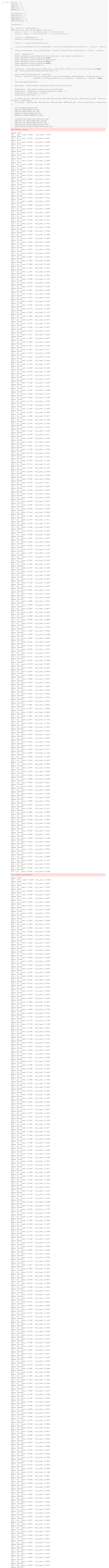
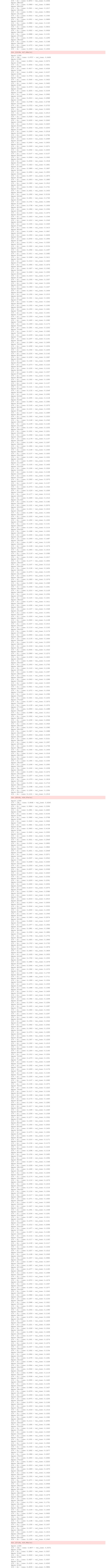
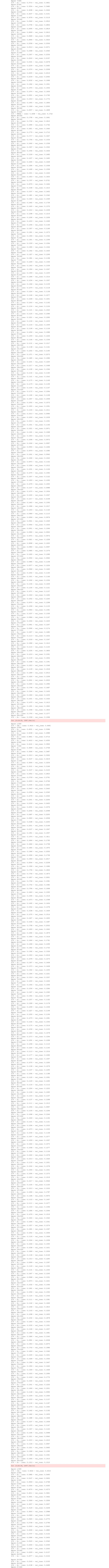
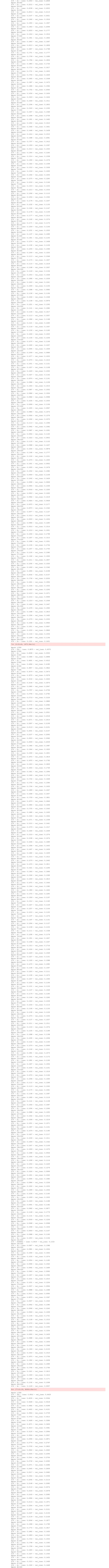
	<pre>import numpy as np import pandas as pd from pathlib import Path import random</pre>					
	<pre>import pandas as pd from pathlib import Path import random import tensorflow.keras as keras from sklearn.metrics import mean_squared_error from sklearn.metrics import mean_absolute_error from sklearn.metrics import r2_score from sklearn.model_selection import KFold from sklearn.model_selection import train_test_split from tqdm import tqdm, tqdm_notebook, trange from tensorflow.keras.models import Sequential, Model from tensorflow.keras.layers import Dropout, Dense, GRU from sklearn.model_selection import train_test_split from sklearn.preprocessing import MinMaxScaler from sklearn.preprocessing import StandardScaler from tensorflow.keras.callbacks import ModelCheckpoint %matplotlib inline import warnings warnings.filterwarnings('ignore')</pre>					
	from typing import List from typing import Tuple from typing import Union Для корректного теста работы сети необходимо задать "random seed" random.seed(5) tf.random.set_seed(5)					
In [17]:	Определяем метрики, с помощью которых будем оценивать результаты работы сети def mean_absolute_percentage_error(y_true, y_pred): y_true, y_pred = np.array(y_true).squeeze(), np.array(y_pred).squeeze() y_m = [y_true != 0] return np.mean(np.abs((y_true[y_m] - y_pred[y_m]) / y_true[y_m])) * 100 def median_mape(y_true, y_pred): v_true_y_nred = np_array(y_true)_squeeze(), np_array(y_pred)_squeeze()					
	<pre>y_true, y_pred = np.array(y_true).squeeze(), np.array(y_pred).squeeze() y_m = [y_true != 0] return np.median(np.abs((y_true[y_m] - y_pred[y_m]) / y_true[y_m])) * 100 def metrics_sum(y_true,y_predicted): R2_sum = r2_score(y_true.sum(axis=1), y_predicted.sum(axis=1)) MAE_sum = mean_absolute_error(y_true.sum(axis=1), y_predicted.sum(axis=1)) MSE_sum = mean_squared_error(y_true.sum(axis=1), y_predicted.sum(axis=1)) MAPE_sum = mean_absolute_percentage_error(y_true.sum(axis=1), y_predicted.sum(axis=1)) MAPE_sum = median_mape(y_true.sum(axis=1), y_predicted.sum(axis=1)) return R2_sum, MAE_sum, MSE_sum, MAPE_sum, MMAPE_sum</pre>					
	<pre>y_true: Union[np.array, pd.DataFrame], y_predicted: Union[np.array, pd.DataFrame]): r2_pw = [] mae_pw = [] mse_pw = [] mape_pw = [] mmape_pw = [] for i, j in zip(y_true.iterrows(), y_predicted): r2_pw.append(r2_score(i[1], j)) mae_pw.append(mean_absolute_error(i[1], j)) mse_pw.append(mean_squared_error(i[1], j))</pre>					
	<pre>mask = [i[1] != 0] mape = np.mean(np.abs((i[1][mask[0].values] - j[mask]) / i[1][mask[0].values])) * 100 if math.isnan(mape):</pre>					
In [18]:	<pre>path_to_params = Path('/datasets/seq/water') debs = Path(path_to_params).glob('*debits.csv') deb = pd.DataFrame() params = Path(path_to_params).glob('*batch.csv') param = pd.DataFrame() for i in params: tmp = pd.read_csv(i,index_col=0) param = pd.concat([param, tmp], ignore_index=True) print(f'Loaded data: {i}') for i in debs: tmp = pd.read_csv(i,index_col=0)</pre>					
	<pre>deb = pd.concat([deb, tmp], ignore_index=True) print(f'Loaded data: {i}') Loaded data:\datasets\seq\water\batch_1_0-99_wo_In_batch.csv Loaded data:\datasets\seq\water\batch_1_200-499_wo_In_batch.csv Loaded data:\datasets\seq\water\batch_1_500-999_wo_In_batch.csv Loaded data:\datasets\seq\water\batch_1_500-999_wo_In_batch.csv Loaded data:\datasets\seq\water\batch_2_wo_In_batch.csv Loaded data:\datasets\seq\water\batch_3_wo_In_batch.csv Loaded data:\datasets\seq\water\batch_4_wo_In_batch.csv Loaded data:\datasets\seq\water\batch_1_0-99_wo_debits.csv Loaded data:\datasets\seq\water\batch_1_1_0-99_wo_debits.csv Loaded data:\datasets\seq\water\batch_1_1_00-199_wo_debits.csv</pre>					
In [20]:	Loaded data:\datasets\seq\water\batch_1_200-499_wo_debits.csv Loaded data:\datasets\seq\water\batch_1_500-999_wo_debits.csv Loaded data:\datasets\seq\water\batch_2_wo_debits.csv Loaded data:\datasets\seq\water\batch_3_wo_debits.csv Loaded data:\datasets\seq\water\batch_4_wo_debits.csv X = param Y = deb ind=len(X) X					
Out[20]:	SO poro VD pres Anisothropy perm inj_rate SQ temp steam_temp heatcr 0 0.84 0.20 8 31 0.60 200 317 0.79 99 271 2390 1 0.75 0.35 8 46 0.69 800 183 0.81 84 247 2408 2 0.74 0.15 16 54 0.97 800 170 0.52 49 278 2578 3 0.51 0.20 14 44 0.94 200 302 0.86 90 208 2680 4 0.67 0.15 4 46 0.11 800 300 0.71 90 228 2324 <t< th=""></t<>					
In [21]:	3282 0.84 0.20 15 64 0.68 900 241 0.74 101 268 2577 3283 0.63 0.40 12 62 0.39 600 310 0.71 69 191 2675 3284 0.65 0.15 10 51 0.51 900 211 0.51 108 243 2779 3285 0.75 0.25 4 62 0.33 400 197 0.89 82 254 1964 X. drop({'SQ', 'steam_temp'}, axis=1, inplace=True) X. drop({'SQ', 'steam_temp'}, axis=1, inplace=True)					
Out[21]:	SO poro VD pres Anisothropy perm inj_rate temp heatcr 0 0.84 0.20 8 31 0.60 200 317 99 2390 1 0.75 0.35 8 46 0.69 800 183 84 2408 2 0.74 0.15 16 54 0.97 800 170 49 2578 3 0.51 0.20 14 44 0.94 200 302 90 2680 4 0.67 0.15 4 46 0.11 800 300 90 2324					
In [22]:	3281 0.87 0.15 13 62 0.29 150 165 74 2151 3282 0.84 0.20 15 64 0.68 900 241 101 2577 3283 0.63 0.40 12 62 0.39 600 310 69 2675 3284 0.65 0.15 10 51 0.51 900 211 108 2779 3285 0.75 0.25 4 62 0.33 400 197 82 1964 3286 rows × 9 columns					
Out[22]:	0 1 2 3 4 5 6 7 8 9 10 0 141.727678 83.129849 91.248891 115.220274 103.826376 95.958622 89.076483 81.293112 73.723770 67.244986 61.704541 56.8 1 130.433223 130.877083 108.439330 91.961432 81.602634 74.817328 68.526982 64.123907 60.719963 57.804083 55.029168 52.7 2 111.830706 66.287333 81.194689 79.964741 75.781038 72.501985 64.959030 60.217281 57.759762 53.344992 47.274737 41.5 3 99.610610 53.081568 33.711720 24.518512 19.167808 16.468650 14.131553 12.617986 11.460548 10.371196 9.501614 8.7 4 62.689597 52.365188 45.623790 40.291627 36.382129 33.136778 30.434036 28.047353 25.680443 23.836651 22.389672 21.1 <					
	3282 759.690384 352.300812 216.415234 146.436272 108.454314 89.906387 77.252374 69.036800 63.533200 60.104973 56.453145 52.8 3283 59.163501 55.135715 54.381975 52.521704 49.522587 46.081740 42.685926 39.064790 36.010256 33.557082 31.060140 28.8 3284 211.224380 93.130698 60.474397 47.785628 41.122073 36.528243 33.009604 30.218247 27.958599 25.951669 24.083923 22.3 3285 76.285642 45.865199 44.798468 41.350271 37.685917 34.563281 31.124686 27.731800 24.307437 21.877599 19.649425 17.4 Задаем гиперпараметры сети					
In [23]:	<pre>verbose = 2 epochs = 200 batch_size = 256 n_timesteps = Y.shape[1] n_features = X.shape[1] dropout_rate=0.2 #a_r=11(0.001)</pre>					
	Задаем саму сеть и обучаем её с 10-блочной кросс-валидацией					

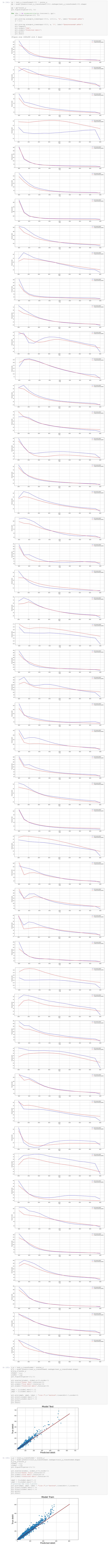








6/6 - 2s - loss: 0.1722 - val loss: 0.1888 Epoch 49/200 6/6 - 2s - loss: 0.1994 - val loss: 0.2202 Epoch 50/200 6/6 - 2s - loss: 0.2077 - val loss: 0.1694 Epoch 51/200 6/6 - 2s - loss: 0.1621 - val loss: 0.1436 Epoch 52/200 6/6 - 2s - loss: 0.1662 - val loss: 0.1442 Epoch 53/200 6/6 - 2s - loss: 0.1471 - val loss: 0.1490 Epoch 54/200 6/6 - 2s - loss: 0.1571 - val_loss: 0.1314 Epoch 55/200 6/6 - 2s - loss: 0.1412 - val loss: 0.1500 Epoch 56/200 6/6 - 2s - loss: 0.1506 - val loss: 0.1334 Epoch 57/200 6/6 - 2s - loss: 0.1438 - val loss: 0.1250 Epoch 58/200 6/6 - 2s - loss: 0.1357 - val loss: 0.1248 Epoch 59/200 6/6 - 2s - loss: 0.1377 - val loss: 0.1217 Epoch 60/200 6/6 - 2s - loss: 0.1333 - val_loss: 0.1403 Epoch 61/200 6/6 - 2s - loss: 0.1308 - val loss: 0.1308 Epoch 62/200 6/6 - 2s - loss: 0.1398 - val loss: 0.1342 Epoch 63/200 6/6 - 2s - loss: 0.1473 - val loss: 0.1192 Epoch 64/200 6/6 - 2s - loss: 0.1335 - val loss: 0.1185 Epoch 65/200 6/6 - 2s - loss: 0.1377 - val loss: 0.1212 Epoch 66/200 6/6 - 2s - loss: 0.1343 - val loss: 0.1175 Epoch 67/200 6/6 - 2s - loss: 0.1286 - val loss: 0.1200 Epoch 68/200 6/6 - 2s - loss: 0.1308 - val_loss: 0.1309 Epoch 69/200 6/6 - 2s - loss: 0.1331 - val loss: 0.1291 Epoch 70/200 6/6 - 3s - loss: 0.1300 - val loss: 0.1246 Epoch 71/200 6/6 - 2s - loss: 0.1473 - val_loss: 0.1325 Epoch 72/200 6/6 - 2s - loss: 0.1414 - val loss: 0.1464 Epoch 73/200 6/6 - 2s - loss: 0.1374 - val loss: 0.1180 Epoch 74/200 6/6 - 2s - loss: 0.1371 - val loss: 0.1214 Epoch 75/200 6/6 - 2s - loss: 0.1292 - val loss: 0.1216 Epoch 76/200 6/6 - 2s - loss: 0.1362 - val_loss: 0.1201 Epoch 77/200 6/6 - 2s - loss: 0.1268 - val loss: 0.1102 Epoch 78/200 6/6 - 2s - loss: 0.1218 - val loss: 0.1069 Epoch 79/200 6/6 - 2s - loss: 0.1227 - val loss: 0.1086 Epoch 80/200 6/6 - 2s - loss: 0.1262 - val loss: 0.1194 Epoch 81/200 6/6 - 2s - loss: 0.1338 - val loss: 0.1499 Epoch 82/200 6/6 - 2s - loss: 0.1261 - val loss: 0.1075 Epoch 83/200 6/6 - 2s - loss: 0.1398 - val_loss: 0.1403 Epoch 84/200 6/6 - 2s - loss: 0.1279 - val_loss: 0.1135 Epoch 85/200 6/6 - 2s - loss: 0.1349 - val loss: 0.1418 Epoch 86/200 6/6 - 2s - loss: 0.1355 - val loss: 0.1304 Epoch 87/200 6/6 - 2s - loss: 0.1283 - val loss: 0.1310 Epoch 88/200 6/6 - 2s - loss: 0.1348 - val loss: 0.1488 Epoch 89/200 6/6 - 2s - loss: 0.1391 - val loss: 0.1574 Epoch 90/200 6/6 - 2s - loss: 0.1439 - val loss: 0.1329 Epoch 91/200 6/6 - 2s - loss: 0.1420 - val loss: 0.1199 Epoch 92/200 6/6 - 2s - loss: 0.1255 - val loss: 0.1039 Epoch 93/200 6/6 - 2s - loss: 0.1371 - val loss: 0.1259 Epoch 94/200 6/6 - 2s - loss: 0.1169 - val loss: 0.1083 Epoch 95/200 6/6 - 2s - loss: 0.1217 - val_loss: 0.1128 Epoch 96/200 6/6 - 2s - loss: 0.1152 - val loss: 0.1111 Epoch 97/200 6/6 - 2s - loss: 0.1130 - val loss: 0.0980 Epoch 98/200 6/6 - 2s - loss: 0.1150 - val loss: 0.1000 Epoch 99/200 6/6 - 2s - loss: 0.1150 - val loss: 0.1150 Epoch 100/200 6/6 - 2s - loss: 0.1106 - val loss: 0.1343 Epoch 101/200 6/6 - 2s - loss: 0.1176 - val_loss: 0.1157 Epoch 102/200 6/6 - 2s - loss: 0.1263 - val loss: 0.1240 Epoch 103/200 6/6 - 2s - loss: 0.1263 - val loss: 0.1333 Epoch 104/200 6/6 - 2s - loss: 0.1195 - val loss: 0.1178 Epoch 105/200 6/6 - 2s - loss: 0.1187 - val loss: 0.1260 Epoch 106/200 6/6 - 2s - loss: 0.1128 - val loss: 0.1262 Epoch 107/200 6/6 - 2s - loss: 0.1129 - val loss: 0.0977 Epoch 108/200 6/6 - 2s - loss: 0.1206 - val loss: 0.1014 Epoch 109/200 6/6 - 2s - loss: 0.1153 - val loss: 0.0969 Epoch 110/200 6/6 - 2s - loss: 0.1080 - val_loss: 0.1296 Epoch 111/200 6/6 - 2s - loss: 0.1078 - val_loss: 0.1112 Epoch 112/200 6/6 - 2s - loss: 0.1104 - val loss: 0.1022 Epoch 113/200 6/6 - 2s - loss: 0.1192 - val loss: 0.1101 Epoch 114/200 6/6 - 2s - loss: 0.1040 - val loss: 0.1031 Epoch 115/200 6/6 - 2s - loss: 0.1077 - val loss: 0.1094 Epoch 116/200 6/6 - 2s - loss: 0.1129 - val_loss: 0.1061 Epoch 117/200 6/6 - 2s - loss: 0.1128 - val loss: 0.1242 Epoch 118/200 6/6 - 2s - loss: 0.1048 - val loss: 0.1114 Epoch 119/200 6/6 - 2s - loss: 0.1068 - val_loss: 0.1099 Epoch 120/200 6/6 - 2s - loss: 0.1201 - val loss: 0.1019 Epoch 121/200 6/6 - 2s - loss: 0.1038 - val loss: 0.1025 Epoch 122/200 6/6 - 2s - loss: 0.1079 - val loss: 0.1096 Epoch 123/200 6/6 - 2s - loss: 0.1015 - val loss: 0.1097 Epoch 124/200 6/6 - 2s - loss: 0.1070 - val loss: 0.0960 Epoch 125/200 6/6 - 2s - loss: 0.1061 - val loss: 0.1090 Epoch 126/200 6/6 - 2s - loss: 0.0969 - val loss: 0.0962 Epoch 127/200 6/6 - 2s - loss: 0.0996 - val loss: 0.1069 Epoch 128/200 6/6 - 2s - loss: 0.1033 - val loss: 0.0946 Epoch 129/200 6/6 - 2s - loss: 0.1101 - val loss: 0.1134 Epoch 130/200 6/6 - 2s - loss: 0.1011 - val loss: 0.1205 Epoch 131/200 6/6 - 2s - loss: 0.1001 - val loss: 0.0962 Epoch 132/200 6/6 - 2s - loss: 0.1056 - val loss: 0.0943 Epoch 133/200 6/6 - 2s - loss: 0.0993 - val loss: 0.0900 Epoch 134/200 6/6 - 2s - loss: 0.0991 - val loss: 0.1165 Epoch 135/200 6/6 - 2s - loss: 0.1016 - val loss: 0.1131 Epoch 136/200 6/6 - 2s - loss: 0.1040 - val loss: 0.1076 Epoch 137/200 6/6 - 2s - loss: 0.1077 - val loss: 0.1082 Epoch 138/200 6/6 - 2s - loss: 0.0969 - val loss: 0.0984 Epoch 139/200 6/6 - 2s - loss: 0.0995 - val loss: 0.1139 Epoch 140/200 6/6 - 2s - loss: 0.0998 - val_loss: 0.1162 Epoch 141/200 6/6 - 2s - loss: 0.1037 - val loss: 0.1000 Epoch 142/200 6/6 - 2s - loss: 0.1024 - val loss: 0.1277 Epoch 143/200 6/6 - 2s - loss: 0.1044 - val loss: 0.1121 Epoch 144/200 6/6 - 2s - loss: 0.1044 - val loss: 0.1245 Epoch 145/200 6/6 - 2s - loss: 0.0983 - val loss: 0.0969 Epoch 146/200 6/6 - 2s - loss: 0.1113 - val loss: 0.0990 Epoch 147/200 6/6 - 2s - loss: 0.1058 - val loss: 0.1125 Epoch 148/200 6/6 - 2s - loss: 0.0994 - val_loss: 0.1181 Epoch 149/200 6/6 - 2s - loss: 0.1000 - val loss: 0.1202 Epoch 150/200 6/6 - 2s - loss: 0.1020 - val_loss: 0.1045 Epoch 151/200 6/6 - 2s - loss: 0.1111 - val loss: 0.1016 Epoch 152/200 6/6 - 2s - loss: 0.0989 - val_loss: 0.1173 Epoch 153/200 6/6 - 2s - loss: 0.0989 - val loss: 0.1077 Epoch 154/200 6/6 - 2s - loss: 0.1018 - val loss: 0.0952 Epoch 155/200 6/6 - 2s - loss: 0.1020 - val loss: 0.0928 Epoch 156/200 6/6 - 2s - loss: 0.0983 - val_loss: 0.1340 Epoch 157/200 6/6 - 2s - loss: 0.1007 - val loss: 0.1172 Epoch 158/200 6/6 - 2s - loss: 0.0978 - val loss: 0.0929 Epoch 159/200 6/6 - 2s - loss: 0.1006 - val loss: 0.1142 Epoch 160/200 6/6 - 2s - loss: 0.0973 - val loss: 0.1215 Epoch 161/200 6/6 - 2s - loss: 0.0966 - val loss: 0.1126 Epoch 162/200 6/6 - 2s - loss: 0.0977 - val loss: 0.0942 Epoch 163/200 6/6 - 2s - loss: 0.1121 - val loss: 0.1210 Epoch 164/200 6/6 - 2s - loss: 0.0937 - val_loss: 0.1340 Epoch 165/200 6/6 - 2s - loss: 0.0981 - val loss: 0.1172 Epoch 166/200 6/6 - 2s - loss: 0.0946 - val loss: 0.0927 Epoch 167/200 6/6 - 2s - loss: 0.1094 - val loss: 0.1510 Epoch 168/200 6/6 - 2s - loss: 0.1014 - val loss: 0.1062 Epoch 169/200 6/6 - 2s - loss: 0.1011 - val loss: 0.1222 Epoch 170/200 6/6 - 2s - loss: 0.1053 - val loss: 0.0988 Epoch 171/200 6/6 - 2s - loss: 0.0986 - val loss: 0.1065 Epoch 172/200 6/6 - 2s - loss: 0.1002 - val loss: 0.1279 Epoch 173/200 6/6 - 2s - loss: 0.0941 - val loss: 0.0943 Epoch 174/200 6/6 - 2s - loss: 0.1010 - val loss: 0.1178 Epoch 175/200 6/6 - 2s - loss: 0.0924 - val loss: 0.1069 Epoch 176/200 6/6 - 2s - loss: 0.0969 - val loss: 0.1035 Epoch 177/200 6/6 - 2s - loss: 0.0987 - val loss: 0.0985 Epoch 178/200 6/6 - 2s - loss: 0.0958 - val loss: 0.1600 Epoch 179/200 6/6 - 2s - loss: 0.1108 - val loss: 0.0885 Epoch 180/200 6/6 - 2s - loss: 0.1061 - val loss: 0.1633 Epoch 181/200 6/6 - 2s - loss: 0.1072 - val loss: 0.0998 Epoch 182/200 6/6 - 2s - loss: 0.0987 - val loss: 0.1469 Epoch 183/200 6/6 - 2s - loss: 0.1023 - val loss: 0.0982 Epoch 184/200 6/6 - 2s - loss: 0.1052 - val loss: 0.1331 Epoch 185/200 6/6 - 2s - loss: 0.0994 - val loss: 0.1177 Epoch 186/200 6/6 - 2s - loss: 0.0965 - val loss: 0.1096 Epoch 187/200 6/6 - 2s - loss: 0.0980 - val loss: 0.1059 Epoch 188/200 6/6 - 2s - loss: 0.0960 - val_loss: 0.1128 Epoch 189/200 6/6 - 2s - loss: 0.1001 - val loss: 0.1288 Epoch 190/200 6/6 - 2s - loss: 0.0980 - val loss: 0.1146 Epoch 191/200 6/6 - 2s - loss: 0.0949 - val loss: 0.1467 Epoch 192/200 6/6 - 2s - loss: 0.1066 - val loss: 0.0995 Epoch 193/200 6/6 - 2s - loss: 0.0960 - val loss: 0.1443 Epoch 194/200 6/6 - 2s - loss: 0.1072 - val loss: 0.1364 Epoch 195/200 6/6 - 2s - loss: 0.1007 - val loss: 0.1581 Epoch 196/200 6/6 - 2s - loss: 0.1152 - val loss: 0.1570 Epoch 197/200 6/6 - 2s - loss: 0.1238 - val loss: 0.1354 Epoch 198/200 6/6 - 2s - loss: 0.1118 - val loss: 0.1392 Epoch 199/200 6/6 - 2s - loss: 0.1256 - val_loss: 0.1458 Epoch 200/200 6/6 - 2s - loss: 0.1282 - val loss: 0.1582 9it [77:09:39, 56603.81s/it] Epoch 1/200 6/6 - 20s - loss: 0.8783 - val loss: 0.6595 Epoch 2/200 6/6 - 2s - loss: 0.5893 - val loss: 0.5481 Epoch 3/200 6/6 - 2s - loss: 0.5035 - val loss: 0.5095 Epoch 4/200 6/6 - 2s - loss: 0.4401 - val loss: 0.4138 Epoch 5/200 6/6 - 2s - loss: 0.3975 - val loss: 0.3910 Epoch 6/200 6/6 - 2s - loss: 0.3832 - val loss: 0.4211 Epoch 7/200 6/6 - 3s - loss: 0.3815 - val_loss: 0.3552 Epoch 8/200 6/6 - 2s - loss: 0.3452 - val loss: 0.3593 Epoch 9/200 6/6 - 2s - loss: 0.3354 - val loss: 0.3163 Epoch 10/200 6/6 - 2s - loss: 0.3162 - val loss: 0.3377 Epoch 11/200 6/6 - 2s - loss: 0.3176 - val loss: 0.2977 Epoch 12/200 6/6 - 2s - loss: 0.2949 - val loss: 0.3165 Epoch 13/200 6/6 - 2s - loss: 0.2987 - val loss: 0.2778 Epoch 14/200 6/6 - 2s - loss: 0.2661 - val loss: 0.2651 Epoch 15/200 6/6 - 2s - loss: 0.2636 - val_loss: 0.2608 Epoch 16/200 6/6 - 2s - loss: 0.2634 - val loss: 0.2553 Epoch 17/200 6/6 - 2s - loss: 0.2503 - val loss: 0.2602 Epoch 18/200 6/6 - 2s - loss: 0.2484 - val loss: 0.2638 Epoch 19/200 6/6 - 2s - loss: 0.2453 - val loss: 0.2411 Epoch 20/200 6/6 - 2s - loss: 0.2388 - val loss: 0.2326 Epoch 21/200 6/6 - 2s - loss: 0.2401 - val loss: 0.2421 Epoch 22/200 6/6 - 2s - loss: 0.2437 - val loss: 0.2529 Epoch 23/200 6/6 - 2s - loss: 0.2404 - val_loss: 0.2350 Epoch 24/200 6/6 - 2s - loss: 0.2260 - val loss: 0.2150 Epoch 25/200 6/6 - 2s - loss: 0.2209 - val loss: 0.2154 Epoch 26/200 6/6 - 2s - loss: 0.2091 - val loss: 0.2103 Epoch 27/200 6/6 - 2s - loss: 0.2104 - val loss: 0.2002 Epoch 28/200 6/6 - 2s - loss: 0.2027 - val loss: 0.2078 Epoch 29/200 6/6 - 2s - loss: 0.2000 - val loss: 0.1936 Epoch 30/200 6/6 - 2s - loss: 0.2024 - val loss: 0.1845 Epoch 31/200 6/6 - 2s - loss: 0.1923 - val_loss: 0.1819 Epoch 32/200 6/6 - 2s - loss: 0.1882 - val loss: 0.1779 Epoch 33/200 6/6 - 2s - loss: 0.1902 - val_loss: 0.1796 Epoch 34/200 6/6 - 2s - loss: 0.1941 - val loss: 0.2087 Epoch 35/200 6/6 - 2s - loss: 0.2051 - val loss: 0.1961 Epoch 36/200 6/6 - 2s - loss: 0.1924 - val loss: 0.1690 Epoch 37/200 6/6 - 2s - loss: 0.1933 - val loss: 0.1729 Epoch 38/200 6/6 - 2s - loss: 0.1836 - val loss: 0.1759 Epoch 39/200 6/6 - 2s - loss: 0.1804 - val_loss: 0.1628 Epoch 40/200 6/6 - 2s - loss: 0.1955 - val loss: 0.1732 Epoch 41/200 6/6 - 2s - loss: 0.2010 - val loss: 0.1784 Epoch 42/200 6/6 - 2s - loss: 0.1754 - val loss: 0.1627 Epoch 43/200 6/6 - 2s - loss: 0.1703 - val loss: 0.1595 Epoch 44/200 6/6 - 2s - loss: 0.1737 - val loss: 0.1632 Epoch 45/200 6/6 - 2s - loss: 0.1737 - val loss: 0.1589 Epoch 46/200 6/6 - 2s - loss: 0.1650 - val loss: 0.1668 Epoch 47/200 6/6 - 2s - loss: 0.1668 - val_loss: 0.1553 Epoch 48/200 6/6 - 2s - loss: 0.1618 - val loss: 0.1510 Epoch 49/200 6/6 - 2s - loss: 0.1651 - val_loss: 0.1564 Epoch 50/200 6/6 - 2s - loss: 0.1602 - val loss: 0.1449 Epoch 51/200 6/6 - 2s - loss: 0.1654 - val_loss: 0.1387 Epoch 52/200 6/6 - 2s - loss: 0.1541 - val loss: 0.1495 Epoch 53/200 6/6 - 2s - loss: 0.1497 - val loss: 0.1482 Epoch 54/200 6/6 - 2s - loss: 0.1466 - val loss: 0.1426 Epoch 55/200 6/6 - 2s - loss: 0.1604 - val_loss: 0.1493 Epoch 56/200 6/6 - 2s - loss: 0.1560 - val loss: 0.1334 Epoch 57/200 6/6 - 2s - loss: 0.1503 - val loss: 0.1542 Epoch 58/200 6/6 - 2s - loss: 0.1427 - val_loss: 0.1531 Epoch 59/200 6/6 - 2s - loss: 0.1517 - val_loss: 0.1515 Epoch 60/200 6/6 - 2s - loss: 0.1623 - val loss: 0.1392 Epoch 61/200 6/6 - 2s - loss: 0.1373 - val loss: 0.1262 Epoch 62/200 6/6 - 2s - loss: 0.1403 - val loss: 0.1287 Epoch 63/200 6/6 - 2s - loss: 0.1404 - val_loss: 0.1353 Epoch 64/200 6/6 - 2s - loss: 0.1306 - val loss: 0.1277 Epoch 65/200 6/6 - 2s - loss: 0.1359 - val loss: 0.1255 Epoch 66/200 6/6 - 2s - loss: 0.1323 - val loss: 0.1165 Epoch 67/200 6/6 - 2s - loss: 0.1351 - val loss: 0.1321 Epoch 68/200 6/6 - 2s - loss: 0.1562 - val loss: 0.2057 Epoch 69/200 6/6 - 2s - loss: 0.1471 - val loss: 0.1229 Epoch 70/200 6/6 - 2s - loss: 0.1409 - val loss: 0.1311 Epoch 71/200 6/6 - 2s - loss: 0.1337 - val_loss: 0.1157 Epoch 72/200 6/6 - 2s - loss: 0.1309 - val loss: 0.1447 Epoch 73/200 6/6 - 2s - loss: 0.1269 - val_loss: 0.1330 Epoch 74/200 6/6 - 2s - loss: 0.1318 - val loss: 0.1246 Epoch 75/200 6/6 - 2s - loss: 0.1429 - val loss: 0.1385 Epoch 76/200 6/6 - 2s - loss: 0.1261 - val loss: 0.1257 Epoch 77/200 6/6 - 2s - loss: 0.1283 - val loss: 0.1269 Epoch 78/200 6/6 - 2s - loss: 0.1280 - val loss: 0.1250 Epoch 79/200 6/6 - 2s - loss: 0.1242 - val_loss: 0.1232 Epoch 80/200 6/6 - 2s - loss: 0.1305 - val loss: 0.1345 Epoch 81/200 6/6 - 2s - loss: 0.1336 - val loss: 0.1444 Epoch 82/200 6/6 - 2s - loss: 0.1359 - val loss: 0.1229 Epoch 83/200 6/6 - 2s - loss: 0.1400 - val loss: 0.1426 Epoch 84/200 6/6 - 2s - loss: 0.1262 - val loss: 0.1170 Epoch 85/200 6/6 - 2s - loss: 0.1228 - val loss: 0.1143 Epoch 86/200 6/6 - 2s - loss: 0.1166 - val loss: 0.1171 Epoch 87/200 6/6 - 2s - loss: 0.1149 - val_loss: 0.1065 Epoch 88/200 6/6 - 2s - loss: 0.1272 - val loss: 0.1189 Epoch 89/200 6/6 - 2s - loss: 0.1204 - val_loss: 0.1122 Epoch 90/200 6/6 - 2s - loss: 0.1187 - val loss: 0.1104 Epoch 91/200 6/6 - 2s - loss: 0.1311 - val_loss: 0.1267 Epoch 92/200 6/6 - 2s - loss: 0.1186 - val loss: 0.1347 Epoch 93/200 6/6 - 2s - loss: 0.1271 - val loss: 0.1132 Epoch 94/200 6/6 - 2s - loss: 0.1378 - val loss: 0.1676 Epoch 95/200 6/6 - 2s - loss: 0.1207 - val_loss: 0.1167 Epoch 96/200 6/6 - 2s - loss: 0.1191 - val loss: 0.1456 Epoch 97/200 6/6 - 2s - loss: 0.1176 - val_loss: 0.1104 Epoch 98/200 6/6 - 2s - loss: 0.1184 - val loss: 0.1233 Epoch 99/200 6/6 - 2s - loss: 0.1095 - val loss: 0.1081 Epoch 100/200 6/6 - 2s - loss: 0.1065 - val loss: 0.1004 Epoch 101/200 6/6 - 2s - loss: 0.1110 - val loss: 0.1034 Epoch 102/200 6/6 - 2s - loss: 0.1039 - val loss: 0.1016 Epoch 103/200 6/6 - 2s - loss: 0.1045 - val loss: 0.1078 Epoch 104/200 6/6 - 2s - loss: 0.1058 - val loss: 0.1613 Epoch 105/200 6/6 - 2s - loss: 0.1232 - val loss: 0.1143 Epoch 106/200 6/6 - 2s - loss: 0.1279 - val loss: 0.1352 Epoch 107/200 6/6 - 2s - loss: 0.1117 - val loss: 0.1109 Epoch 108/200 6/6 - 2s - loss: 0.1093 - val loss: 0.1216 Epoch 109/200 6/6 - 2s - loss: 0.1093 - val loss: 0.1051 Epoch 110/200 6/6 - 2s - loss: 0.1106 - val loss: 0.1168 Epoch 111/200 6/6 - 2s - loss: 0.1079 - val_loss: 0.1077 Epoch 112/200 6/6 - 2s - loss: 0.1052 - val loss: 0.1069 Epoch 113/200 6/6 - 2s - loss: 0.1036 - val_loss: 0.0929 Epoch 114/200 6/6 - 2s - loss: 0.1041 - val loss: 0.1029 Epoch 115/200 6/6 - 2s - loss: 0.1043 - val loss: 0.1396 Epoch 116/200 6/6 - 2s - loss: 0.1073 - val loss: 0.1229 Epoch 117/200 6/6 - 2s - loss: 0.1072 - val loss: 0.1083 Epoch 118/200 6/6 - 2s - loss: 0.1132 - val loss: 0.1073 Epoch 119/200 6/6 - 2s - loss: 0.1169 - val_loss: 0.1486 Epoch 120/200 6/6 - 2s - loss: 0.1183 - val loss: 0.1386 Epoch 121/200 6/6 - 2s - loss: 0.1236 - val loss: 0.1458 Epoch 122/200 6/6 - 2s - loss: 0.1308 - val loss: 0.1179 Epoch 123/200 6/6 - 2s - loss: 0.1174 - val loss: 0.1359 Epoch 124/200 6/6 - 2s - loss: 0.1090 - val loss: 0.1118 Epoch 125/200 6/6 - 2s - loss: 0.1188 - val loss: 0.1660 Epoch 126/200 6/6 - 2s - loss: 0.1165 - val loss: 0.1174 Epoch 127/200 6/6 - 2s - loss: 0.1218 - val_loss: 0.1329 Epoch 128/200 6/6 - 2s - loss: 0.1183 - val loss: 0.1074 Epoch 129/200 6/6 - 2s - loss: 0.1056 - val_loss: 0.1219 Epoch 130/200 6/6 - 2s - loss: 0.1061 - val loss: 0.1019 Epoch 131/200 6/6 - 2s - loss: 0.1030 - val loss: 0.1094 Epoch 132/200 6/6 - 2s - loss: 0.1010 - val loss: 0.0977 Epoch 133/200 6/6 - 2s - loss: 0.0974 - val loss: 0.1105 Epoch 134/200 6/6 - 2s - loss: 0.0937 - val loss: 0.1031 Epoch 135/200 6/6 - 2s - loss: 0.0992 - val_loss: 0.1067 Epoch 136/200 6/6 - 2s - loss: 0.1077 - val loss: 0.1284 Epoch 137/200 6/6 - 2s - loss: 0.0994 - val_loss: 0.1096 Epoch 138/200 6/6 - 2s - loss: 0.1100 - val loss: 0.1158 Epoch 139/200 6/6 - 2s - loss: 0.1047 - val loss: 0.1129 Epoch 140/200 6/6 - 2s - loss: 0.0983 - val loss: 0.1411 Epoch 141/200 6/6 - 2s - loss: 0.1021 - val loss: 0.0994 Epoch 142/200 6/6 - 2s - loss: 0.1059 - val loss: 0.1056 Epoch 143/200 6/6 - 2s - loss: 0.1011 - val_loss: 0.1144 Epoch 144/200 6/6 - 2s - loss: 0.0944 - val loss: 0.1242 Epoch 145/200 6/6 - 2s - loss: 0.0963 - val loss: 0.1066 Epoch 146/200 6/6 - 2s - loss: 0.1068 - val loss: 0.0975 Epoch 147/200 6/6 - 2s - loss: 0.0968 - val loss: 0.0985 Epoch 148/200 6/6 - 2s - loss: 0.0882 - val loss: 0.1289 Epoch 149/200 6/6 - 2s - loss: 0.0927 - val loss: 0.1022 Epoch 150/200 6/6 - 2s - loss: 0.0974 - val loss: 0.0919 Epoch 151/200 6/6 - 2s - loss: 0.1055 - val_loss: 0.1241 Epoch 152/200 6/6 - 2s - loss: 0.0928 - val loss: 0.1378 Epoch 153/200 6/6 - 2s - loss: 0.0974 - val loss: 0.1092 Epoch 154/200 6/6 - 2s - loss: 0.1049 - val loss: 0.1223 Epoch 155/200 6/6 - 2s - loss: 0.0956 - val loss: 0.0978 Epoch 156/200 6/6 - 2s - loss: 0.0969 - val loss: 0.1415 Epoch 157/200 6/6 - 2s - loss: 0.0948 - val loss: 0.0908 Epoch 158/200 6/6 - 2s - loss: 0.1004 - val loss: 0.1237 Epoch 159/200 6/6 - 2s - loss: 0.0943 - val_loss: 0.1207 Epoch 160/200 6/6 - 2s - loss: 0.0956 - val loss: 0.1179 Epoch 161/200 6/6 - 2s - loss: 0.0941 - val loss: 0.1195 Epoch 162/200 6/6 - 2s - loss: 0.0980 - val loss: 0.0911 Epoch 163/200 6/6 - 2s - loss: 0.0943 - val loss: 0.1105 Epoch 164/200 6/6 - 2s - loss: 0.1002 - val loss: 0.1153 Epoch 165/200 6/6 - 2s - loss: 0.0900 - val loss: 0.1410 Epoch 166/200 6/6 - 2s - loss: 0.0919 - val loss: 0.0981 Epoch 167/200 6/6 - 2s - loss: 0.0926 - val_loss: 0.1179 Epoch 168/200 6/6 - 2s - loss: 0.0868 - val loss: 0.1502 Epoch 169/200 6/6 - 2s - loss: 0.0932 - val loss: 0.1249 Epoch 170/200 6/6 - 2s - loss: 0.0994 - val loss: 0.0947 Epoch 171/200 6/6 - 2s - loss: 0.0994 - val loss: 0.1368 Epoch 172/200 6/6 - 2s - loss: 0.0901 - val loss: 0.1270 Epoch 173/200 6/6 - 2s - loss: 0.0946 - val loss: 0.0928 Epoch 174/200 6/6 - 2s - loss: 0.1036 - val loss: 0.1653 Epoch 175/200 6/6 - 2s - loss: 0.1076 - val_loss: 0.0886 Epoch 176/200 6/6 - 2s - loss: 0.1176 - val loss: 0.1641 Epoch 177/200 6/6 - 2s - loss: 0.1123 - val_loss: 0.1174 Epoch 178/200 6/6 - 2s - loss: 0.0941 - val loss: 0.1298 Epoch 179/200 6/6 - 2s - loss: 0.0970 - val_loss: 0.1112 Epoch 180/200 6/6 - 2s - loss: 0.0910 - val loss: 0.1283 Epoch 181/200 6/6 - 2s - loss: 0.0907 - val loss: 0.1184 Epoch 182/200 6/6 - 2s - loss: 0.0871 - val loss: 0.1005 Epoch 183/200 6/6 - 2s - loss: 0.1026 - val loss: 0.1878 Epoch 184/200 6/6 - 2s - loss: 0.1030 - val loss: 0.1073 Epoch 185/200 6/6 - 2s - loss: 0.0977 - val loss: 0.1467 Epoch 186/200 6/6 - 2s - loss: 0.1006 - val loss: 0.1187 Epoch 187/200 6/6 - 2s - loss: 0.1058 - val loss: 0.1955 Epoch 188/200 6/6 - 2s - loss: 0.1169 - val loss: 0.1158 Epoch 189/200 6/6 - 2s - loss: 0.1017 - val loss: 0.1420 Epoch 190/200 6/6 - 2s - loss: 0.1089 - val loss: 0.1545 Epoch 191/200 6/6 - 2s - loss: 0.1269 - val_loss: 0.1908 Epoch 192/200 6/6 - 2s - loss: 0.1239 - val loss: 0.1826 Epoch 193/200 6/6 - 2s - loss: 0.1392 - val_loss: 0.1671 Epoch 194/200 6/6 - 2s - loss: 0.1519 - val loss: 0.1417 Epoch 195/200 6/6 - 2s - loss: 0.1767 - val loss: 0.1723 Epoch 196/200 6/6 - 2s - loss: 0.1820 - val loss: 0.1838 Epoch 197/200 6/6 - 2s - loss: 0.1813 - val loss: 0.2253 Epoch 198/200 6/6 - 2s - loss: 0.1748 - val loss: 0.2085 Epoch 199/200 6/6 - 2s - loss: 0.1737 - val_loss: 0.1862 Epoch 200/200 6/6 - 2s - loss: 0.1732 - val loss: 0.1434 10it [77:16:48, 27820.85s/it] Выводим оценки результатов работы сети print('Средний R2 для суммарного дебита: ', np.array(R2 sum).mean()) print('Средний МАЕ для суммарного дебита: ', np.array(MAE sum).mean()) print('Средний MSE для суммарного дебита: ', np.array(MSE sum).mean()) print('Средний МАРЕ для суммарного дебита: ', np.array(МАРЕ sum).mean()) print('Медианный МАРЕ для суммарного дебита: ', np.array(ММАРЕ sum).mean()) print('Средний медианный R2 по экспериментам: ', np.array(R2 median pw).mean()) print('Средний МАЕ по экспериментам: ', np.array(МАЕ mean pw).mean()) print('Средний MSE по экспериментам: ', np.array(MSE mean pw).mean()) print('Средний МАРЕ по экспериментам: ', np.array(MAPE_mean_pw).mean()) print('Медианный МАРЕ по экспериментам: ', np.array(MAPE median pw).mean()) Средний R2 для суммарного дебита: 0.9849860621963972 Средний МАЕ для суммарного дебита: 47.946394183864776 Средний MSE для суммарного дебита: 5748.576419518755 Средний МАРЕ для суммарного дебита: 5.856212510607195 Медианный МАРЕ для суммарного дебита: 4.63432133644403 Средний медианный R2 по экспериментам: 0.8423165308821584 Средний МАЕ по экспериментам: 4.726912257648467 Средний MSE по экспериментам: 129.27777761970378 Средний МАРЕ по экспериментам: 10.781858237527436 Медианный МАРЕ по экспериментам: 8.858505673680288 In [12]: dfsave=pd.DataFrame({'r2 sum':R2 sum, 'mae sum':MAE sum, 'mse sum':MSE sum, 'mape sum':MAPE sum, 'mmape su m':MMAPE sum, 'r2 pw':R2 median pw,'mae pw':MAE mean pw,'mse pw':MSE mean pw,'mape pw':MAPE mean pw,'mmape pw':MAPE median pw}) dfsave.to csv(f'results {ind}.csv') Выводим график обучения сети на последней итерации 10блочной кросс-валидации In [13]: plt.plot(histories[9].history['loss']) plt.plot(histories[9].history['val loss']) plt.title('model loss') plt.ylabel('loss') plt.xlabel('epoch') plt.legend(['train', 'test'], loc='upper left') plt.show() model loss 0.9 train test 0.8 0.6 S 0.5 0.4 0.1 50 100 125 150 175 epoch Сравнение предсказанных значений истинным



 3810.275864 3682.925773 3510.132787 3324.266232 3322.636049 3272.103526 3255.472605 3252.159600 3230.370258 3066.018461 	3019.693604 2628.070312 2731.246582 2978.948730 3144.968506 2603.178223 2760.041260	_ml 4 3 1 14 8 2 0 15 7 9	