ETA: 0s - loss: 0.0412
Epoch 00024: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0412 - val_loss: 0.0416
Epoch 25/40
441/441 [==============================] - ETA: 0s - loss: 0.0405
Epoch 00025: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0405 - val_loss: 0.0384
Epoch 26/40
441/441 [==============================] - ETA: 0s - loss: 0.0388
Epoch 00026: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0388 - val_loss: 0.0427
Epoch 27/40
441/441 [==============================] - ETA: 0s - loss: 0.0392
Epoch 00027: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 93ms/step - loss: 0.0392 - val_loss: 0.0351
Epoch 28/40
441/441 [==============================] - ETA: 0s - loss: 0.0372
Epoch 00028: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 40s 92ms/step - loss: 0.0372 - val_loss: 0.0375
Epoch 29/40
441/441 [==============================] - ETA: 0s - loss: 0.0376
Epoch 00029: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0376 - val_loss: 0.0357
Epoch 30/40
441/441 [==============================] - ETA: 0s - loss: 0.0362
Epoch 00030: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0362 - val_loss: 0.0356
Epoch 31/40
441/441 [==============================] - ETA: 0s - loss: 0.0366
Epoch 00031: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0366 - val_loss: 0.0352
Epoch 32/40
441/441 [==============================] - ETA: 0s - loss: 0.0356
Epoch 00032: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0356 - val_loss: 0.0441
Epoch 33/40
441/441 [==============================] - ETA: 0s - loss: 0.0347
Epoch 00033: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 40s 92ms/step - loss: 0.0347 - val_loss: 0.0363
Epoch 34/40
441/441 [==============================] - ETA: 0s - loss: 0.0342
Epoch 00034: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0342 - val_loss: 0.0360
Epoch 35/40
441/441 [==============================] - ETA: 0s - loss: 0.0347
Epoch 00035: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0347 - val_loss: 0.0401
```

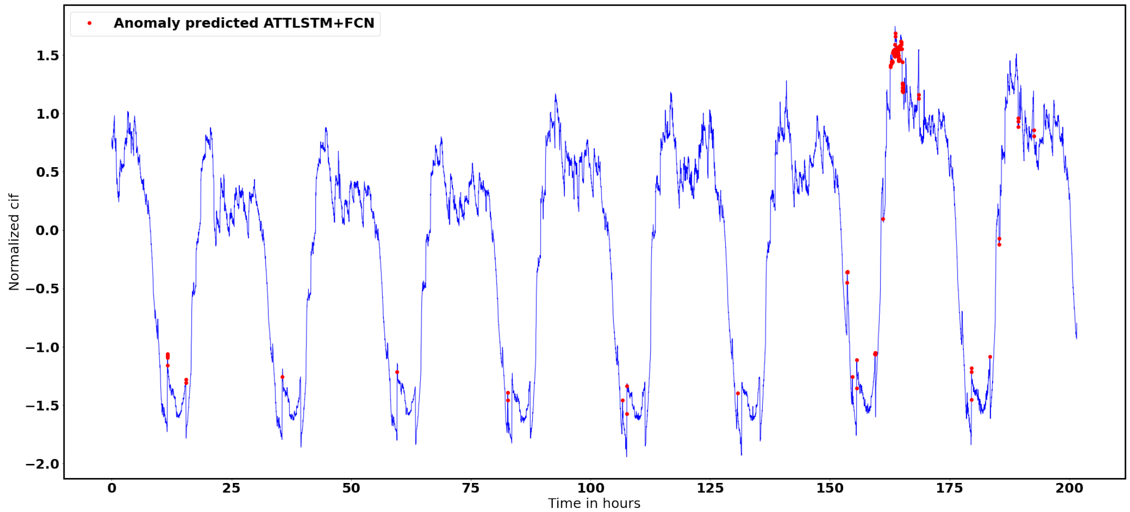
```
Epoch 36/40
441/441 [==============================] - ETA: 0s - loss: 0.0341
Epoch 00036: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 40s 92ms/step - loss: 0.0341 - val_loss: 0.0341
Epoch 37/40
441/441 [==============================] - ETA: 0s - loss: 0.0330
Epoch 00037: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0330 - val_loss: 0.0342
Epoch 38/40
441/441 [==============================] - ETA: 0s - loss: 0.0337
Epoch 00038: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 93ms/step - loss: 0.0337 - val_loss: 0.0347
Epoch 39/40
441/441 [==============================] - ETA: 0s - loss: 0.0350
Epoch 00039: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0350 - val_loss: 0.0385
Epoch 40/40
441/441 [==============================] - ETA: 0s - loss: 0.0329
Epoch 00040: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 41s 92ms/step - loss: 0.0329 - val_loss: 0.0310
```

In [121]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=Fal
y_pre = model.predict(X_test)
font = {'family': 'normal','weight': 'bold',
        'size': 25}

matplotlib.rc('font', **font)
rc('axes', linewidth=3)


timeline = np.arange(0,len(y_test),1)

plt.plot(timeline/60,y_test,"k",label="data",alpha=1,linewidth=1)
plt.plot(timeline/60,y_pre[:,0],"r",label="Predicted",alpha=1,linewidth=1)

plt.xlabel("Time in hours")
plt.ylabel("Normalized %s"%names_array[index_name])

plt.legend()

fig = matplotlib.pyplot.gcf()


fig.set_size_inches(35,16)
save_path = plot_path + "ATTLSTM_FCN_results_5D" + ".png"

fig.savefig(save_path, dpi=150)
```

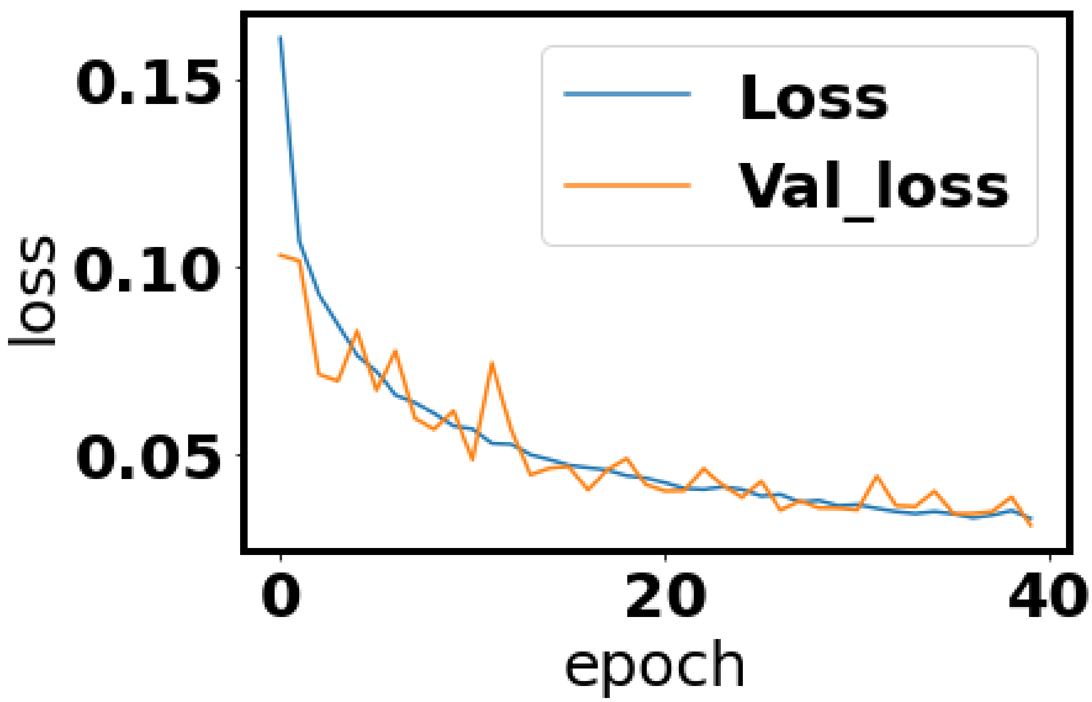



```
In [122]: # Predict Anomaly using this rule: Bigger difference between data and prediction mea

          diff = y_test-y_pre[:,0]
          anomaly_ratio = 0.01
          mask = abs(diff)>np.nanpercentile(abs(diff),100-100*anomaly_ratio)



          font = {'family': 'normal','weight': 'bold',
                  'size': 25}

          matplotlib.rc('font', **font)
          rc('axes', linewidth=3)


          timeline = np.arange(0,len(y_test),1)

          plt.plot(timeline/60,y_test,"b",alpha=1,linewidth=1)
          plt.plot(timeline[mask]/60,y_test[mask],"ro",label="Anomaly predicted ATTLSTM+FCN",al

          plt.xlabel("Time in hours")
          plt.ylabel("Normalized %s"%names_array[index_name])

          plt.legend()

          fig = matplotlib.pyplot.gcf()


          fig.set_size_inches(35,16)
          save_path = plot_path + "ATTLSTM_FCN_anomaly_prediction_5D" + ".png"
```

```
fig.savefig(save_path, dpi=150)
```




```
In [123]: # Only for diagnostic
          plt.plot(history.history['loss'],label="Loss")
          plt.plot(history.history['val_loss'],label="Val_loss")
          plt.xlabel("epoch")
          plt.ylabel("loss")
          plt.legend()

Out[123]: <matplotlib.legend.Legend at 0x7ff6241a65e0>
```



## 2.1 Attention without LSTM:

In [108]:
```
# Attention simple model
delta_t = 1440
n_epoch=10
n_cell = 50
# predict 1 minute for now
N_output=1
N_input = 5
index_name= 0
```

In [109]:
```
# model:
# https://www.tensorflow.org/api_docs/python/tf/keras/layers/Attention
NB_CLASS = N_output

def squeeze_excite_block(input):

    filters = input._shape[-1] # channel_axis = -1 for TF

    se = GlobalAveragePooling1D()(input)
    se = Reshape((1, filters))(se)
    se = Dense(filters // 16,  activation='relu', kernel_initializer='he_normal', use
    se = Dense(filters, activation='sigmoid', kernel_initializer='he_normal', use_bia
    se = multiply([input, se])
    return se

def generate_model(MAX_TIMESTEPS,MAX_NB_VARIABLES):
    ip = Input(shape=(MAX_TIMESTEPS,MAX_NB_VARIABLES))
    # split into x and y two channels

    x = Masking()(ip)

    # CNN+attention
    cnn_layer = tf.keras.layers.Conv1D(
    filters=200,
    kernel_size=4,padding='same')
    a1 = cnn_layer(x)
    a2 = cnn_layer(x)

    attention = tf.keras.layers.Attention()
    x2 = attention([a1,a2])
    x2 = tf.keras.layers.GlobalAveragePooling1D()(x2)
    x = tf.keras.layers.GlobalAveragePooling1D()(x)

    x = concatenate([x, x2])
```

```
    x = Dropout(0.8)(x)
    # convert to 1d pooling




    y = Permute((2, 1))(ip)
    y = Conv1D(128, 8, padding='same', kernel_initializer='he_uniform')(y)
    y = BatchNormalization()(y)
    y = Activation('relu')(y)
    y = squeeze_excite_block(y)

    y = Conv1D(256, 5, padding='same', kernel_initializer='he_uniform')(y)
    y = BatchNormalization()(y)
    y = Activation('relu')(y)
    y = squeeze_excite_block(y)

    y = Conv1D(128, 3, padding='same', kernel_initializer='he_uniform')(y)
    y = BatchNormalization()(y)
    y = Activation('relu')(y)

    y = GlobalAveragePooling1D()(y)
    # combine (Optional)
    print("check",y.shape,x.shape)
    x = concatenate([x, y])

    #out = Dense(NB_CLASS, activation='softmax')(x)
    # For regression model use MAE
    out = Dense(N_output)(x)
    print(out.shape)

    model = Model(ip, out)
    model.summary()

    # add load model code here to fine-tune

    return model
```

In [110]:
```
model = generate_model(delta_t,5)

model.compile(loss='mae', optimizer='adam')
#model.summary()

callback = tf.keras.callbacks.ModelCheckpoint(filepath=checkpoint_path,
                                              save_weights_only=True,
                                              verbose=1)
```

```
WARNING:tensorflow:Tensor._shape is private, use Tensor.shape instead. Tensor._shape will even
WARNING:tensorflow:Tensor._shape is private, use Tensor.shape instead. Tensor._shape will even
```

```
check (None, 128) (None, 205)
(None, 1)
Model: "model_11"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_28 (InputLayer)           [(None, 1440, 5)]    0
__________________________________________________________________________________________________
permute_13 (Permute)            (None, 5, 1440)      0           input_28[0][0]
__________________________________________________________________________________________________
conv1d_47 (Conv1D)              (None, 5, 128)       1474688     permute_13[0][0]
__________________________________________________________________________________________________
batch_normalization_33 (BatchNo (None, 5, 128)       512         conv1d_47[0][0]
__________________________________________________________________________________________________
activation_33 (Activation)      (None, 5, 128)       0           batch_normalization_33[0][0]
__________________________________________________________________________________________________
global_average_pooling1d_46 (Gl (None, 128)          0           activation_33[0][0]
__________________________________________________________________________________________________
reshape_22 (Reshape)            (None, 1, 128)       0           global_average_pooling1d_46[0
__________________________________________________________________________________________________
dense_77 (Dense)                (None, 1, 8)         1024        reshape_22[0][0]
__________________________________________________________________________________________________
dense_78 (Dense)                (None, 1, 128)       1024        dense_77[0][0]
__________________________________________________________________________________________________
multiply_22 (Multiply)          (None, 5, 128)       0           activation_33[0][0]
                                                                 dense_78[0][0]
__________________________________________________________________________________________________
conv1d_48 (Conv1D)              (None, 5, 256)       164096      multiply_22[0][0]
__________________________________________________________________________________________________
batch_normalization_34 (BatchNo (None, 5, 256)       1024        conv1d_48[0][0]
__________________________________________________________________________________________________
activation_34 (Activation)      (None, 5, 256)       0           batch_normalization_34[0][0]
__________________________________________________________________________________________________
global_average_pooling1d_47 (Gl (None, 256)          0           activation_34[0][0]
__________________________________________________________________________________________________
reshape_23 (Reshape)            (None, 1, 256)       0           global_average_pooling1d_47[0
__________________________________________________________________________________________________
dense_79 (Dense)                (None, 1, 16)        4096        reshape_23[0][0]
__________________________________________________________________________________________________
masking_14 (Masking)            (None, 1440, 5)      0           input_28[0][0]
__________________________________________________________________________________________________
dense_80 (Dense)                (None, 1, 256)       4096        dense_79[0][0]
__________________________________________________________________________________________________
conv1d_46 (Conv1D)              (None, 1440, 200)    4200        masking_14[0][0]
                                                                 masking_14[0][0]
__________________________________________________________________________________________________
multiply_23 (Multiply)          (None, 5, 256)       0           activation_34[0][0]
                                                                 dense_80[0][0]
```

```
________________________________________________________________________________________________
attention_26 (Attention)        (None, 1440, 200)    0           conv1d_46[0][0]
                                                                 conv1d_46[1][0]
________________________________________________________________________________________________
conv1d_49 (Conv1D)              (None, 5, 128)       98432       multiply_23[0][0]
________________________________________________________________________________________________
global_average_pooling1d_45 (Gl (None, 5)            0           masking_14[0][0]
________________________________________________________________________________________________
global_average_pooling1d_44 (Gl (None, 200)          0           attention_26[0][0]
________________________________________________________________________________________________
batch_normalization_35 (BatchNo (None, 5, 128)       512         conv1d_49[0][0]
________________________________________________________________________________________________
concatenate_11 (Concatenate)    (None, 205)          0           global_average_pooling1d_45[0
                                                                 global_average_pooling1d_44[0
________________________________________________________________________________________________
activation_35 (Activation)      (None, 5, 128)       0           batch_normalization_35[0][0]
________________________________________________________________________________________________
dropout_12 (Dropout)            (None, 205)          0           concatenate_11[0][0]
________________________________________________________________________________________________
global_average_pooling1d_48 (Gl (None, 128)          0           activation_35[0][0]
________________________________________________________________________________________________
concatenate_12 (Concatenate)    (None, 333)          0           dropout_12[0][0]
                                                                 global_average_pooling1d_48[0
________________________________________________________________________________________________
dense_81 (Dense)                (None, 1)            334         concatenate_12[0][0]
================================================================================================
Total params: 1,754,038
Trainable params: 1,753,014
Non-trainable params: 1,024
________________________________________________________________________________________________
```

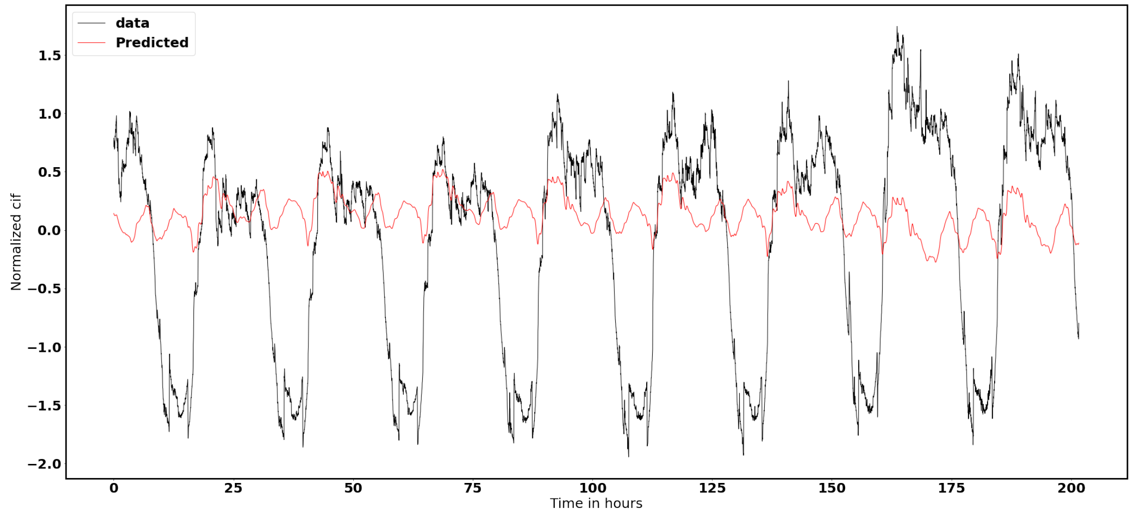
```
In [111]: history = model.fit(X_train, y_train, epochs=n_epoch, batch_size=64, validation_data=
```

```
Epoch 1/10
441/441 [==============================] - ETA: 0s - loss: 0.5658
Epoch 00001: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 106s 241ms/step - loss: 0.5658 - val_loss: 0.7671
Epoch 2/10
441/441 [==============================] - ETA: 0s - loss: 0.3253
Epoch 00002: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 103s 234ms/step - loss: 0.3253 - val_loss: 1.0139
Epoch 3/10
441/441 [==============================] - ETA: 0s - loss: 0.2639
Epoch 00003: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 103s 234ms/step - loss: 0.2639 - val_loss: 0.8707
Epoch 4/10
441/441 [==============================] - ETA: 0s - loss: 0.2500
```

```
Epoch 00004: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 103s 234ms/step - loss: 0.2500 - val_loss: 1.0599
Epoch 5/10
441/441 [==============================] - ETA: 0s - loss: 0.2438
Epoch 00005: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 103s 234ms/step - loss: 0.2438 - val_loss: 0.9434
Epoch 6/10
441/441 [==============================] - ETA: 0s - loss: 0.2200
Epoch 00006: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 103s 234ms/step - loss: 0.2200 - val_loss: 0.6992
Epoch 7/10
441/441 [==============================] - ETA: 0s - loss: 0.2053
Epoch 00007: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 103s 234ms/step - loss: 0.2053 - val_loss: 0.7899
Epoch 8/10
441/441 [==============================] - ETA: 0s - loss: 0.2105
Epoch 00008: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 103s 234ms/step - loss: 0.2105 - val_loss: 0.7978
Epoch 9/10
441/441 [==============================] - ETA: 0s - loss: 0.2121
Epoch 00009: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 103s 234ms/step - loss: 0.2121 - val_loss: 0.7946
Epoch 10/10
441/441 [==============================] - ETA: 0s - loss: 0.1943
Epoch 00010: saving model to LSTM_ATT/cp.ckpt
441/441 [==============================] - 103s 234ms/step - loss: 0.1943 - val_loss: 0.7570
```

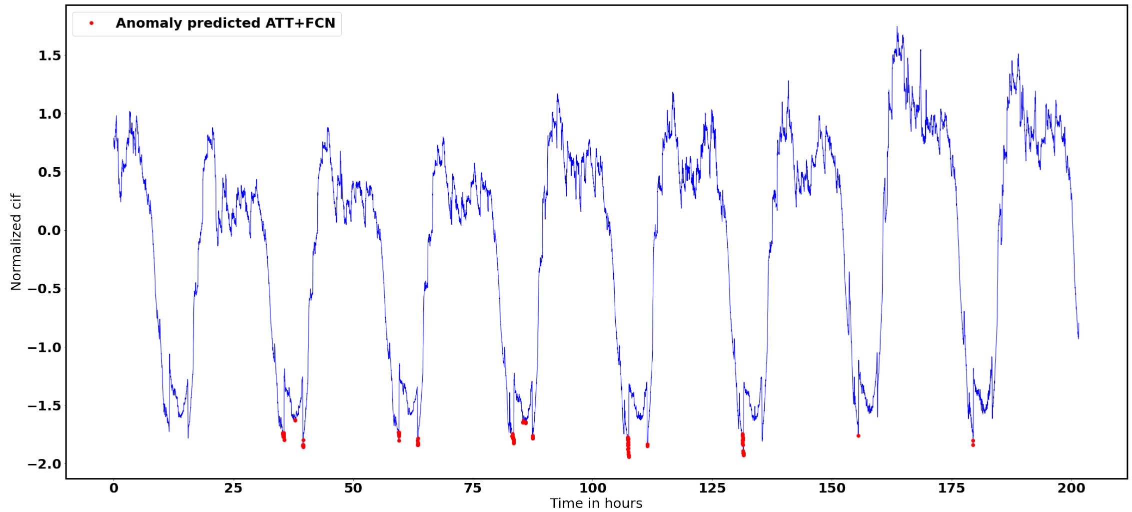
In [112]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=Fals
y_pre = model.predict(X_test)
font = {'family': 'normal','weight': 'bold',
        'size': 25}

matplotlib.rc('font', **font)
rc('axes', linewidth=3)


timeline = np.arange(0,len(y_test),1)

plt.plot(timeline/60,y_test,"k",label="data",alpha=1,linewidth=1)
plt.plot(timeline/60,y_pre[:,0],"r",label="Predicted",alpha=1,linewidth=1)

plt.xlabel("Time in hours")
plt.ylabel("Normalized %s"%names_array[index_name])

plt.legend()

fig = matplotlib.pyplot.gcf()
```

```
fig.set_size_inches(35,16)
save_path = plot_path + "ATT_FCN_results_5D" + ".png"

fig.savefig(save_path, dpi=150)
```



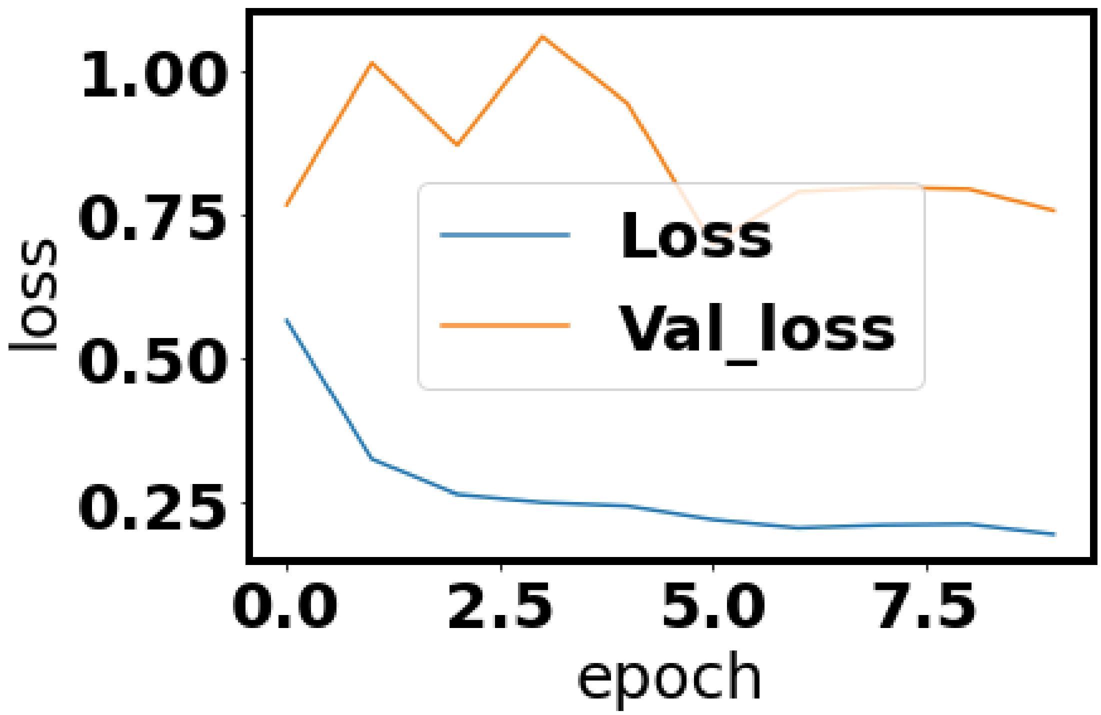

In [113]:
```
# Predict Anomaly using this rule: Bigger difference between data and prediction mea

diff = y_test-y_pre[:,0]
anomaly_ratio = 0.01
mask = abs(diff)>np.nanpercentile(abs(diff),100-100*anomaly_ratio)



font = {'family': 'normal','weight': 'bold',
        'size': 25}

matplotlib.rc('font', **font)
rc('axes', linewidth=3)


timeline = np.arange(0,len(y_test),1)

plt.plot(timeline/60,y_test,"b",alpha=1,linewidth=1)
plt.plot(timeline[mask]/60,y_test[mask],"ro",label="Anomaly predicted ATT+FCN",alpha=

plt.xlabel("Time in hours")
plt.ylabel("Normalized %s"%names_array[index_name])
```

```
plt.legend()

fig = matplotlib.pyplot.gcf()


fig.set_size_inches(35,16)
save_path = plot_path + "ATT_FCN_anomaly_prediction_5D" + ".png"

fig.savefig(save_path, dpi=150)
```




```
In [114]: # Only for diagnostic
          plt.plot(history.history['loss'],label="Loss")
          plt.plot(history.history['val_loss'],label="Val_loss")
          plt.xlabel("epoch")
          plt.ylabel("loss")
          plt.legend()
```

```
Out[114]: <matplotlib.legend.Legend at 0x7ff5f8784130>
```




In [ ]:

In [ ]: