Лабораторная работа №8

Методы прогнозирования на основе искусственных нейронных сетей

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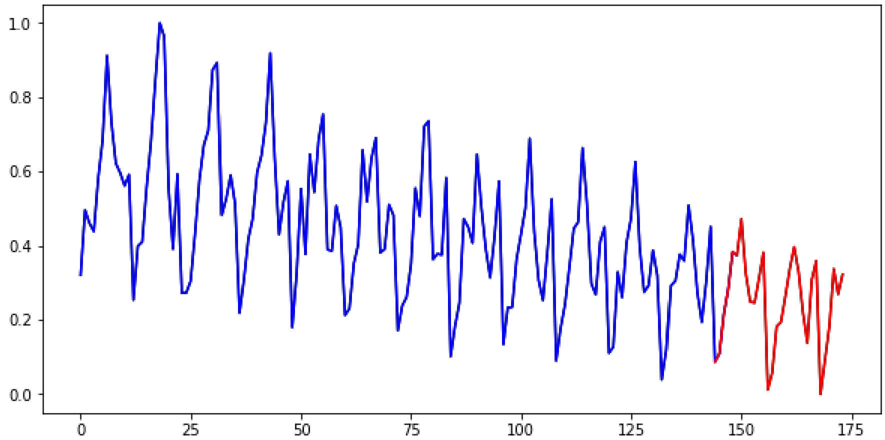
Вариант №19

In [2]:
```
import numpy as np
import matplotlib.pyplot as plt
import h5py

%matplotlib inline

from sklearn.preprocessing import MinMaxScaler
from keras.preprocessing.sequence import TimeseriesGenerator
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout
```

Загрузим ВР из файла Fort.mat, содержащий отсчеты некоторого реального ВР, всего 174 отсчета в вектор-строке, и отмаштабируем его в диапазон от 0 до 1, так как функция активации слоя LSTM корректно обрабатывает значения только в данном диапазоне:

In [3]:
```
file = h5py.File('Fort.mat', 'r')
data = file.get('Fort')
Fort = np.array(data)
F = Fort

scaler = MinMaxScaler(feature_range=(0, 1))
F = scaler.fit_transform(F)
F_tr = F[:150]
F_test = F[144:]

plt.figure(figsize = (10, 5))
plt.plot(F, 'k')
plt.plot(np.r_[:150],F_tr, 'b')
plt.plot(np.r_[144:174],F_test, 'r')
plt.show()
```



Произведем предобработку исходных данных в формат, понимаемый слоем LSTM-сети, в виде «порций» (batches) для обучения/валидации. Ниже приведен пример для модели сети 6 порядка авторегрессии на (150-6)=144 смежных точках ряда.

In [4]:
```
data_gen = TimeseriesGenerator(F_tr,
                               F_tr,
                               length=6,
                               sampling_rate=1,
                               batch_size=150)

batch_0 = data_gen[0]
x, y= batch_0 # вход и обучающий выход для сети
print(x.shape) # 144 точки обучения, прогноз 1 точки по 6 прошлым
xx_tr=np.reshape(x, (x.shape[0], 1, x.shape[1]))
yy_tr=y
print(xx_tr.shape)# меняем местами размерности
print(yy_tr.shape)
```

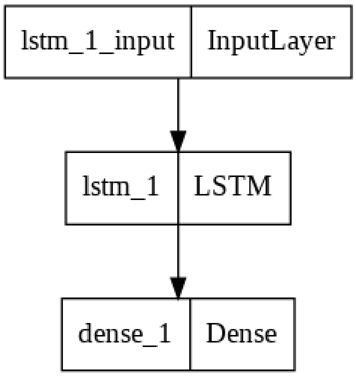
```
(144, 6, 1)
(144, 1, 6)
```

```
(144, 1)
```

Составляем модель прогнозной сети. В простейшем случае нам понадобится только 1 внутренний LSTM-слой и 1 выходной слой. Тогда модель строится как:

In [6]:
```
from keras.utils.vis_utils import plot_model

model = Sequential()# слои соединены последовательно
model.add(LSTM(units=20, input_shape=(1, 6))) # 20 нейронов
model.add(Dense(units=1)) # выход одномерный

model.compile(optimizer = 'adam', loss = 'mean_squared_error')
plot_model(model, to_file='model.png') # рисунок полученной сети
```

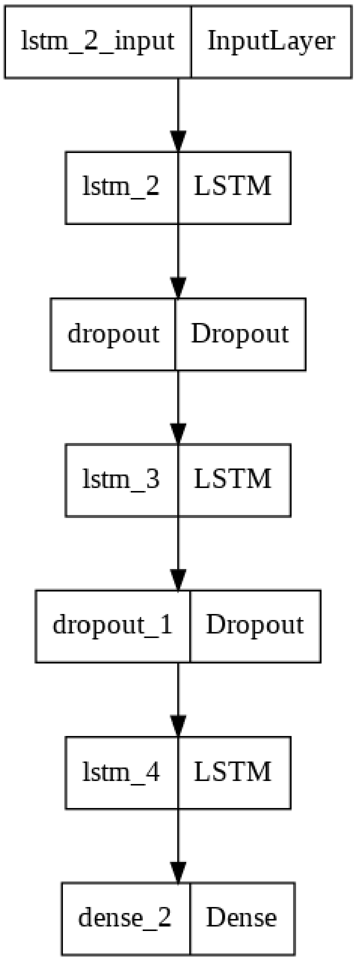
Out[6]:



Добавим Dropout слои, которые со случайной заданной вероятностью обнуляют входы следующего слоя при обучении, тем самым позволяя избежать переобучения всей нейронной сети в целом. Например, модель из 3 слоев LSTM может быть построена примерно следующим образом:

In [7]:
```
model = Sequential()
model.add(LSTM(units=20, return_sequences=True, input_shape=(1, 6)))
model.add(Dropout(0.2))
model.add(LSTM(units=20, return_sequences=True))
model.add(Dropout(0.2))
model.add(LSTM(units=20))
model.add(Dense(units = 1))

model.compile(optimizer = 'adam', loss = 'mean_squared_error')
plot_model(model, to_file='model.png')
```

Out[7]:



Производим обучение модели:

In [10]:
```
model.fit(xx_tr, yy_tr, epochs=100) # 100 эпох по 144 точки
```

```
Epoch 1/100
5/5 [==============================] - 5s 6ms/step - loss: 0.2290
Epoch 2/100
5/5 [==============================] - 0s 6ms/step - loss: 0.2179
Epoch 3/100
5/5 [==============================] - 0s 6ms/step - loss: 0.2075
Epoch 4/100
5/5 [==============================] - 0s 5ms/step - loss: 0.1963
Epoch 5/100
5/5 [==============================] - 0s 6ms/step - loss: 0.1847
Epoch 6/100
5/5 [==============================] - 0s 5ms/step - loss: 0.1713
Epoch 7/100
5/5 [==============================] - 0s 6ms/step - loss: 0.1580
Epoch 8/100
5/5 [==============================] - 0s 5ms/step - loss: 0.1424
Epoch 9/100
5/5 [==============================] - 0s 7ms/step - loss: 0.1251
Epoch 10/100
5/5 [==============================] - 0s 6ms/step - loss: 0.1056
Epoch 11/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0849
Epoch 12/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0659
Epoch 13/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0497
Epoch 14/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0429
Epoch 15/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0412
Epoch 16/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0403
Epoch 17/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0364
Epoch 18/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0358
Epoch 19/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0363
Epoch 20/100
5/5 [==============================] - 0s 8ms/step - loss: 0.0385
Epoch 21/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0386
Epoch 22/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0367
```

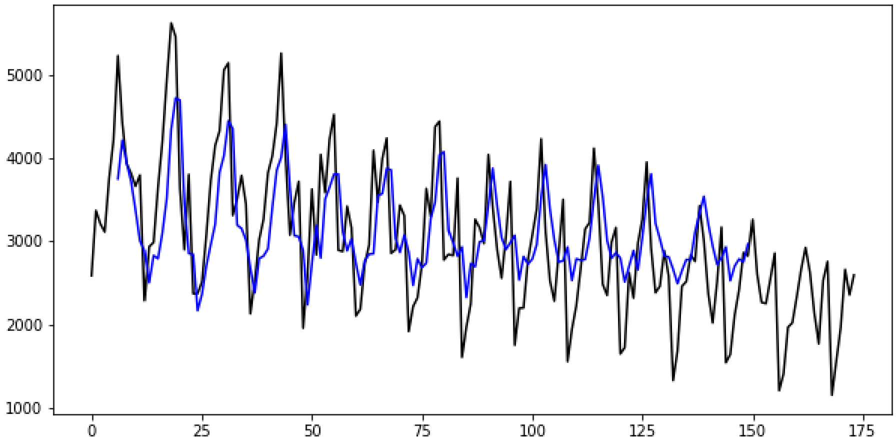
```
Epoch 23/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0335
Epoch 24/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0349
Epoch 25/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0365
Epoch 26/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0358
Epoch 27/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0360
Epoch 28/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0345
Epoch 29/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0338
Epoch 30/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0345
Epoch 31/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0375
Epoch 32/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0337
Epoch 33/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0359
Epoch 34/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0318
Epoch 35/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0325
Epoch 36/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0323
Epoch 37/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0315
Epoch 38/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0341
Epoch 39/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0311
Epoch 40/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0311
Epoch 41/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0300
Epoch 42/100
5/5 [==============================] - 0s 9ms/step - loss: 0.0297
Epoch 43/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0311
Epoch 44/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0303
Epoch 45/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0294
Epoch 46/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0297
Epoch 47/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0294
Epoch 48/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0297
Epoch 49/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0291
Epoch 50/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0279
Epoch 51/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0286
Epoch 52/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0300
Epoch 53/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0274
Epoch 54/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0261
Epoch 55/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0285
Epoch 56/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0272
Epoch 57/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0294
Epoch 58/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0286
Epoch 59/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0266
Epoch 60/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0266
Epoch 61/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0250
Epoch 62/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0278
Epoch 63/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0271
Epoch 64/100
5/5 [==============================] - 0s 8ms/step - loss: 0.0265
Epoch 65/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0271
Epoch 66/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0265
Epoch 67/100
5/5 [==============================] - 0s 9ms/step - loss: 0.0278
Epoch 68/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0287
Epoch 69/100
```

```
5/5 [==============================] - 0s 6ms/step - loss: 0.0265
Epoch 70/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0258
Epoch 71/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0261
Epoch 72/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0262
Epoch 73/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0237
Epoch 74/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0275
Epoch 75/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0284
Epoch 76/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0243
Epoch 77/100
5/5 [==============================] - 0s 9ms/step - loss: 0.0254
Epoch 78/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0240
Epoch 79/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0249
Epoch 80/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0251
Epoch 81/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0235
Epoch 82/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0270
Epoch 83/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0241
Epoch 84/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0266
Epoch 85/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0243
Epoch 86/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0241
Epoch 87/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0248
Epoch 88/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0246
Epoch 89/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0250
Epoch 90/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0259
Epoch 91/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0259
Epoch 92/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0249
Epoch 93/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0239
Epoch 94/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0253
Epoch 95/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0243
Epoch 96/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0246
Epoch 97/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0243
Epoch 98/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0248
Epoch 99/100
5/5 [==============================] - 0s 6ms/step - loss: 0.0249
Epoch 100/100
5/5 [==============================] - 0s 7ms/step - loss: 0.0247
```

Out[10]:
```
<keras.callbacks.History at 0x7fc2312533d0>
```

Построим ретроспективный прогноз, с переходом обратно к исходному масштабу данных:

In [11]:
```
trainPredict = model.predict(xx_tr)
trainPredict = scaler.inverse_transform(trainPredict)

plt.figure(figsize = (10, 5))
plt.plot(Fort, 'k')
plt.plot(np.r_[6:150], trainPredict,'b')
plt.show()
```



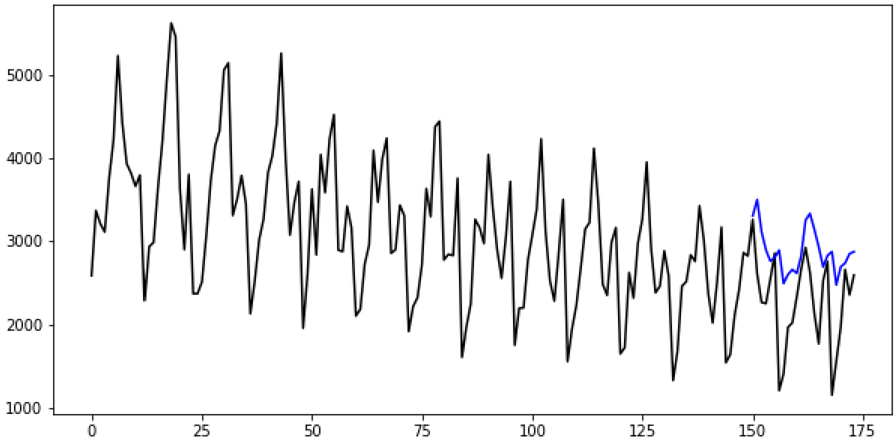
Для тестовой проверки прогноза преобразуем исходные точки в формат, понятный для модели LSTM-сети:

In [12]:
```
data_gen = TimeseriesGenerator(F_test,
                               F_test,
                               length=6,
                               sampling_rate=1,
                               batch_size=150)

batch_0 = data_gen[0]
x, y = batch_0
xx_test = np.reshape(x, (x.shape[0], 1, x.shape[1]))
yy_test = y

print(xx_test.shape) # прогноз на 24 точки по 6 наблюдениям
print(yy_test.shape) #
```

```
(24, 1, 6)
(24, 1)
```

Строим получившийся тестовый прогноз в нужном масштабе:

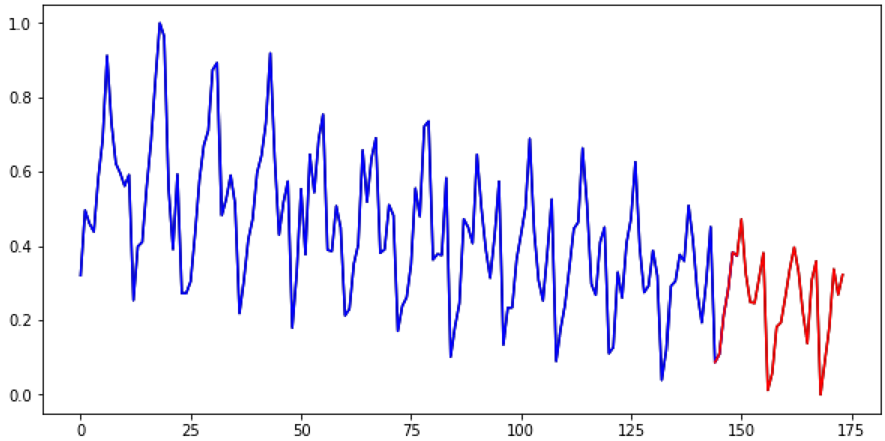
In [13]:
```
testPredict = model.predict(xx_test)
testPredict = scaler.inverse_transform(testPredict)

plt.figure(figsize = (10, 5))
plt.plot(Fort, 'k')
plt.plot(np.r_[150:174], testPredict, 'b')
plt.show()
```



Еще раз импортируем

In [14]:
```
file = h5py.File('Fort.mat', 'r')
data = file.get('Fort')
Fort = np.array(data)
F = Fort
look_back = 6
threshold = 150

scaler = MinMaxScaler(feature_range=(0, 1))
F = scaler.fit_transform(F)
F_tr = F[:threshold]
F_test = F[threshold-look_back:]

plt.figure(figsize = (10, 5))
plt.plot(F, 'k')
plt.plot(np.r_[:threshold], F_tr, 'b')
```

```
plt.plot(np.r_[threshold-look_back:F.shape[0]], F_test, 'r')
plt.show()
```



Для удобства будем использовать генераторы полностью:

In [22]:
```
train_data_gen = TimeseriesGenerator(F_tr,
                                     F_tr,
                                     length=look_back,
                                     sampling_rate=1,
                                     stride=1,
                                     batch_size=3)

test_data_gen = TimeseriesGenerator(F_test,
                                    F_test,
                                    length=look_back,
                                    sampling_rate=1,
                                    stride=1,
                                    batch_size=1)
```

In [23]:
```
model = Sequential()
model.add(LSTM(50, activation='relu', return_sequences=True, input_shape=(look_back, 1)))
model.add(Dropout(0.5))
model.add(LSTM(50, activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
model.fit(train_data_gen, epochs=100)
```

```
Epoch 1/100
48/48 [==============================] - 3s 7ms/step - loss: 0.0833
Epoch 2/100
48/48 [==============================] - 0s 8ms/step - loss: 0.0423
Epoch 3/100
48/48 [==============================] - 0s 8ms/step - loss: 0.0397
Epoch 4/100
48/48 [==============================] - 0s 8ms/step - loss: 0.0430
Epoch 5/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0375
Epoch 6/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0377
Epoch 7/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0377
Epoch 8/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0384
Epoch 9/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0365
Epoch 10/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0458
Epoch 11/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0388
Epoch 12/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0384
Epoch 13/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0353
Epoch 14/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0332
Epoch 15/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0325
Epoch 16/100
48/48 [==============================] - 0s 8ms/step - loss: 0.0332
Epoch 17/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0339
Epoch 18/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0359
Epoch 19/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0314
Epoch 20/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0316
Epoch 21/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0305
```

```
Epoch 22/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0317
Epoch 23/100
48/48 [==============================] - 0s 6ms/step - loss: 0.0321
Epoch 24/100
48/48 [==============================] - 0s 6ms/step - loss: 0.0301
Epoch 25/100
48/48 [==============================] - 0s 8ms/step - loss: 0.0304
Epoch 26/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0318
Epoch 27/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0287
Epoch 28/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0316
Epoch 29/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0313
Epoch 30/100
48/48 [==============================] - 0s 9ms/step - loss: 0.0288
Epoch 31/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0297
Epoch 32/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0336
Epoch 33/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0286
Epoch 34/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0306
Epoch 35/100
48/48 [==============================] - 0s 6ms/step - loss: 0.0282
Epoch 36/100
48/48 [==============================] - 0s 8ms/step - loss: 0.0293
Epoch 37/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0275
Epoch 38/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0344
Epoch 39/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0300
Epoch 40/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0297
Epoch 41/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0265
Epoch 42/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0262
Epoch 43/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0284
Epoch 44/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0279
Epoch 45/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0275
Epoch 46/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0291
Epoch 47/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0283
Epoch 48/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0297
Epoch 49/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0272
Epoch 50/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0248
Epoch 51/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0262
Epoch 52/100
48/48 [==============================] - 0s 9ms/step - loss: 0.0286
Epoch 53/100
48/48 [==============================] - 0s 6ms/step - loss: 0.0289
Epoch 54/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0280
Epoch 55/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0262
Epoch 56/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0280
Epoch 57/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0256
Epoch 58/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0254
Epoch 59/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0289
Epoch 60/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0259
Epoch 61/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0252
Epoch 62/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0240
Epoch 63/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0286
Epoch 64/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0293
Epoch 65/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0256
Epoch 66/100
48/48 [==============================] - 0s 6ms/step - loss: 0.0237
Epoch 67/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0246
Epoch 68/100
```

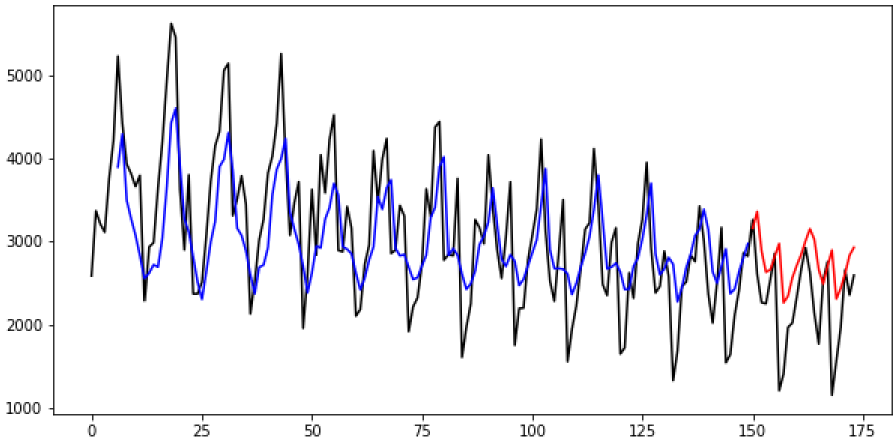
```
48/48 [==============================] - 0s 7ms/step - loss: 0.0232
Epoch 69/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0263
Epoch 70/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0261
Epoch 71/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0255
Epoch 72/100
48/48 [==============================] - 0s 6ms/step - loss: 0.0272
Epoch 73/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0272
Epoch 74/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0265
Epoch 75/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0242
Epoch 76/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0235
Epoch 77/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0259
Epoch 78/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0243
Epoch 79/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0237
Epoch 80/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0228
Epoch 81/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0229
Epoch 82/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0241
Epoch 83/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0240
Epoch 84/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0275
Epoch 85/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0258
Epoch 86/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0240
Epoch 87/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0247
Epoch 88/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0225
Epoch 89/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0271
Epoch 90/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0224
Epoch 91/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0232
Epoch 92/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0222
Epoch 93/100
48/48 [==============================] - 0s 8ms/step - loss: 0.0224
Epoch 94/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0233
Epoch 95/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0221
Epoch 96/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0231
Epoch 97/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0219
Epoch 98/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0223
Epoch 99/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0235
Epoch 100/100
48/48 [==============================] - 0s 7ms/step - loss: 0.0242
```

Out[23]:

```
<keras.callbacks.History at 0x7fc22e258a50>
```

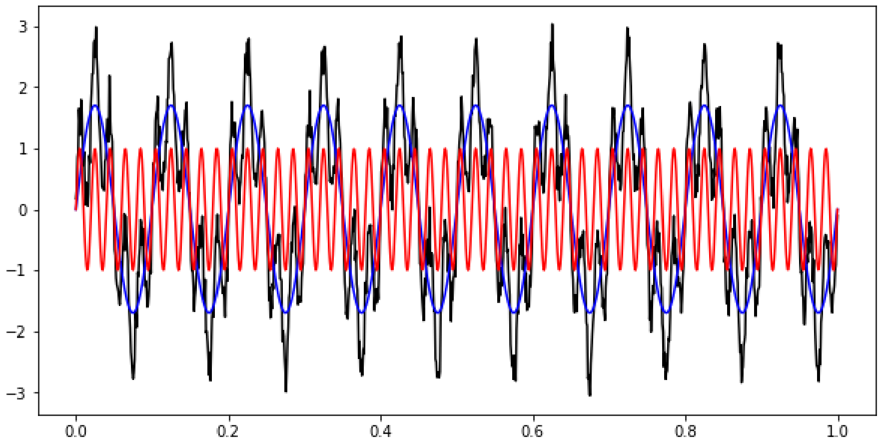
In [24]:

```python
trainPredict = model.predict(train_data_gen)
testPredict = model.predict(test_data_gen)

trainPredict = scaler.inverse_transform(trainPredict)
testPredict = scaler.inverse_transform(testPredict)

plt.figure(figsize = (10, 5))
plt.plot(Fort, 'k')
plt.plot(np.r_[look_back:threshold], trainPredict,'b')
plt.plot(np.r_[threshold:F.shape[0]], testPredict, 'r')
plt.show()
```



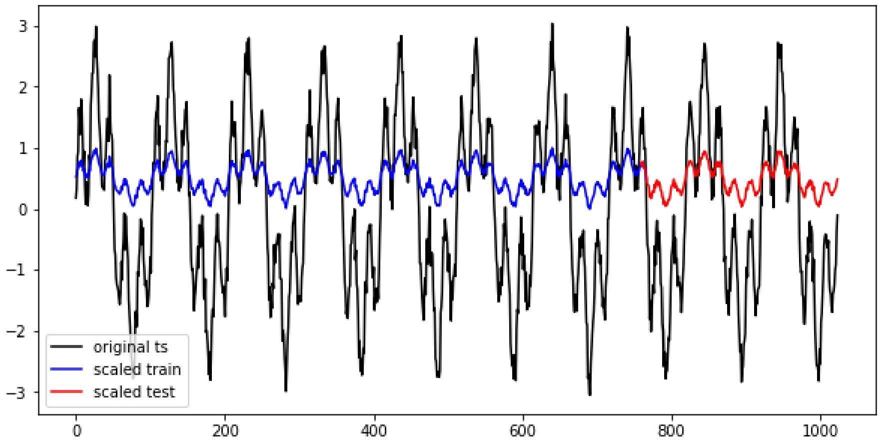
Построим прогноз на 256 точек для следующего модельного временного ряда:

In [66]:
```
import numpy.random

t = np.linspace(0, 1, 1024)
f1 = 10
f2 = 50
F = 1.7 * np.sin(2*np.pi*f1*t) + np.sin(2*np.pi*f2*t) + 0.2 * np.random.randn(len(t))

plt.figure(figsize = (10, 5))
plt.plot(t, F, 'k')
plt.plot(t, 1.7*np.sin(2*np.pi*f1*t), 'b')
plt.plot(t, np.sin(2*np.pi*f2*t), 'r')
plt.show()
```



Несмотря на то, что данные находятся в промежутке от -3 до 3, отмаштабируем их до диапазона 0–1, который является диапазоном значений с плавающей запятой, где у нас наибольшая точность. Также разобьем на обучающие и тестовые данные:

In [74]:
```
look_back = 9
threshold = 768

scaler = MinMaxScaler(feature_range=(0, 1))
Fs = scaler.fit_transform(F.reshape(-1, 1))
F_tr = Fs[:threshold]
F_test = Fs[threshold-look_back:]

plt.figure(figsize = (10, 5))
plt.plot(F, 'k', label = 'original ts')
plt.plot(np.r_[:threshold], F_tr, 'b', label='scaled train')
plt.plot(np.r_[threshold-look_back:F.shape[0]], F_test, 'r', label='scaled test')
plt.legend()
plt.show()
```



In [75]:
```
train_data_gen = TimeseriesGenerator(F_tr,
                                     F_tr,
                                     length=look_back,
                                     sampling_rate=1,
                                     stride=1,
                                     batch_size=3)

test_data_gen = TimeseriesGenerator(F_test,
                                    F_test,
                                    length=look_back,
                                    sampling_rate=1,
                                    stride=1,
                                    batch_size=1)
```

Для поиска оптимальной модели на основе LSTM, воспользуемся KerasTuner, который на основе функции-сборщика модели будет строить и обучать различные вариатны нейронной сети и сравнивать их между собой по метрике MSE. Модель с наименьшим MSE и будет оптимальной моделью для данного временного ряда.

In [29]:
```
def build_model(hp):
  model = Sequential()

  model.add(LSTM(hp.Int('input_unit', min_value=35, max_value=50, step=5),
               return_sequences=True,
               input_shape=(train_data_gen[0][0].shape[1], (train_data_gen[0][0].shape[2]))))

  for i in range(hp.Int('n_layers', 1, 3)):
    model.add(LSTM(hp.Int(f'lstm_{i}_units',min_value=35,max_value=50,step=5),
               return_sequences=True))

  model.add(LSTM(hp.Int('layer_2_neurons', min_value=35, max_value=50, step=5)))

  model.add(Dropout(hp.Float('Dropout_rate', min_value=0, max_value=0.5, step=0.1)))

  model.add(Dense(train_data_gen[0][1].shape[1],
                activation=hp.Choice('dense_activation', values=['relu', 'sigmoid'], default='relu')))

  model.compile(loss='mean_squared_error', optimizer='adam', metrics = ['mse'])
  return model
```

In [32]:
```
from keras_tuner import RandomSearch
tuner= RandomSearch(
        build_model,
        objective='mse',
        max_trials=2,
        executions_per_trial=1,
        directory='tuner_1')
```

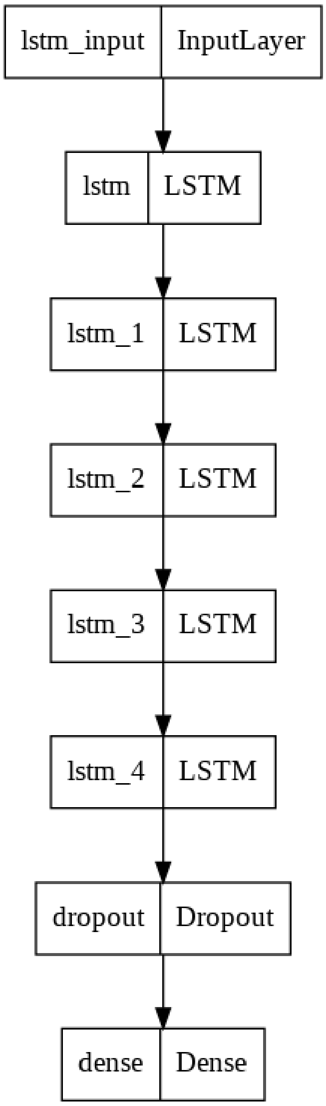
In [33]:
```
tuner.search(
        train_data_gen,
        epochs=20,
        batch_size=10,
        validation_data=test_data_gen)
```

```
Trial 2 Complete [00h 03m 11s]
mse: 0.0047436789609491825

Best mse So Far: 0.0047436789609491825
Total elapsed time: 00h 05m 53s
INFO:tensorflow:Oracle triggered exit
```

In [84]:
```
best_model = tuner.get_best_models(num_models=1)[0]
print(tuner.results_summary())
plot_model(best_model, to_file='model.png')
```

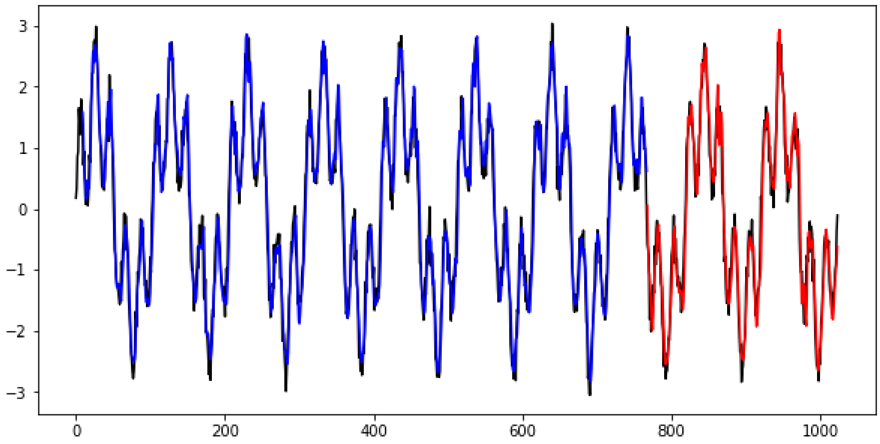
```
Results summary
Results in ./untitled_project
Showing 10 best trials
<keras_tuner.engine.objective.Objective object at 0x7fc229a42390>
Trial summary
Hyperparameters:
input_unit: 50
n_layers: 3
lstm_0_units: 35
layer_2_neurons: 45
Dropout_rate: 0.1
dense_activation: relu
lstm_1_units: 50
lstm_2_units: 35
Score: 0.0047436789609491825
Trial summary
Hyperparameters:
input_unit: 40
n_layers: 2
lstm_0_units: 45
layer_2_neurons: 40
Dropout_rate: 0.5
dense_activation: relu
lstm_1_units: 35
Score: 0.005200523417443037
None
```

Out[84]:



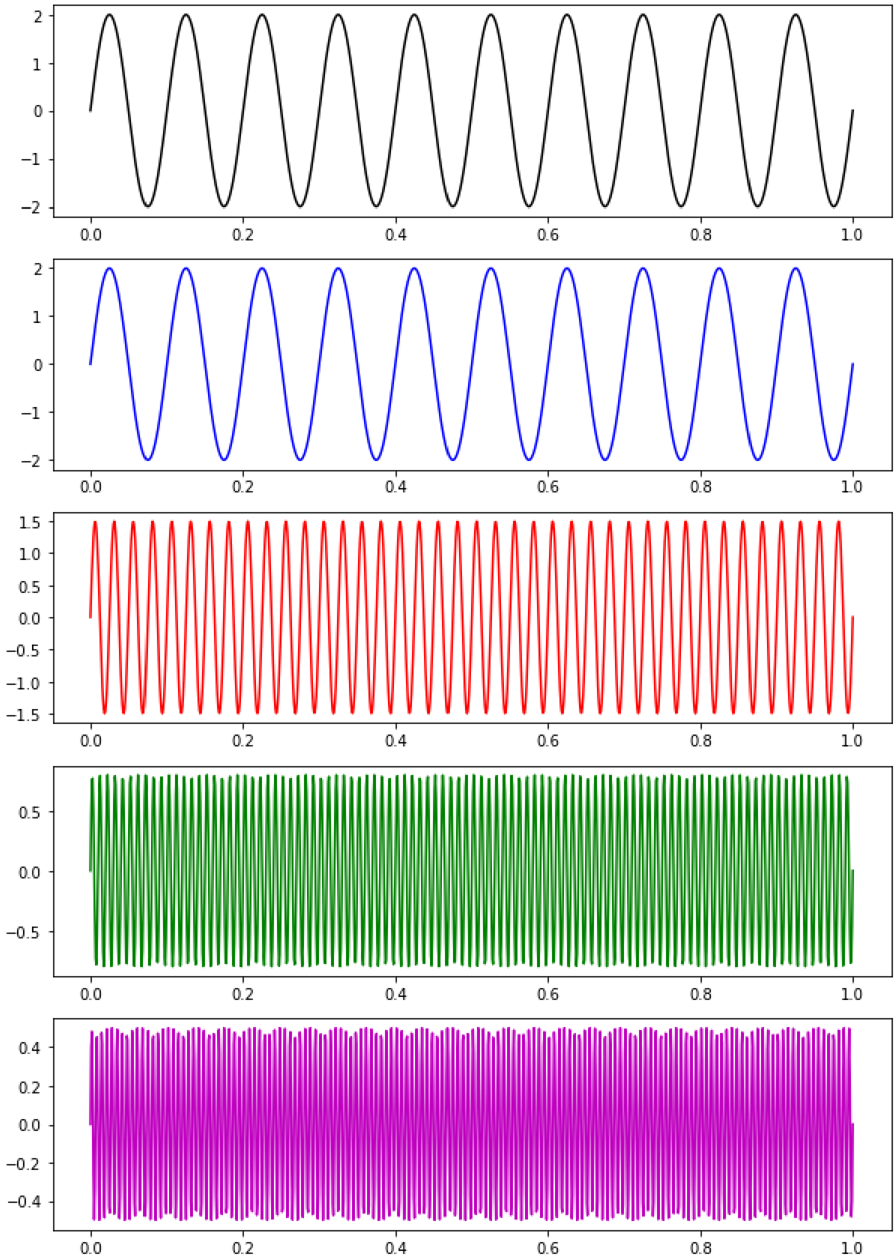
In [85]:

```
trainPredict = best_model.predict(train_data_gen)
testPredict = best_model.predict(test_data_gen)

trainPredict = scaler.inverse_transform(trainPredict)
testPredict = scaler.inverse_transform(testPredict)

plt.figure(figsize = (10, 5))
plt.plot(F, 'k')
plt.plot(np.r_[look_back:threshold], trainPredict,'b')
plt.plot(np.r_[threshold:F.shape[0]], testPredict, 'r')
plt.show()
```



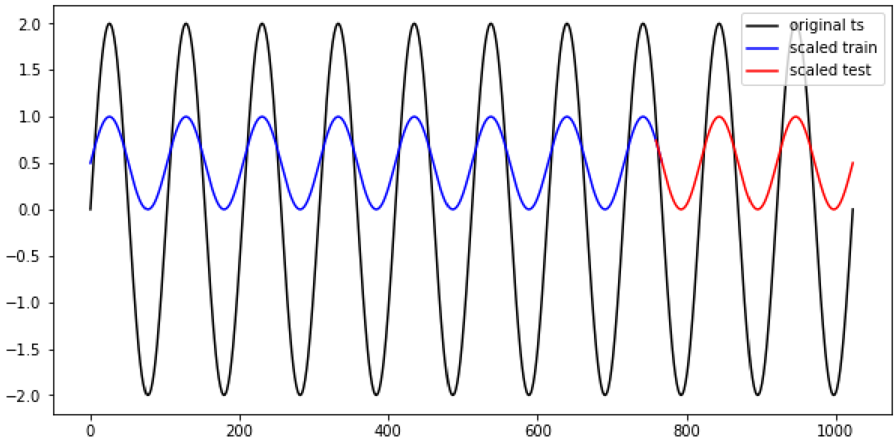
Построим прогноз на 256 точек для следующего модельного временного ряда:

In [86]:
```
t = np.linspace(0,1,1024)
f1 = 10
f2 = 40
f3 = 100
f4 = 150

F = 2.0*np.sin(2*np.pi*f1*t)
+ 1.5*np.sin(2*np.pi*f2*t)
+ 0.8*np.sin(2*np.pi*f3*t)
+ 0.5*np.sin(2*np.pi*f4*t)
+ np.random.randn(len(t))

plt.figure(figsize = (10, 15))
plt.subplot(5,1,1)
plt.plot(t, F, 'k')
plt.subplot(5,1,2)
plt.plot(t, 2.0*np.sin(2*np.pi*f1*t), 'b')
plt.subplot(5,1,3)
plt.plot(t, 1.5*np.sin(2*np.pi*f2*t), 'r')
plt.subplot(5,1,4)
plt.plot(t, 0.8*np.sin(2*np.pi*f3*t), 'g')
plt.subplot(5,1,5)
plt.plot(t, 0.5*np.sin(2*np.pi*f4*t), 'm')
plt.show()
```



In [87]:

```
look_back = 10
threshold = 768

scaler = MinMaxScaler(feature_range=(0, 1))
Fs = scaler.fit_transform(F.reshape(-1, 1))
F_tr = Fs[:threshold]
F_test = Fs[threshold-look_back:]

plt.figure(figsize = (10, 5))
plt.plot(F, 'k', label = 'original ts')
plt.plot(np.r_[:threshold], F_tr, 'b', label='scaled train')
plt.plot(np.r_[threshold-look_back:F.shape[0]], F_test, 'r', label='scaled test')
plt.legend()
plt.show()
```



In [92]:
```
train_data_gen = TimeseriesGenerator(F_tr,
                                     F_tr,
                                     length=look_back,
                                     sampling_rate=1,
                                     stride=1,
                                     batch_size=6)

test_data_gen = TimeseriesGenerator(F_test,
                                    F_test,
                                    length=look_back,
                                    sampling_rate=1,
                                    stride=1,
                                    batch_size=1)
```

In [98]:
```
tuner = RandomSearch(
        build_model,
        objective='mse',
        max_trials=2,
        executions_per_trial=1,
        directory='tuner_2')
```

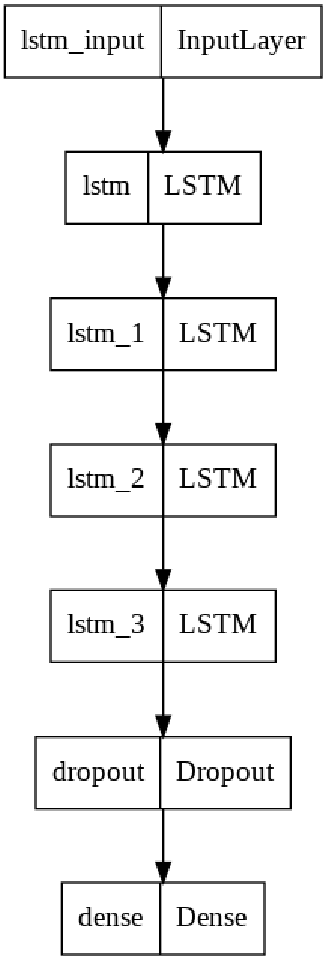
In [99]:
```
tuner.search(
        train_data_gen,
        epochs=20,
        batch_size=10,
        validation_data=test_data_gen)
```

```
Trial 2 Complete [00h 02m 54s]
mse: 0.000831178214866668

Best mse So Far: 0.000831178214866668
Total elapsed time: 00h 05m 51s
INFO:tensorflow:Oracle triggered exit
```

In [100…
```
best_model = tuner.get_best_models(num_models=1)[0]
print(tuner.results_summary())
plot_model(best_model, to_file='model.png')
```

```
Results summary
Results in tuner_2/untitled_project
Showing 10 best trials
<keras_tuner.engine.objective.Objective object at 0x7fc2ba13b590>
Trial summary
Hyperparameters:
input_unit: 45
n_layers: 2
lstm_0_units: 35
layer_2_neurons: 45
Dropout_rate: 0.1
dense_activation: sigmoid
lstm_1_units: 45
Score: 0.000831178214866668
Trial summary
Hyperparameters:
input_unit: 45
n_layers: 2
lstm_0_units: 45
layer_2_neurons: 45
Dropout_rate: 0.4
dense_activation: relu
lstm_1_units: 35
Score: 0.004835531581193209
None
```

Out[100…



In [101…

```
trainPredict = best_model.predict(train_data_gen)
testPredict = best_model.predict(test_data_gen)

trainPredict = scaler.inverse_transform(trainPredict)
testPredict = scaler.inverse_transform(testPredict)

plt.figure(figsize = (10, 5))
plt.plot(F, 'k')
plt.plot(np.r_[look_back:threshold], trainPredict,'b')
plt.plot(np.r_[threshold:F.shape[0]], testPredict, 'r')
plt.show()
```