Estimate generation v2

Use advanced models for generation estimation in the Global Power Plant Database. Primary model is a two-hidden-layer neural network.

In [50]:

```
# import what we'll need and set parameters

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from keras.models import Sequential
from keras.layers import Flatten, Dense, Lambda
from keras.layers import Conv2D, Dropout, Activation, MaxPooling2D
from keras.callbacks import EarlyStopping, ModelCheckpoint
from keras.utils.vis_utils import model_to_dot
from IPython.display import SVG
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn import metrics
import pydot

GPPD_FILENAME = '../../output_database/global_power_plant_database.csv'
WEIGHTS_FILE = "model/estimate_generation.h5"
VALIDATION_FRACTION = 0.2
```

In [37]:

```
# set up fuel colors

fuel_color = { 'Biomass':'#33a02c',
                'Coal':'sienna',
                'Cogeneration':'#e31a1c',
                'Gas':'#a6cee3',
                'Geothermal':'#b2df8a',
                'Hydro':'#1f78b4',
                'Nuclear':'#6a3d9a',
                'Oil':'black',
                'Other':'gray',
                'Petcoke':'#fb9a99',
                'Solar':'#ffff99',
                'Storage':'#ff1010',    # need better color
                'Waste':'#fdbf6f',
                'Wave_and_Tidal':'#b15928',
                'Wind':'#ff7f00'
}
```

In [2]:

```
# read in database
df = pd.read_csv(GPPD_FILENAME)
df.head()
```

Out[2]:

	country	country_long	name	gppd_idnr	capacity_mw	latitude	longitu
0	AFG	Afghanistan	Kajaki Hydroelectric Power Plant Afghanistan	GEODB0040538	33.00	32.3220	65.119(
1	AFG	Afghanistan	Mahipar Hydroelectric Power Plant Afghanistan	GEODB0040541	66.00	34.5560	69.4787
2	AFG	Afghanistan	Naghlu Dam Hydroelectric Power Plant Afghanistan	GEODB0040534	100.00	34.6410	69.717(
3	AFG	Afghanistan	Nangarhar (Darunta) Hydroelectric Power Plant ...	GEODB0040536	11.55	34.4847	70.3633
4	AFG	Afghanistan	Northwest Kabul Power Plant Afghanistan	GEODB0040540	42.00	34.5638	69.1134

5 rows × 22 columns

In [3]:

```
# show count for number of valid entries in each column
df.count()
```

Out[3]:

```
country                    25657
country_long               25657
name                       25637
gppd_idnr                  25657
capacity_mw                25657
latitude                   25657
longitude                  25657
fuel1                      25657
fuel2                       1670
fuel3                        295
fuel4                        107
commissioning_year         13933
owner                      17157
source                     25657
url                        25657
geolocation_source         25657
year_of_capacity_data      16065
generation_gwh_2013          371
generation_gwh_2014          386
generation_gwh_2015          887
generation_gwh_2016         8326
estimated_generation_gwh   24633
dtype: int64
```

In [4]:

```
# prepare data for training

# convert string-type columns to categories (assume no NaNs in these columns)
factorized_countries,country_key = df['country'].factorize()
df['country'] = factorized_countries
factorized_fuel1,fuel1_key = df['fuel1'].factorize()
df['fuel1'] = factorized_fuel1

# create new data frame with relevant predictor variable (X) columns and 2016 ge
neration
# clean data frame by removing NaNs
X_columns = ['country','capacity_mw','latitude','longitude','commissioning_year'
,'fuel1']
df_clean = df[X_columns + ['generation_gwh_2016']].dropna(how='any')

# convert 2016 generation into capacity factor and remove rows with erroneous ca
pacity factors
df_clean['capacity_factor'] = df_clean.apply(lambda row:row['generation_gwh_2016
']/(24.0*365.0*0.001*row['capacity_mw']),axis=1)
df_clean = df_clean[df_clean.capacity_factor >= 0.0]
df_clean = df_clean[df_clean.capacity_factor <= 1.0]

# create np arrays from data frame
X_data = df_clean[X_columns].as_matrix()
y_column = ['capacity_factor']
y_data = df_clean[y_column].as_matrix()

# show results
print(X_data)
print(y_data)
print(len(X_data))
print(len(y_data))
```

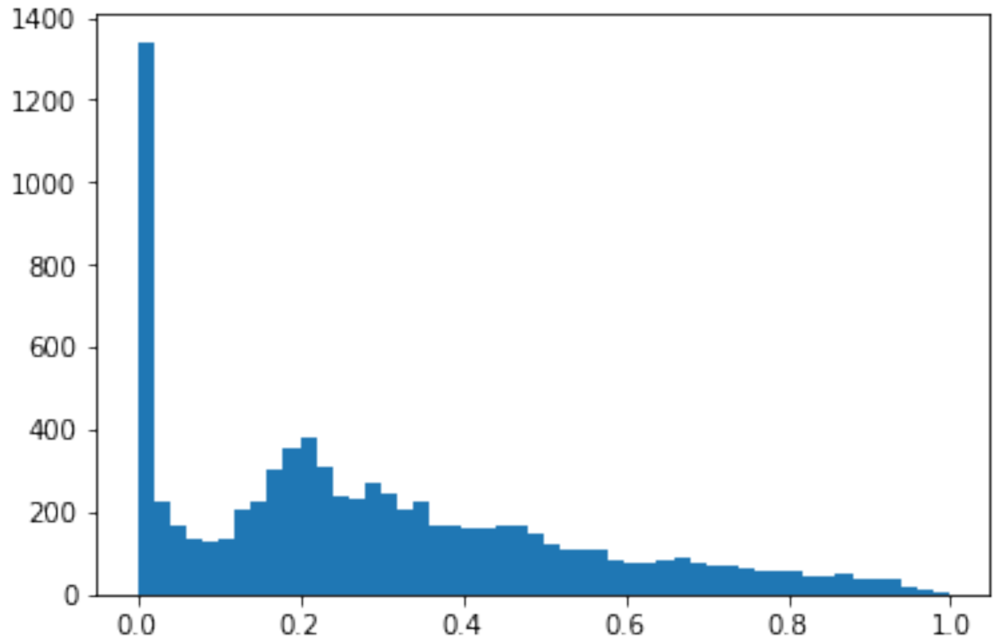
```
[[  8.00000000e+00   2.89000000e+02   4.72078000e+01   1.10057000e+0
1
    1.98100000e+03   0.00000000e+00]
 [  8.00000000e+00   5.00000000e+02   4.72696000e+01   1.09678000e+0
1
    1.98100000e+03   0.00000000e+00]
 [  4.30000000e+01   2.25000000e+03   3.02483000e+01   3.09471000e+0
1
    2.01400000e+03   1.00000000e+00]
 ...,
 [  1.57000000e+02   2.80000000e+01   1.43611000e+01   1.08720300e+0
2
    2.01400000e+03   0.00000000e+00]
 [  1.57000000e+02   1.95000000e+01   1.21526000e+01   1.08378700e+0
2
    2.01000000e+03   0.00000000e+00]
 [  1.57000000e+02   3.00000000e+01   1.58600000e+01   1.07653800e+0
2
    2.00900000e+03   0.00000000e+00]]
[[ 0.04692255]
 [ 0.02934475]
 [ 0.00674784]
 ...,
 [ 0.41992825]
 [ 0.46247512]
 [ 0.46689498]]
8055
8055
```

In [5]:

```
# examine training data to confirm valid capacity factors

print(u"Y data max: {0}, min: {1}".format(y_data.max(),y_data.min()))
plt.hist(y_data,bins=50)
plt.show()
```

```
Y data max: 0.998536954444, min: 0.0
```



In [6]:

```
# calculate scaling values for input data

mean_vals = np.mean(X_data,axis=0)
range_vals = np.max(X_data,axis=0) - np.min(X_data,axis=0)
```

In [41]:

```
# set up neural network

INPUT_SHAPE = X_data[0].shape
print(u"Input shape is: {0}".format(INPUT_SHAPE))
DROPOUT_RATE = 0.15
DENSE_LAYER_SIZE = 128

def myNet():
    model = Sequential()
    model.add(Lambda(lambda x: x - mean_vals,input_shape = INPUT_SHAPE))   # pla
ceholder for normalization
    model.add(Dense(DENSE_LAYER_SIZE,activation='relu'))
    model.add(Dropout(DROPOUT_RATE))
    model.add(Dense(DENSE_LAYER_SIZE,activation='relu'))
    model.add(Dropout(DROPOUT_RATE))
    model.add(Dense(DENSE_LAYER_SIZE,activation='relu'))
    model.add(Dense(1))
    return model

model = myNet()
model.compile(loss='mean_squared_error',optimizer='adam',metrics=['mean_absolute
_error'])
print("Model contains {0} parameters.".format(model.count_params()))
print(model.summary())
```

```
Input shape is: (6,)
Model contains 34049 parameters.
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda_2 (Lambda)            (None, 6)                 0
_________________________________________________________________
dense_5 (Dense)              (None, 128)               896
_________________________________________________________________
dropout_3 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_6 (Dense)              (None, 128)               16512
_________________________________________________________________
dropout_4 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_7 (Dense)              (None, 128)               16512
_________________________________________________________________
dense_8 (Dense)              (None, 1)                 129
=================================================================
Total params: 34,049
Trainable params: 34,049
Non-trainable params: 0
_________________________________________________________________
None
```

In [46]:

```
# fit model

BATCH_SIZE = 64
NUM_EPOCHS = 512
early_stop = EarlyStopping(monitor='val_loss',min_delta=0.001,patience=64)
check_point = ModelCheckpoint(WEIGHTS_FILE,monitor='val_loss',save_best_only=Tru
e,mode='max')
history_object = model.fit(x=X_data, y=y_data,
                           batch_size = BATCH_SIZE,
                           epochs = NUM_EPOCHS,
                           verbose = 1,
                           callbacks = [early_stop,check_point],
                           validation_split = VALIDATION_FRACTION)

# reload model with best weights from training
model = myNet()
model.load_weights(WEIGHTS_FILE)
model.compile(loss='mean_squared_error',optimizer='adam',metrics=['mean_absolute
_error'])
print("Finished training; model reloaded with optimum weights.")
#model.save(WEIGHTS_FILE)
```

```
Train on 6444 samples, validate on 1611 samples
Epoch 1/512
6444/6444 [==============================] - 1s 79us/step - loss: 0.
0365 - mean_absolute_error: 0.1393 - val_loss: 0.0739 - val_mean_abs
olute_error: 0.1800
Epoch 2/512
6444/6444 [==============================] - 0s 76us/step - loss: 0.
0352 - mean_absolute_error: 0.1374 - val_loss: 0.0419 - val_mean_abs
olute_error: 0.1469
Epoch 3/512
6444/6444 [==============================] - 0s 73us/step - loss: 0.
0355 - mean_absolute_error: 0.1381 - val_loss: 0.0556 - val_mean_abs
olute_error: 0.1665
Epoch 4/512
6444/6444 [==============================] - 0s 75us/step - loss: 0.
0356 - mean_absolute_error: 0.1381 - val_loss: 0.0494 - val_mean_abs
olute_error: 0.1576
Epoch 5/512
6444/6444 [==============================] - 0s 75us/step - loss: 0.
0351 - mean_absolute_error: 0.1363 - val_loss: 0.0731 - val_mean_abs
olute_error: 0.1799
Epoch 6/512
6444/6444 [==============================] - 0s 74us/step - loss: 0.
0357 - mean_absolute_error: 0.1388 - val_loss: 0.0501 - val_mean_abs
olute_error: 0.1593
Epoch 7/512
6444/6444 [==============================] - 0s 74us/step - loss: 0.
0356 - mean_absolute_error: 0.1375 - val_loss: 0.0635 - val_mean_abs
olute_error: 0.1704
```

```
Epoch 8/512
6444/6444 [==============================] - 0s 72us/step - loss: 0.
0354 - mean_absolute_error: 0.1371 - val_loss: 0.0517 - val_mean_abs
olute_error: 0.1596
Epoch 9/512
6444/6444 [==============================] - 0s 70us/step - loss: 0.
0354 - mean_absolute_error: 0.1372 - val_loss: 0.0863 - val_mean_abs
olute_error: 0.1856
Epoch 10/512
6444/6444 [==============================] - 0s 71us/step - loss: 0.
0352 - mean_absolute_error: 0.1372 - val_loss: 0.0812 - val_mean_abs
olute_error: 0.1831
Epoch 11/512
6444/6444 [==============================] - 0s 72us/step - loss: 0.
0354 - mean_absolute_error: 0.1375 - val_loss: 0.0492 - val_mean_abs
olute_error: 0.1584
Epoch 12/512
6444/6444 [==============================] - 0s 75us/step - loss: 0.
0361 - mean_absolute_error: 0.1385 - val_loss: 0.0439 - val_mean_abs
olute_error: 0.1500
Epoch 13/512
6444/6444 [==============================] - 0s 76us/step - loss: 0.
0356 - mean_absolute_error: 0.1371 - val_loss: 0.0451 - val_mean_abs
olute_error: 0.1518
Epoch 14/512
6444/6444 [==============================] - 0s 75us/step - loss: 0.
0347 - mean_absolute_error: 0.1365 - val_loss: 0.0345 - val_mean_abs
olute_error: 0.1305
Epoch 15/512
6444/6444 [==============================] - 0s 76us/step - loss: 0.
0347 - mean_absolute_error: 0.1365 - val_loss: 0.0464 - val_mean_abs
olute_error: 0.1539
Epoch 16/512
6444/6444 [==============================] - 0s 72us/step - loss: 0.
0355 - mean_absolute_error: 0.1374 - val_loss: 0.0371 - val_mean_abs
olute_error: 0.1393
Epoch 17/512
6444/6444 [==============================] - 0s 76us/step - loss: 0.
0352 - mean_absolute_error: 0.1368 - val_loss: 0.0922 - val_mean_abs
olute_error: 0.1930
Epoch 18/512
6444/6444 [==============================] - 0s 74us/step - loss: 0.
0353 - mean_absolute_error: 0.1372 - val_loss: 0.0748 - val_mean_abs
olute_error: 0.1780
Epoch 19/512
6444/6444 [==============================] - 0s 75us/step - loss: 0.
0357 - mean_absolute_error: 0.1372 - val_loss: 0.0487 - val_mean_abs
olute_error: 0.1572
Epoch 20/512
6444/6444 [==============================] - 0s 75us/step - loss: 0.
0346 - mean_absolute_error: 0.1357 - val_loss: 0.0379 - val_mean_abs
olute_error: 0.1393
Epoch 21/512
```

```
6444/6444 [==============================] - 0s 76us/step - loss: 0.
0352 - mean_absolute_error: 0.1368 - val_loss: 0.0525 - val_mean_abs
olute_error: 0.1599
Epoch 22/512
6444/6444 [==============================] - 0s 74us/step - loss: 0.
0359 - mean_absolute_error: 0.1371 - val_loss: 0.0365 - val_mean_abs
olute_error: 0.1398
Epoch 23/512
6444/6444 [==============================] - 0s 76us/step - loss: 0.
0350 - mean_absolute_error: 0.1364 - val_loss: 0.0355 - val_mean_abs
olute_error: 0.1359
Epoch 24/512
6444/6444 [==============================] - 0s 74us/step - loss: 0.
0354 - mean_absolute_error: 0.1368 - val_loss: 0.0412 - val_mean_abs
olute_error: 0.1454
Epoch 25/512
6444/6444 [==============================] - 0s 72us/step - loss: 0.
0347 - mean_absolute_error: 0.1363 - val_loss: 0.0387 - val_mean_abs
olute_error: 0.1362
Epoch 26/512
6444/6444 [==============================] - 0s 75us/step - loss: 0.
0349 - mean_absolute_error: 0.1368 - val_loss: 0.0362 - val_mean_abs
olute_error: 0.1352
Epoch 27/512
6444/6444 [==============================] - 0s 75us/step - loss: 0.
0353 - mean_absolute_error: 0.1371 - val_loss: 0.0356 - val_mean_abs
olute_error: 0.1335
Epoch 28/512
6444/6444 [==============================] - 0s 73us/step - loss: 0.
0342 - mean_absolute_error: 0.1349 - val_loss: 0.0390 - val_mean_abs
olute_error: 0.1418
Epoch 29/512
6444/6444 [==============================] - 0s 76us/step - loss: 0.
0348 - mean_absolute_error: 0.1364 - val_loss: 0.0354 - val_mean_abs
olute_error: 0.1331
Epoch 30/512
6444/6444 [==============================] - 0s 75us/step - loss: 0.
0348 - mean_absolute_error: 0.1359 - val_loss: 0.0330 - val_mean_abs
olute_error: 0.1255
Epoch 31/512
6444/6444 [==============================] - 0s 75us/step - loss: 0.
0345 - mean_absolute_error: 0.1358 - val_loss: 0.0454 - val_mean_abs
olute_error: 0.1523
Epoch 32/512
6444/6444 [==============================] - 0s 76us/step - loss: 0.
0350 - mean_absolute_error: 0.1359 - val_loss: 0.0608 - val_mean_abs
olute_error: 0.1688
Epoch 33/512
6444/6444 [==============================] - 0s 74us/step - loss: 0.
0350 - mean_absolute_error: 0.1360 - val_loss: 0.0341 - val_mean_abs
olute_error: 0.1303
Epoch 34/512
6444/6444 [==============================] - 0s 76us/step - loss: 0.
```

```
0351 - mean_absolute_error: 0.1366 - val_loss: 0.0402 - val_mean_abs
olute_error: 0.1425
Epoch 35/512
6444/6444 [==============================] - 0s 74us/step - loss: 0.
0356 - mean_absolute_error: 0.1368 - val_loss: 0.0913 - val_mean_abs
olute_error: 0.1891
Epoch 36/512
6444/6444 [==============================] - 0s 77us/step - loss: 0.
0349 - mean_absolute_error: 0.1362 - val_loss: 0.0456 - val_mean_abs
olute_error: 0.1522
Epoch 37/512
6444/6444 [==============================] - 0s 72us/step - loss: 0.
0347 - mean_absolute_error: 0.1364 - val_loss: 0.0486 - val_mean_abs
olute_error: 0.1502
Epoch 38/512
6444/6444 [==============================] - 0s 76us/step - loss: 0.
0359 - mean_absolute_error: 0.1371 - val_loss: 0.0515 - val_mean_abs
olute_error: 0.1581
Epoch 39/512
6444/6444 [==============================] - 0s 75us/step - loss: 0.
0348 - mean_absolute_error: 0.1359 - val_loss: 0.0438 - val_mean_abs
olute_error: 0.1471
Epoch 40/512
6444/6444 [==============================] - 1s 79us/step - loss: 0.
0347 - mean_absolute_error: 0.1361 - val_loss: 0.0411 - val_mean_abs
olute_error: 0.1439
Epoch 41/512
6444/6444 [==============================] - 0s 77us/step - loss: 0.
0346 - mean_absolute_error: 0.1353 - val_loss: 0.0405 - val_mean_abs
olute_error: 0.1428
Epoch 42/512
6444/6444 [==============================] - 1s 81us/step - loss: 0.
0345 - mean_absolute_error: 0.1351 - val_loss: 0.0416 - val_mean_abs
olute_error: 0.1441
Epoch 43/512
6444/6444 [==============================] - 0s 76us/step - loss: 0.
0346 - mean_absolute_error: 0.1353 - val_loss: 0.0340 - val_mean_abs
olute_error: 0.1286
Epoch 44/512
6444/6444 [==============================] - 1s 85us/step - loss: 0.
0344 - mean_absolute_error: 0.1348 - val_loss: 0.0360 - val_mean_abs
olute_error: 0.1335
Epoch 45/512
6444/6444 [==============================] - 1s 78us/step - loss: 0.
0348 - mean_absolute_error: 0.1358 - val_loss: 0.0427 - val_mean_abs
olute_error: 0.1491
Epoch 46/512
6444/6444 [==============================] - 1s 85us/step - loss: 0.
0356 - mean_absolute_error: 0.1378 - val_loss: 0.0367 - val_mean_abs
olute_error: 0.1365
Epoch 47/512
6444/6444 [==============================] - 1s 78us/step - loss: 0.
0343 - mean_absolute_error: 0.1349 - val_loss: 0.0330 - val_mean_abs
```

```
olute_error: 0.1262
Epoch 48/512
6444/6444 [==============================] - 1s 96us/step - loss: 0.
0345 - mean_absolute_error: 0.1352 - val_loss: 0.0380 - val_mean_abs
olute_error: 0.1395
Epoch 49/512
6444/6444 [==============================] - 1s 78us/step - loss: 0.
0355 - mean_absolute_error: 0.1370 - val_loss: 0.0361 - val_mean_abs
olute_error: 0.1332
Epoch 50/512
6444/6444 [==============================] - 1s 81us/step - loss: 0.
0344 - mean_absolute_error: 0.1348 - val_loss: 0.0399 - val_mean_abs
olute_error: 0.1446
Epoch 51/512
6444/6444 [==============================] - 0s 75us/step - loss: 0.
0348 - mean_absolute_error: 0.1359 - val_loss: 0.0657 - val_mean_abs
olute_error: 0.1735
Epoch 52/512
6444/6444 [==============================] - 0s 71us/step - loss: 0.
0343 - mean_absolute_error: 0.1347 - val_loss: 0.0343 - val_mean_abs
olute_error: 0.1263
Epoch 53/512
6444/6444 [==============================] - 0s 73us/step - loss: 0.
0341 - mean_absolute_error: 0.1342 - val_loss: 0.0345 - val_mean_abs
olute_error: 0.1259
Epoch 54/512
6444/6444 [==============================] - 1s 90us/step - loss: 0.
0360 - mean_absolute_error: 0.1374 - val_loss: 0.0778 - val_mean_abs
olute_error: 0.1810
Epoch 55/512
6444/6444 [==============================] - 0s 74us/step - loss: 0.
0349 - mean_absolute_error: 0.1364 - val_loss: 0.0483 - val_mean_abs
olute_error: 0.1562
Epoch 56/512
6444/6444 [==============================] - 1s 86us/step - loss: 0.
0346 - mean_absolute_error: 0.1350 - val_loss: 0.0425 - val_mean_abs
olute_error: 0.1474
Epoch 57/512
6444/6444 [==============================] - 1s 81us/step - loss: 0.
0348 - mean_absolute_error: 0.1354 - val_loss: 0.0541 - val_mean_abs
olute_error: 0.1632
Epoch 58/512
6444/6444 [==============================] - 1s 88us/step - loss: 0.
0346 - mean_absolute_error: 0.1348 - val_loss: 0.0596 - val_mean_abs
olute_error: 0.1670
Epoch 59/512
6444/6444 [==============================] - 1s 84us/step - loss: 0.
0341 - mean_absolute_error: 0.1345 - val_loss: 0.0650 - val_mean_abs
olute_error: 0.1712
Epoch 60/512
6444/6444 [==============================] - 1s 81us/step - loss: 0.
0341 - mean_absolute_error: 0.1342 - val_loss: 0.0386 - val_mean_abs
olute_error: 0.1417
```

```
Epoch 61/512
6444/6444 [==============================] - 1s 82us/step - loss: 0.
0351 - mean_absolute_error: 0.1364 - val_loss: 0.0425 - val_mean_abs
olute_error: 0.1482
Epoch 62/512
6444/6444 [==============================] - 1s 90us/step - loss: 0.
0349 - mean_absolute_error: 0.1356 - val_loss: 0.0360 - val_mean_abs
olute_error: 0.1333
Epoch 63/512
6444/6444 [==============================] - 1s 80us/step - loss: 0.
0348 - mean_absolute_error: 0.1347 - val_loss: 0.0358 - val_mean_abs
olute_error: 0.1348
Epoch 64/512
6444/6444 [==============================] - 1s 90us/step - loss: 0.
0345 - mean_absolute_error: 0.1348 - val_loss: 0.0363 - val_mean_abs
olute_error: 0.1331
Epoch 65/512
6444/6444 [==============================] - 1s 80us/step - loss: 0.
0338 - mean_absolute_error: 0.1344 - val_loss: 0.0635 - val_mean_abs
olute_error: 0.1684
Epoch 66/512
6444/6444 [==============================] - 1s 82us/step - loss: 0.
0346 - mean_absolute_error: 0.1342 - val_loss: 0.0412 - val_mean_abs
olute_error: 0.1454
Epoch 67/512
6444/6444 [==============================] - 1s 81us/step - loss: 0.
0348 - mean_absolute_error: 0.1346 - val_loss: 0.0403 - val_mean_abs
olute_error: 0.1422
Epoch 68/512
6444/6444 [==============================] - 1s 85us/step - loss: 0.
0371 - mean_absolute_error: 0.1396 - val_loss: 0.0383 - val_mean_abs
olute_error: 0.1427
Epoch 69/512
6444/6444 [==============================] - 1s 85us/step - loss: 0.
0356 - mean_absolute_error: 0.1378 - val_loss: 0.0343 - val_mean_abs
olute_error: 0.1309
Epoch 70/512
6444/6444 [==============================] - 1s 84us/step - loss: 0.
0350 - mean_absolute_error: 0.1369 - val_loss: 0.0341 - val_mean_abs
olute_error: 0.1297
Epoch 71/512
6444/6444 [==============================] - 1s 83us/step - loss: 0.
0347 - mean_absolute_error: 0.1360 - val_loss: 0.0458 - val_mean_abs
olute_error: 0.1488
Epoch 72/512
6444/6444 [==============================] - 1s 84us/step - loss: 0.
0342 - mean_absolute_error: 0.1342 - val_loss: 0.0396 - val_mean_abs
olute_error: 0.1428
Epoch 73/512
6444/6444 [==============================] - 1s 82us/step - loss: 0.
0346 - mean_absolute_error: 0.1360 - val_loss: 0.0456 - val_mean_abs
olute_error: 0.1520
Epoch 74/512
```

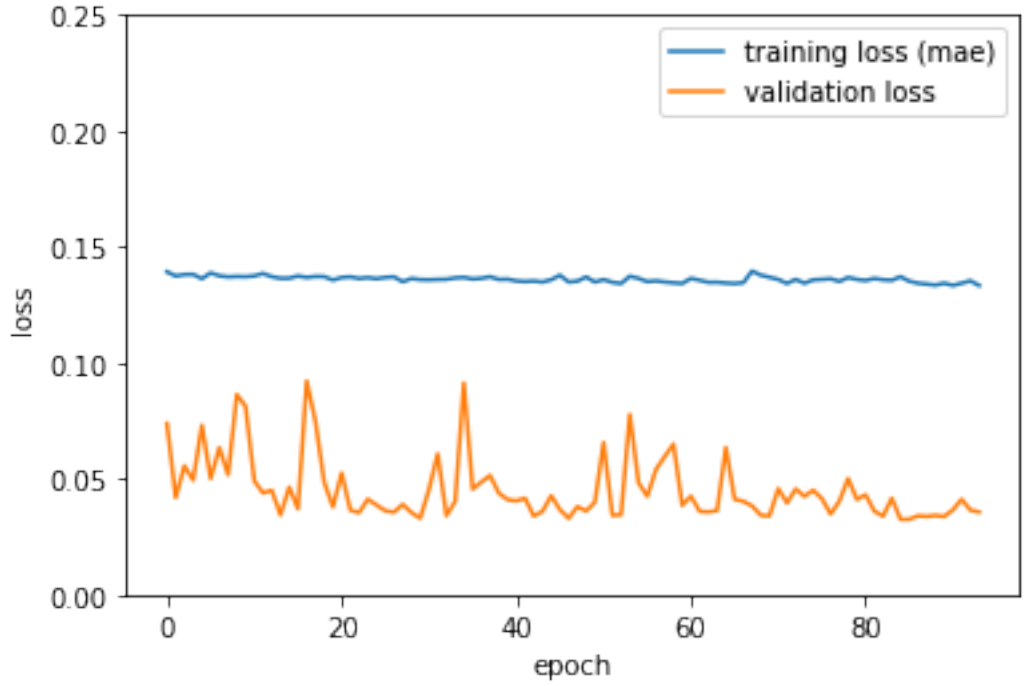
```
6444/6444 [==============================] - 1s 83us/step - loss: 0.
0340 - mean_absolute_error: 0.1343 - val_loss: 0.0424 - val_mean_abs
olute_error: 0.1452
Epoch 75/512
6444/6444 [==============================] - 1s 84us/step - loss: 0.
0348 - mean_absolute_error: 0.1358 - val_loss: 0.0451 - val_mean_abs
olute_error: 0.1517
Epoch 76/512
6444/6444 [==============================] - 1s 86us/step - loss: 0.
0352 - mean_absolute_error: 0.1360 - val_loss: 0.0415 - val_mean_abs
olute_error: 0.1455
Epoch 77/512
6444/6444 [==============================] - 1s 86us/step - loss: 0.
0347 - mean_absolute_error: 0.1363 - val_loss: 0.0348 - val_mean_abs
olute_error: 0.1324
Epoch 78/512
6444/6444 [==============================] - 1s 95us/step - loss: 0.
0344 - mean_absolute_error: 0.1351 - val_loss: 0.0404 - val_mean_abs
olute_error: 0.1442
Epoch 79/512
6444/6444 [==============================] - 1s 96us/step - loss: 0.
0352 - mean_absolute_error: 0.1368 - val_loss: 0.0501 - val_mean_abs
olute_error: 0.1598
Epoch 80/512
6444/6444 [==============================] - 1s 84us/step - loss: 0.
0349 - mean_absolute_error: 0.1360 - val_loss: 0.0411 - val_mean_abs
olute_error: 0.1454
Epoch 81/512
6444/6444 [==============================] - 1s 88us/step - loss: 0.
0346 - mean_absolute_error: 0.1355 - val_loss: 0.0432 - val_mean_abs
olute_error: 0.1516
Epoch 82/512
6444/6444 [==============================] - 1s 87us/step - loss: 0.
0349 - mean_absolute_error: 0.1364 - val_loss: 0.0361 - val_mean_abs
olute_error: 0.1357
Epoch 83/512
6444/6444 [==============================] - 1s 83us/step - loss: 0.
0349 - mean_absolute_error: 0.1358 - val_loss: 0.0339 - val_mean_abs
olute_error: 0.1270
Epoch 84/512
6444/6444 [==============================] - 1s 88us/step - loss: 0.
0346 - mean_absolute_error: 0.1356 - val_loss: 0.0416 - val_mean_abs
olute_error: 0.1462
Epoch 85/512
6444/6444 [==============================] - 1s 86us/step - loss: 0.
0353 - mean_absolute_error: 0.1371 - val_loss: 0.0326 - val_mean_abs
olute_error: 0.1258
Epoch 86/512
6444/6444 [==============================] - 1s 92us/step - loss: 0.
0342 - mean_absolute_error: 0.1352 - val_loss: 0.0326 - val_mean_abs
olute_error: 0.1263
Epoch 87/512
6444/6444 [==============================] - 1s 92us/step - loss: 0.
```

```
0341 - mean_absolute_error: 0.1343 - val_loss: 0.0341 - val_mean_abs
olute_error: 0.1309
Epoch 88/512
6444/6444 [==============================] - 1s 92us/step - loss: 0.
0341 - mean_absolute_error: 0.1339 - val_loss: 0.0338 - val_mean_abs
olute_error: 0.1313
Epoch 89/512
6444/6444 [==============================] - 1s 91us/step - loss: 0.
0340 - mean_absolute_error: 0.1335 - val_loss: 0.0343 - val_mean_abs
olute_error: 0.1317
Epoch 90/512
6444/6444 [==============================] - 1s 89us/step - loss: 0.
0340 - mean_absolute_error: 0.1343 - val_loss: 0.0338 - val_mean_abs
olute_error: 0.1289
Epoch 91/512
6444/6444 [==============================] - 1s 88us/step - loss: 0.
0339 - mean_absolute_error: 0.1334 - val_loss: 0.0366 - val_mean_abs
olute_error: 0.1364
Epoch 92/512
6444/6444 [==============================] - 1s 85us/step - loss: 0.
0344 - mean_absolute_error: 0.1343 - val_loss: 0.0412 - val_mean_abs
olute_error: 0.1439
Epoch 93/512
6444/6444 [==============================] - 1s 83us/step - loss: 0.
0349 - mean_absolute_error: 0.1354 - val_loss: 0.0365 - val_mean_abs
olute_error: 0.1325
Epoch 94/512
6444/6444 [==============================] - 1s 83us/step - loss: 0.
0338 - mean_absolute_error: 0.1333 - val_loss: 0.0357 - val_mean_abs
olute_error: 0.1324
Finished training; model reloaded with optimum weights.
```

In [47]:

```
# plot training loss history

plt.plot(history_object.history['mean_absolute_error'])
plt.plot(history_object.history['val_loss'])
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['training loss (mae)','validation loss'],loc='upper right')
plt.ylim([0,0.25])
plt.show()
```



In [12]:

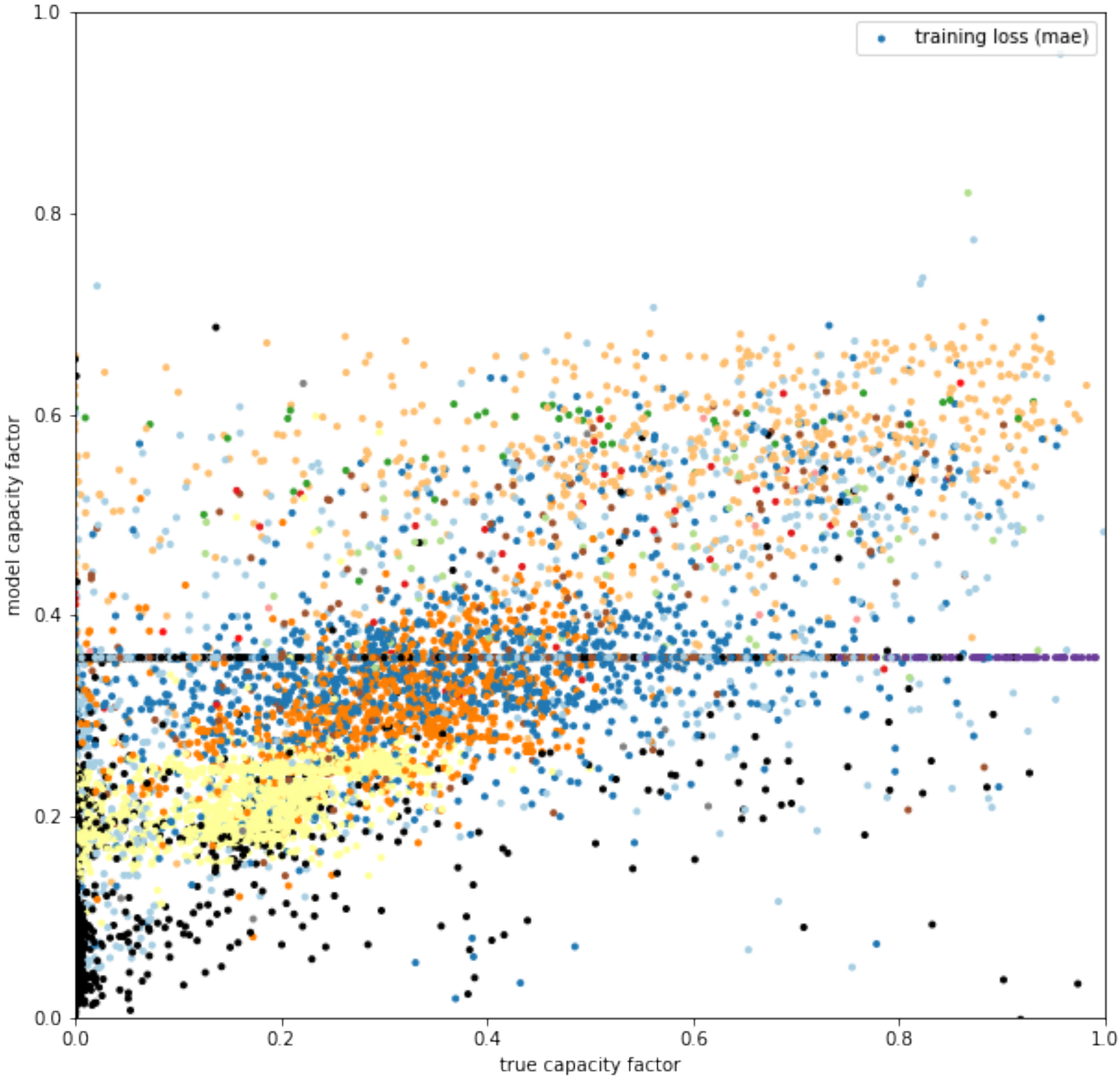
```
# visualize model

#SVG(model_to_dot(model).create(prog='dot',format='svg'))
```

In [49]:

```
# apply model

prediction_values = model.predict(X_data)
fig = plt.figure(figsize=(10,10))
colors = [fuel_color[fuel1_key[int(c)]] for c in X_data[:,5]]
plt.scatter(y_data,prediction_values,marker='.',c=colors)
plt.xlabel('true capacity factor')
plt.ylabel('model capacity factor')
plt.legend(['training loss (mae)','validation loss'],loc='upper right')
plt.xlim([0,1])
plt.ylim([0,1])
plt.show()
```



In [51]:

```
# calculate simple r2 for training data, model value

r2_score = metrics.r2_score(y_data,prediction_values)
print(u"R2 score: {0}".format(r2_score))
```

```
R2 score: 0.222965090425
```