RUL Prediction as Classification

RUL Prediction as Classification

RUL-based maintenance can also be tackled using a classifier

- We build a classifier to determine whether a failure will occur in ε steps
- We stop as soon as the classifier outputs (say) a 0, i.e.

$$f_\varepsilon(x, \theta) = 0$$

- f is the classifier, with parameter vector θ
- ε is the horizon for detecting a failure

In a sense, we are trying to learn directly a maintenance policy

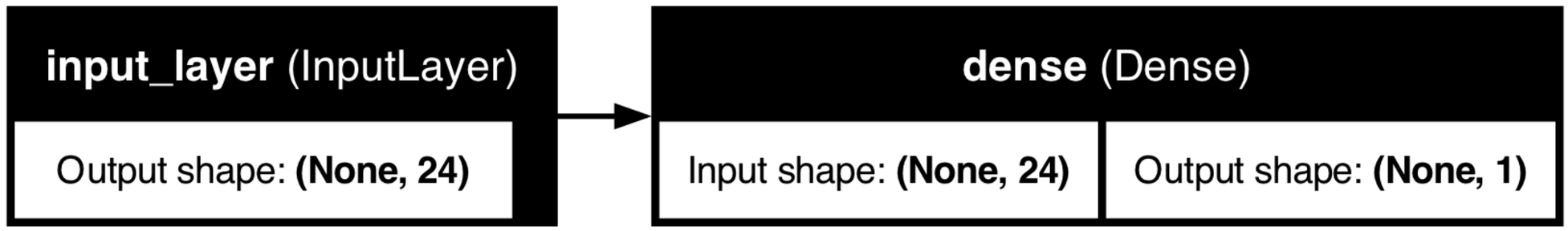
- The policy is the form "stop ε units before a failure"
- The classifier tries to learn it

Classifier Architecture

We can therefore immediately define our classifier architecture:

In [3]:
```
nn1 = util.build_nn_model(input_shape=(len(dt_in), ), output_shape=1, hidden=[], output_act
util.plot_nn_model(nn1)
```

Out[3]:



- Like in the regression case, we use a Multilayer Perceptron
- The only difference is the use of a sigmoid activation in the output layer
- For `hidden = []` we get Logistic Regression
- ...Which of course if going to be out first model

Training

Before training, we need to define the classes

In turn, this requires to define the detection horizon ε:

In [4]:
```
class_thr = 20
tr_lbl = (tr['rul'] >= class_thr)
ts_lbl = (ts['rul'] >= class_thr)
```

- The class is "1" if a failure is more than ε steps away
- The class if "0" otherwise

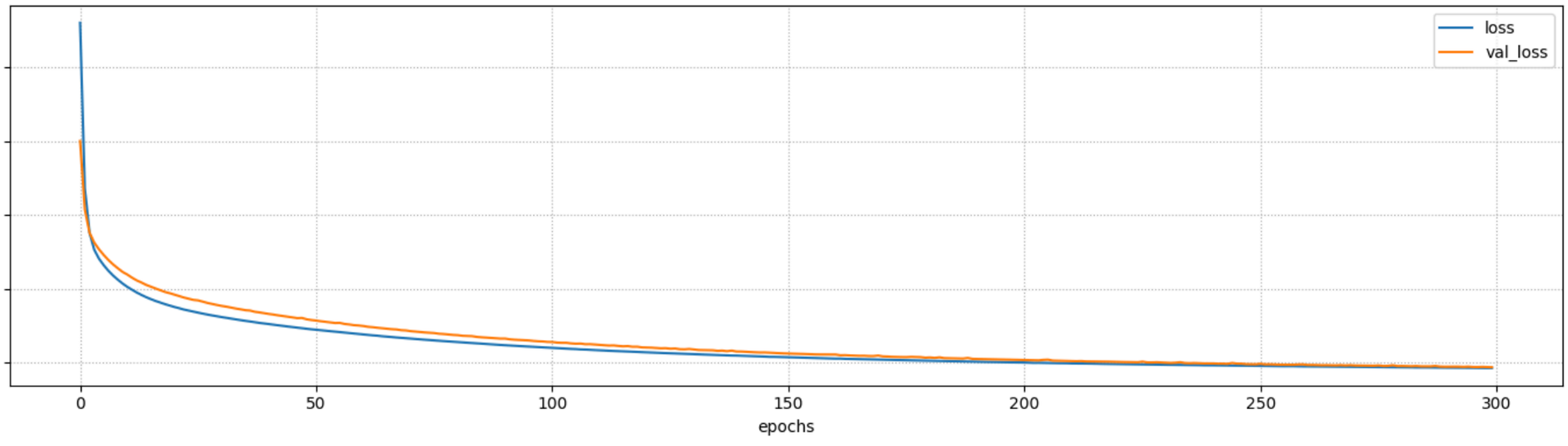
Classification problems tend to be easier than regression problems

- On the other hand, learning the whole policy
- ...May be trickier than just estimating the RUL


Training

Let's start by training the simplest possible model

In [14]:
```
nn1 = util.build_nn_model(input_shape=(len(dt_in), ), output_shape=1, hidden=[], output_act
history = util.train_nn_model(nn1, tr_s[dt_in], tr_lbl, loss='binary_crossentropy', epochs=
        verbose=0, patience=10, batch_size=32, validation_split=0.2)
util.plot_training_history(history, figsize=figsize)
```



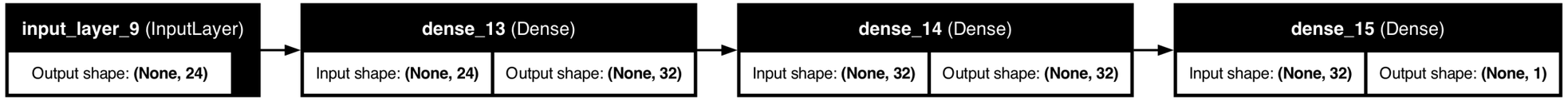

```
Final loss: 0.0928 (training), 0.0939 (validation)
```

Training

Then let's try with a deeper model

In [15]:
```
nn2 = util.build_nn_model(input_shape=(len(dt_in), ), output_shape=1, hidden=[32, 32], outpu
util.plot_nn_model(nn2)
```

Out[15]:

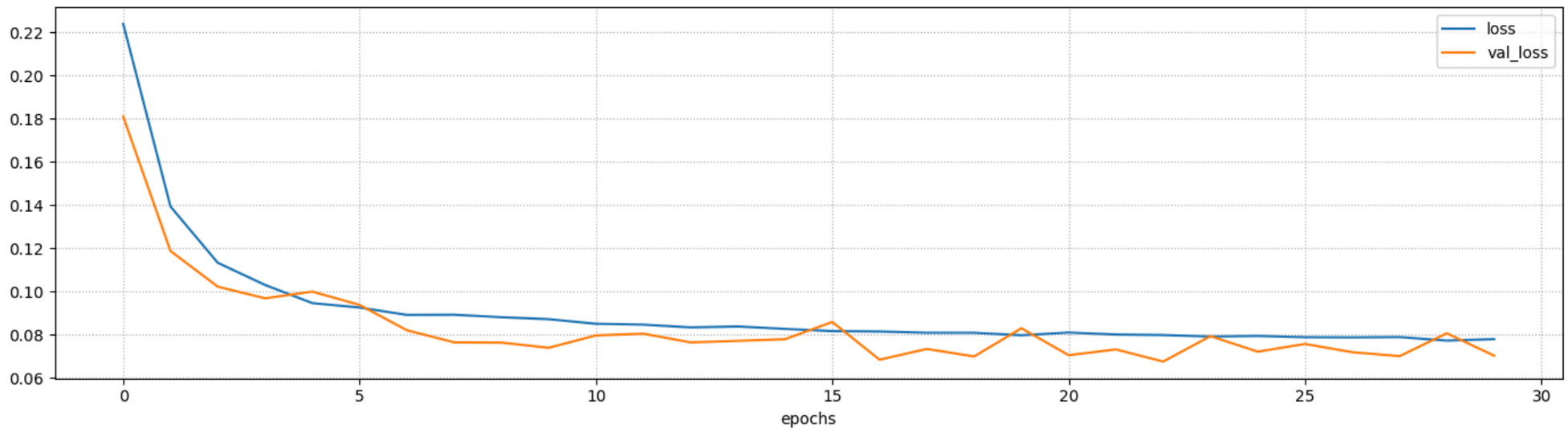


- Now we have two hidden layers
- ...Each with 32 neurons

Training

Let's train it and check the results

In [16]:
```
nn2 = util.build_nn_model(input_shape=(len(dt_in), ), output_shape=1, hidden=[32, 32], outpu
history = util.train_nn_model(nn2, tr_s[dt_in], tr_lbl, loss='binary_crossentropy', epochs=1
        verbose=0, patience=10, batch_size=32, validation_split=0.2)
util.plot_training_history(history, figsize=figsize)
```

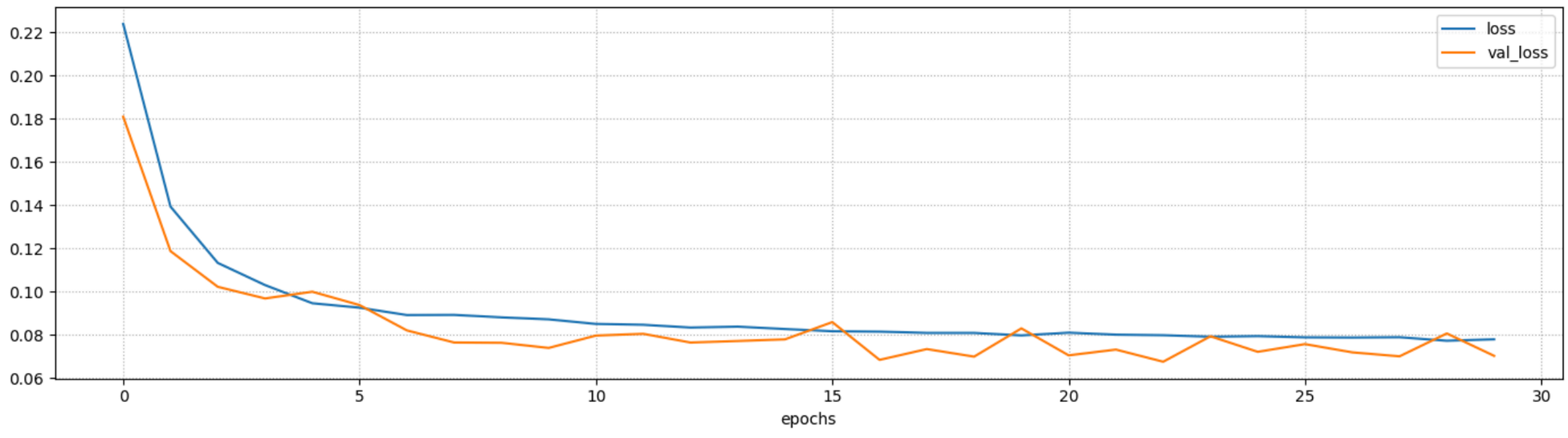



```
Final loss: 0.0780 (training), 0.0703 (validation)
```

Training

Let's train it and check the results

In [16]:
```
nn2 = util.build_nn_model(input_shape=(len(dt_in), ), output_shape=1, hidden=[32, 32], outpu
history = util.train_nn_model(nn2, tr_s[dt_in], tr_lbl, loss='binary_crossentropy', epochs=1
        verbose=0, patience=10, batch_size=32, validation_split=0.2)
util.plot_training_history(history, figsize=figsize)
```



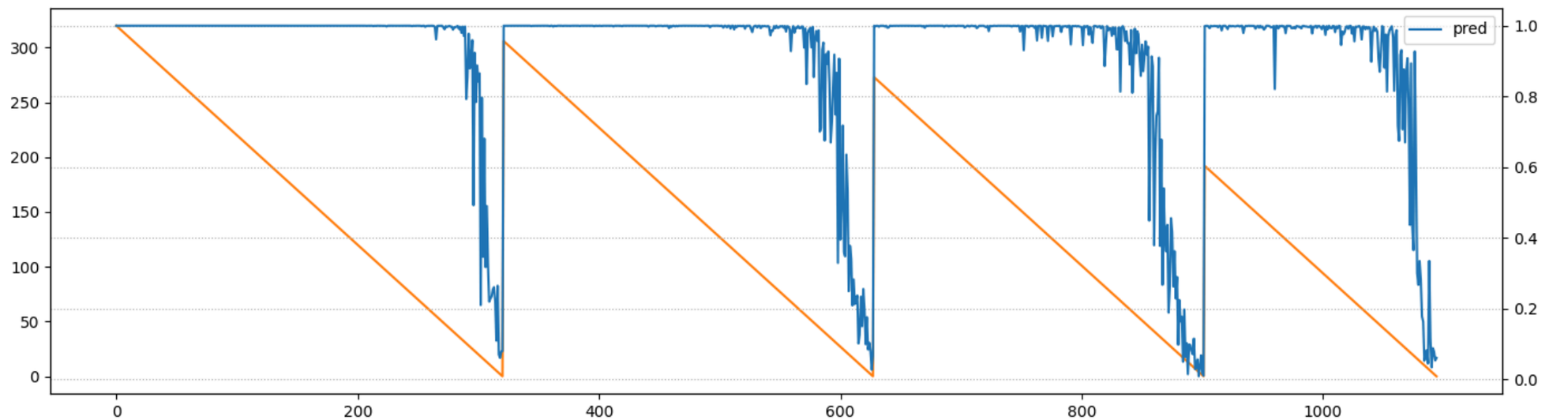

```
Final loss: 0.0780 (training), 0.0703 (validation)
```

There is a significant improvement over Logistic Regression

Predictions

The model prediction can be interpreted as a probabilities of not stopping

In [17]:
```
tr_pred2_prob = nn2.predict(tr_s[dt_in], verbose=0).ravel()
stop = 1095
util.plot_rul(tr_pred2_prob[:stop], tr['rul'][:stop], same_scale=False, figsize=figsize)
```



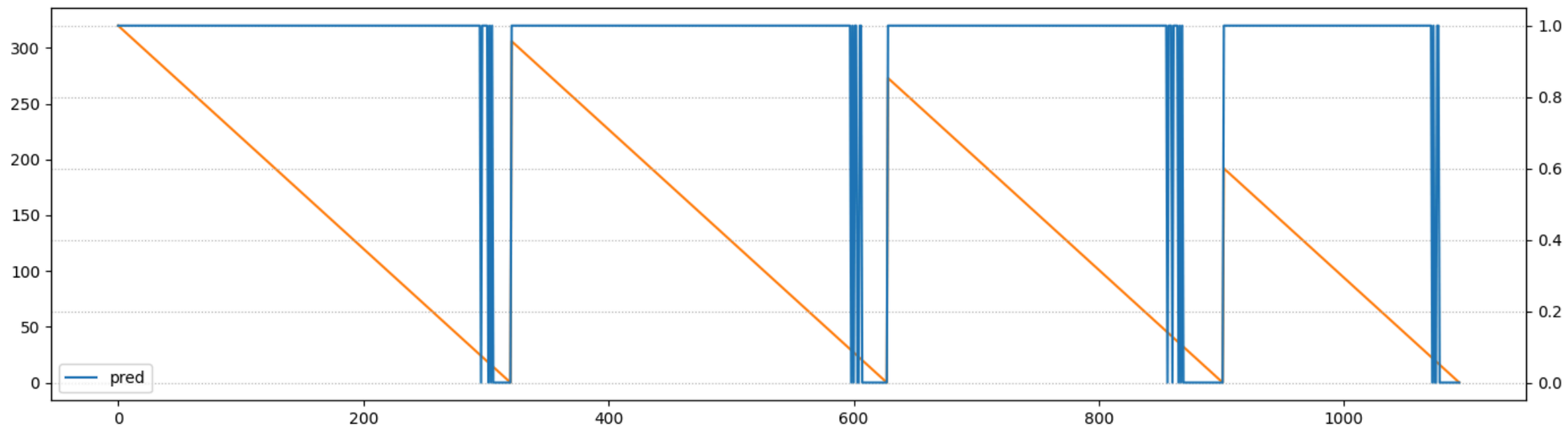
- The probability falls when closer to failures

Predictions

In practice, we'll need to convert the predictions into integers via rounding

...Unless we want to deal with one more threshold (in addition to θ)

In [18]:
```
tr_pred2 = np.round(nn2.predict(tr_s[dt_in], verbose=0).ravel())
util.plot_rul(tr_pred2[:stop], tr['rul'][:stop], same_scale=False, figsize=figsize)
```

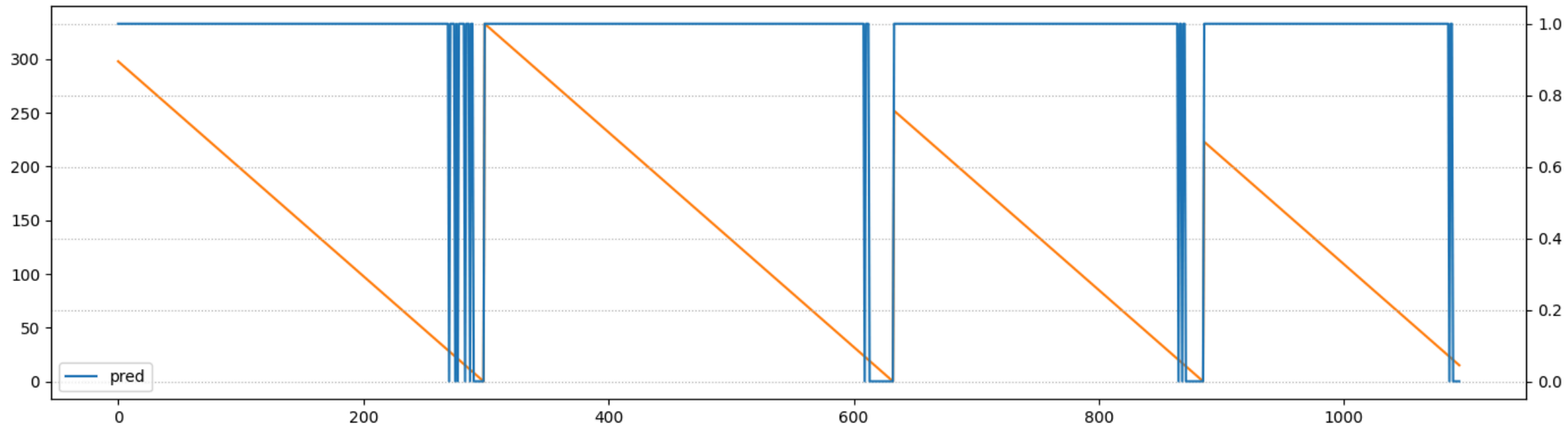


- Still, the behavior seems to be reasonable

Predictions

Let's see the behavior on the test set

In [19]:
```
ts_pred2 = np.round(nn2.predict(ts_s[dt_in], verbose=0).ravel())
util.plot_rul(ts_pred2[:stop], ts['rul'][:stop], same_scale=False, figsize=figsize)
```



- Apparently a decent degree of generalization

Evaluation

We can evaluate the classifier directly

...Because it defines the whole policy, with no need for additional calibration!

- On one hand this makes this stage of the process simpler
- ...On the other, this is (apparently) a missed opportunity

In [20]:
```
tr_c2, tr_f2, tr_s2 = cmodel.cost(tr['machine'].values, tr_pred2, 0.5, return_margin=True)
ts_c2, ts_f2, ts_s2 = cmodel.cost(ts['machine'].values, ts_pred2, 0.5, return_margin=True)
print(f'Cost: {tr_c2/len(tr_mcn):.2f} (training), {ts_c2/len(ts_mcn):.2f} (test)')
print(f'Avg. fails: {tr_f2/len(tr_mcn):.2f} (training), {ts_f2/len(ts_mcn):.2f} (test)')
print(f'Avg. slack: {tr_s2/len(tr_mcn):.2f} (training), {ts_s2/len(ts_mcn):.2f} (test)')
```

```
Cost: -89.35 (training), -98.87 (test)
Avg. fails: 0.00 (training), 0.00 (test)
Avg. slack: 27.02 (training), 25.06 (test)
```

- Still pretty good results, but worse than the best regression approach

Why do you think this is the case?

Why do you think this is the case?

There are a few reasons, we will explore one

Uncalibrated Threshold

In the example from this notebook, we are defining the classes using:

```
class_thr = 20
tr_lbl = (tr['rul'] >= class_thr)
ts_lbl = (ts['rul'] >= class_thr)
```

- Like in the regression case, we are using a threshold θ
- ...But here θ is employed for defining the classes

This approach has both PROs and CONs

- PRO: we can (ideally) choose how close the failure we should stop
- CON: early signs of failure might not be evident in the chosen interval
- CON: we did not calibrate θ

The last point should be elaborated a bit more

Taking a Step Back

In the regression case, we are formally solving:

$$\underset{\varepsilon}{\operatorname{argmin}} \sum_{k \in K} cost(f(x_k, \theta^*), \varepsilon)$$

$$\text{s.t.: } \theta^* = \underset{\theta}{\operatorname{argmin}}\ L(f(x_k, \theta), y_k)$$

- Where θ^* is the optimal parameter vector (i.e. the network weights)
- L is the loss function (i.e. the MSE), and $cost$ is our cost model
- The threshold ε is chosen so as to minimize the cost

This is a bilevel optimization problem

- However, since ε appears neither in L nor in f
- ...It can be decomposed into two sequential subproblems

Taking a Step Back

In the classification case, we are formally solving:

$$\underset{\varepsilon}{\operatorname{argmin}} \sum_{k \in K} cost(f(x_k, \theta^*), 1/2)$$

$$\text{s.t.: } \theta^* = \underset{\theta}{\operatorname{argmin}}\ L(f(x_k, \theta), \mathbb{1}_{y_k \geq \varepsilon})$$

- We use a canonical threshold in the cost model (i.e. 0.5)
- L is again the loss function (binary cross entropy)
- $\mathbb{1}_{y_k \geq \varepsilon}$ is the indicator function of $y_k \geq \varepsilon$ (i.e. our class labels)

Unlike the previous one, this problem cannot be decomposed

...Because ε appears in the loss function!

- This means we need to optimize ε and θ at the same time

Black Box Optimization

Let's sketch a possible optimization approach

1. We search over the possible values of ε
2. For the given ε value, we compute $\mathbb{1}_{y_k \geq \varepsilon}$ (i.e. the class labels)
3. We train the model to compute θ^*
4. Then we compute the cost
5. ...And finally we repeat, for the next value of ε

At the end of the process, we choose the configuration with the best cost

In principle we could use grid search again, but...

- Evaluating the cost is slow, since it requires retraining
- The search space is grows exponentially with the number of parameters

We need a better optimization method!