Regression Model

Training and Test Set

We want to use this data to train a RUL estimator

We will use 75% of the experiments for training, 25% for testing

```
In [2]: tr, ts = util.split_train_test_machines(data, tr_ratio=0.75, seed=42)
        print(f'#Examples: {len(tr)} (traning), {len(ts)} (test)')
        print(f'#Experiments: {len(tr["machine"].unique())} (traning), {len(ts["machine"].unique())}

#Examples: 45385 (traning), 15864 (test)
#Experiments: 186 (traning), 63 (test)
```

- We have more than enough data for training and for testing

What if we didn't?

Things would become more complicated, but there are a few options:

- Choose a less data-hungry approach
- Try to use lower-quality data (e.g. unsupervised data)
- Rely on external knowledge (empirical rules, physics...)

Rescaling

We will standardiza all input attributes and normalize the RUL

```
In [3]: tr_s, ts_s, nparams = util.rescale_CMAPSS(tr, ts)
        tr_s.describe()
```

Out[3]:

	machine	cycle	p1	p2	p3	s1	s2	s3
count	45385.000000	45385.000000	4.538500e+04	4.538500e+04	4.538500e+04	4.538500e+04	4.538500e+04	4.538500e+04
mean	122.490955	133.323896	2.894775e-16	1.302570e-16	1.178889e-16	4.664830e-15	2.522791e-15	1.727041e-15
std	71.283034	89.568561	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
min	1.000000	1.000000	-1.623164e+00	-1.838222e+00	-2.381839e+00	-1.055641e+00	-1.176507e+00	-1.646830e+00
25%	61.000000	62.000000	-9.461510e-01	-1.031405e+00	4.198344e-01	-1.055641e+00	-8.055879e-01	-6.341243e-01
50%	125.000000	123.000000	6.868497e-02	4.154560e-01	4.198344e-01	-3.917563e-01	-6.336530e-01	-4.718540e-01
75%	179.000000	189.000000	1.218855e+00	8.661917e-01	4.198344e-01	6.926385e-01	7.407549e-01	7.495521e-01
max	248.000000	543.000000	1.219524e+00	8.726308e-01	4.198344e-01	1.732749e+00	1.741030e+00	1.837978e+00

8 rows × 27 columns

Building an MLP with Keras

We will use the following function to build our model

```
def build_ml_model(input_size, output_size, hidden=[],
        output_activation='linear', name=None):
    ll = [keras.Input(input_size)]
    for h in hidden:
        ll.append(layers.Dense(h, activation='relu'))
    ll.append(layers.Dense(output_size, activation=output_activation))
    model = keras.Sequential(ll, name=name)
    return model
```

- The output activation function can be specified when calling the code
- We build the layers one by one (in a list)
- For each of them we specify the number of neurons and the activation function

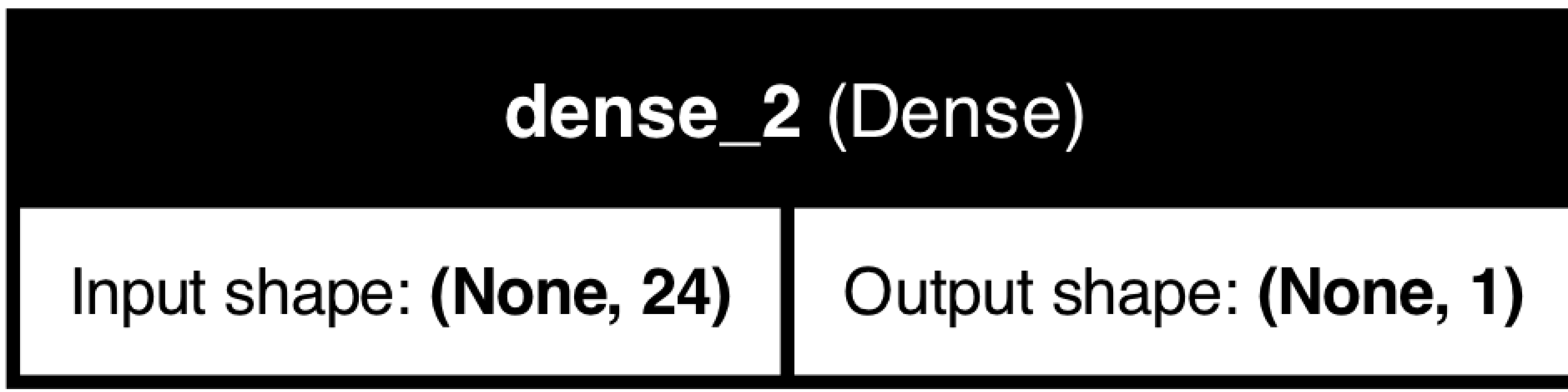
This is an alternative method to use the Keras sequential API

A Linear Regression Model for RUL Estimation

We will start by building a Linear Regressor

In [9]:
```
hidden = []
nn = util.build_ml_model(input_size=(len(dt_in),), output_size=1, hidden=hidden, output_act
util.plot_ml_model(nn)
```

Out[9]:



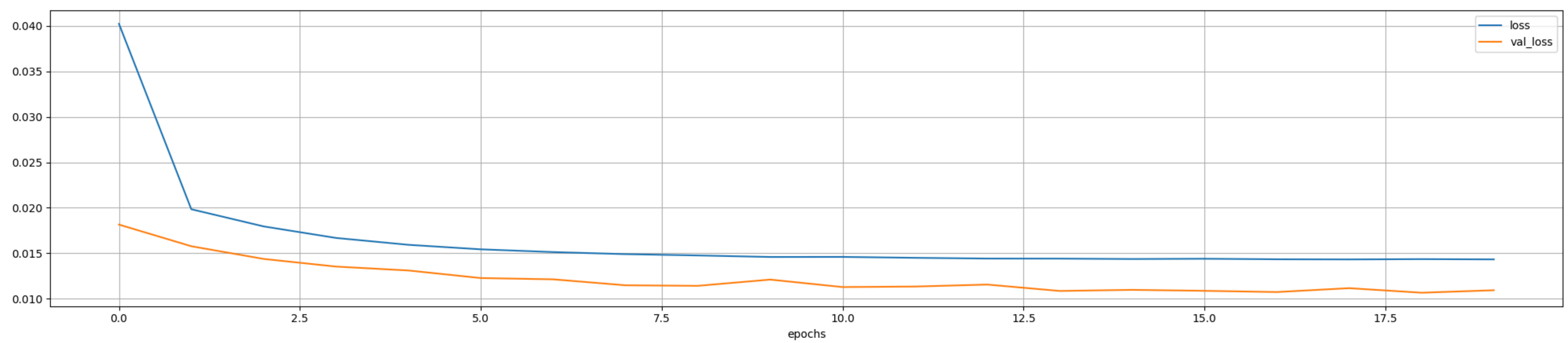
- The plot we obtain contains a few more details
- Since the `Sequential` object was able to process all layers in one go

A Linear Regression Model for RUL Estimation

Next, we trigger the training process

We will use an early stoppping callback to prevent overfitting

```
In [10]: history = util.train_ml_model(nn, tr_s[dt_in], tr_s['rul'], epochs=20, validation_split=0.2
         nn.save('lr_model.keras')
         util.plot_training_history(history, figsize=figsize)
```



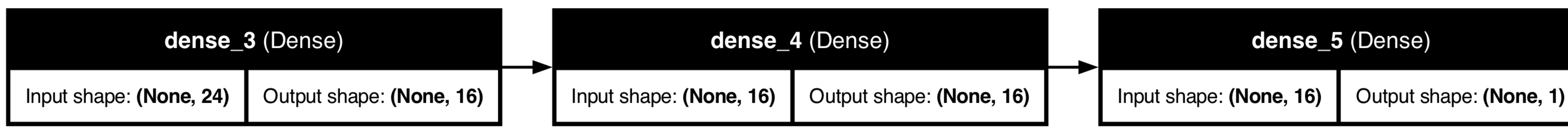

```
Final loss: 0.0143 (training), 0.0109 (validation)
```

An MLP for RUL Estimation

Let's switch to a Neural Network with 2 hidden layers

In [12]:
```
hidden = [16, 16]
nn2 = util.build_ml_model(input_size=(len(dt_in),), output_size=1, hidden=hidden, output_ac
util.plot_ml_model(nn2)
```

Out[12]:

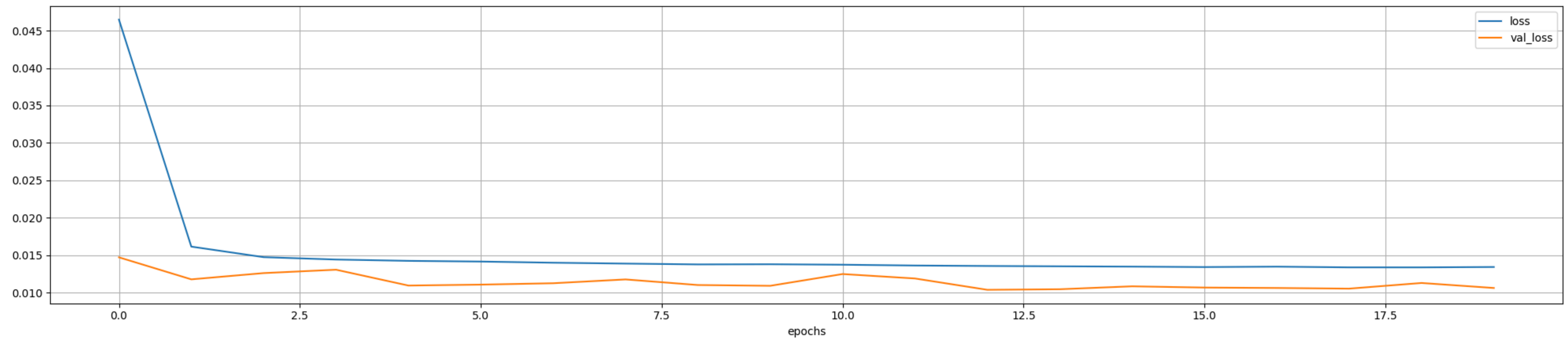


- Now we have two hidden layers with 16 neurons each
- The activation function for this is not displayed
- ...But we know we are using a ReLU

An MLP for RUL Estimation

Let's train this new model

In [13]:
```
history = util.train_ml_model(nn2, tr_s[dt_in], tr_s['rul'], epochs=20, validation_split=0.2
nn2.save('mlp_model.keras')
util.plot_training_history(history, figsize=figsize)
```



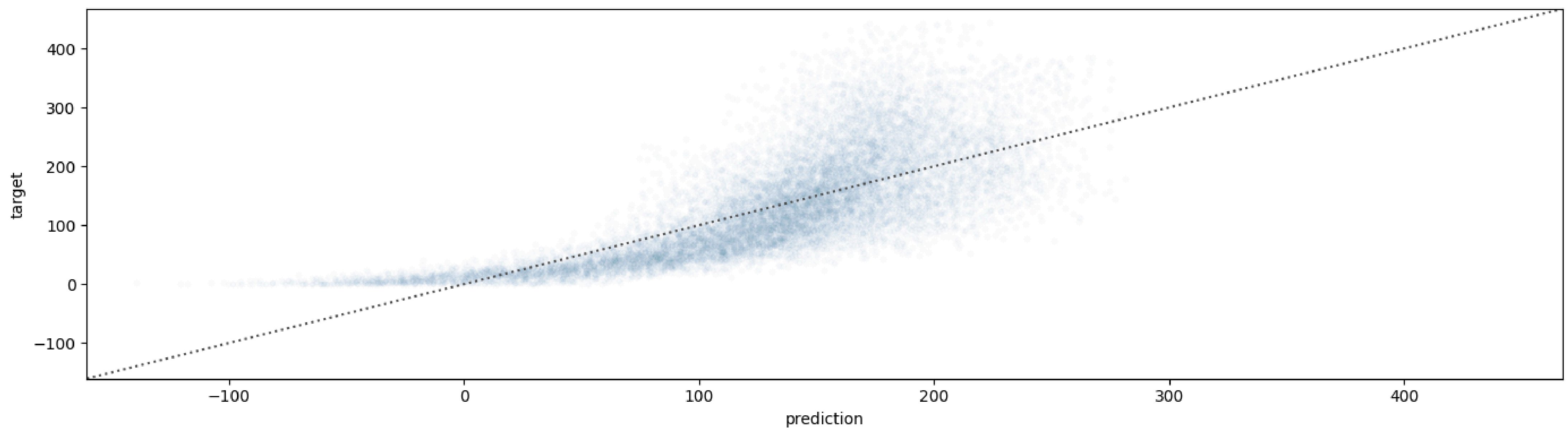

```
Final loss: 0.0134 (training), 0.0106 (validation)
```

We are doing better with this one (but only slighly)

Evaluating Our Model

Let's check the prediction quality for our model

In [14]:
```
ts_pred = nn.predict(ts_s[dt_in], verbose=0).ravel() * nparams['trmaxrul']
util.plot_pred_scatter(ts_pred, ts['rul'], figsize=(14, 4))
```



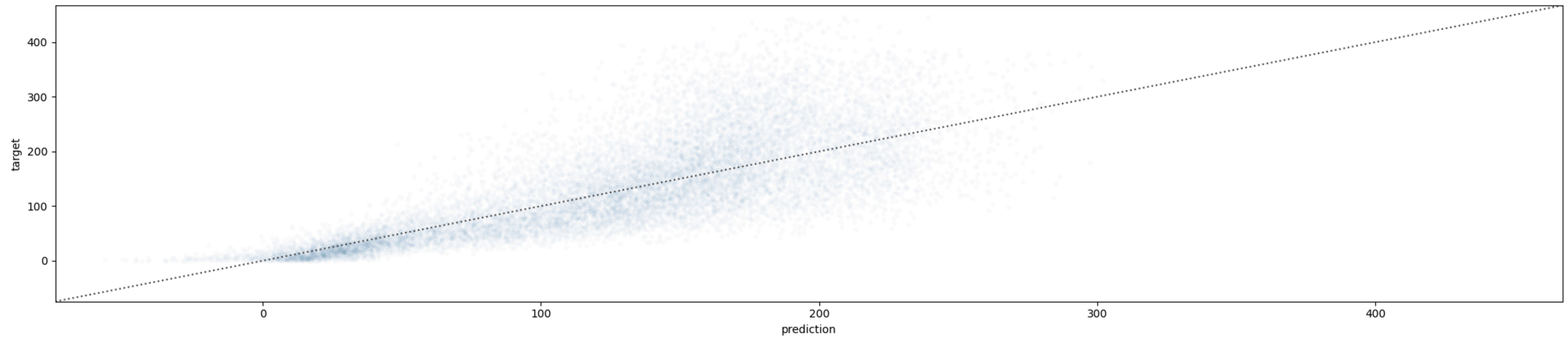

```
R2 score: 0.541
```

The Linear Regression model does not seem to work very well

Evaluating Regression Models

Here are the results for the deeper network

In [15]:
```
ts_pred = nn2.predict(ts_s[dt_in], verbose=0).ravel() * nparams['trmaxrul']
util.plot_pred_scatter(ts_pred, ts['rul'], figsize=figsize)
```




```
R2 score: 0.573
```

The deeper model does not work much better