# 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 $\varepsilon$ 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 $\theta$
- $\varepsilon$ is the horizon for detecting a failure

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

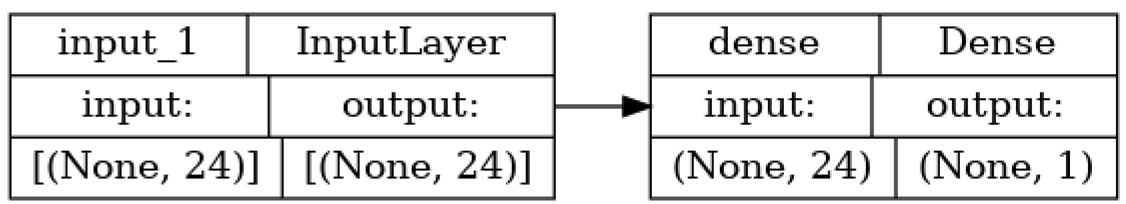
- The policy is the form "stop $\varepsilon$ units before a failure"
- The classifier tries to learn it

# Classifier Architecture

## We can therefore immediately define our classifier architecture:

In [2]:
```
nn1 = util.build_nn_model(input_shape=(len(dt_in), ), output_shape=1, hidden=[], output_acti
util.plot_nn_model(nn1)
```

Out[2]:




- 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 $\theta$:

```
In [13]: 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 $\theta$ steps away
- The class if "0" otherwise

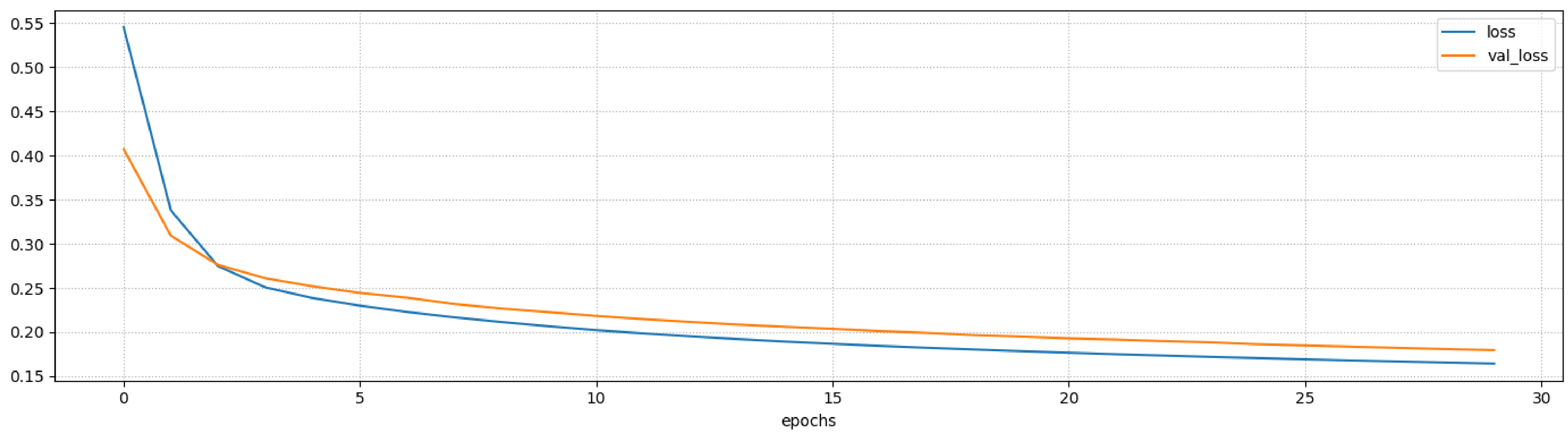
## Classification problems tend to be easier than regression problems

- 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_acti
history = util.train_nn_model(nn1, tr_s[dt_in], tr_lbl, loss='binary_crossentropy', epochs=3
        verbose=0, patience=10, batch_size=32, validation_split=0.2)
util.plot_training_history(history, figsize=figsize)
```



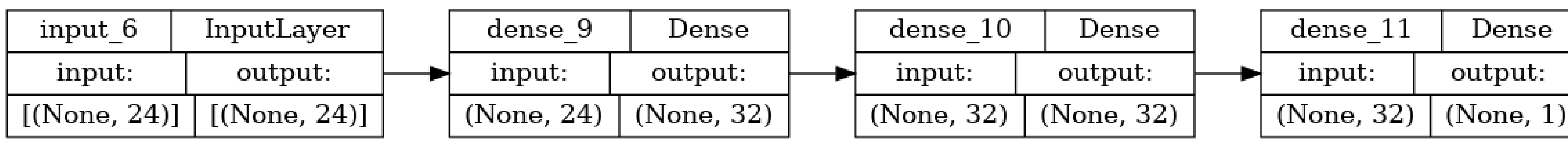

```
Final loss: 0.1642 (training), 0.1795 (validation)
```

# 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]:

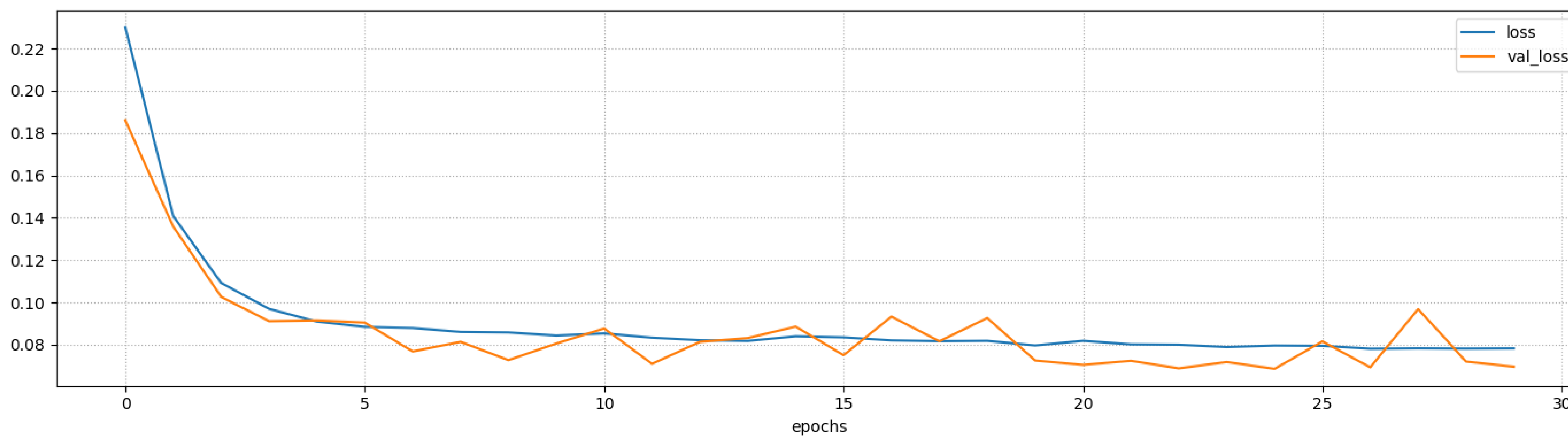



- Now we have two hidden layers
- ...Each with 32 neurons

# 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=3
        verbose=0, patience=10, batch_size=32, validation_split=0.2)
util.plot_training_history(history, figsize=figsize)
```

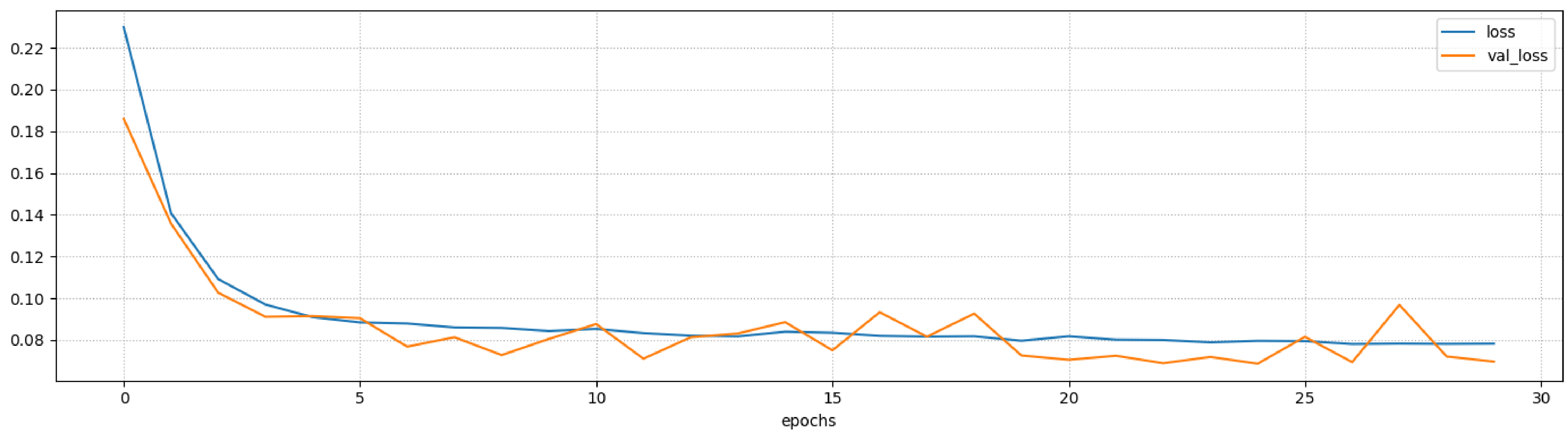



```
Final loss: 0.0782 (training), 0.0696 (validation)
```

# 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=3
                 verbose=0, patience=10, batch_size=32, validation_split=0.2)
         util.plot_training_history(history, figsize=figsize)
```



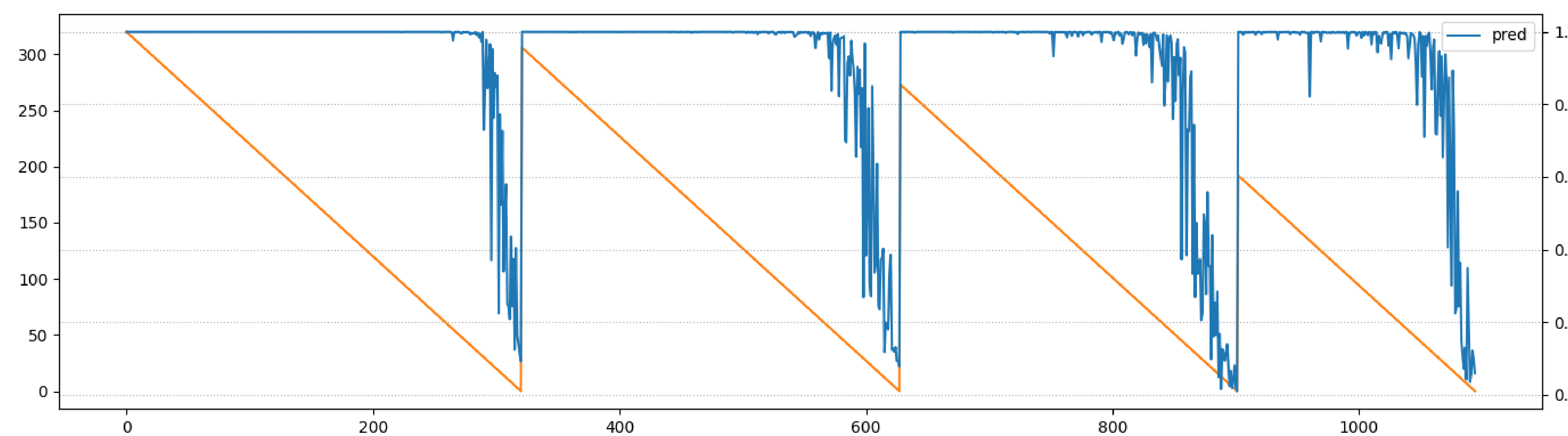

```
Final loss: 0.0782 (training), 0.0696 (validation)
```

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)
```



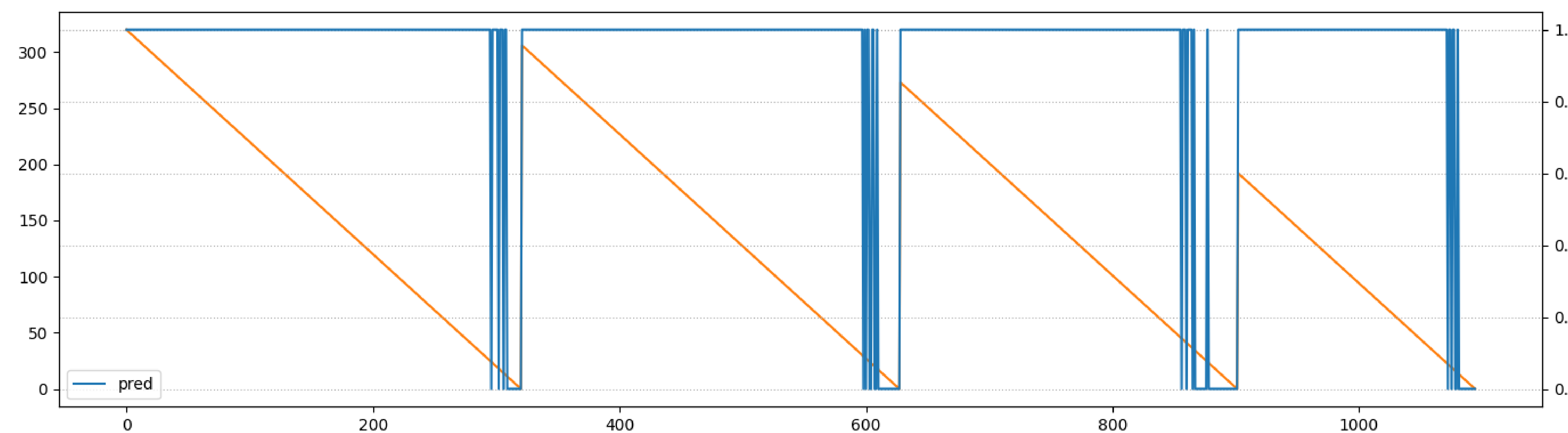

- The probability falls when closer to failures

## 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 $\theta$)

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)
```

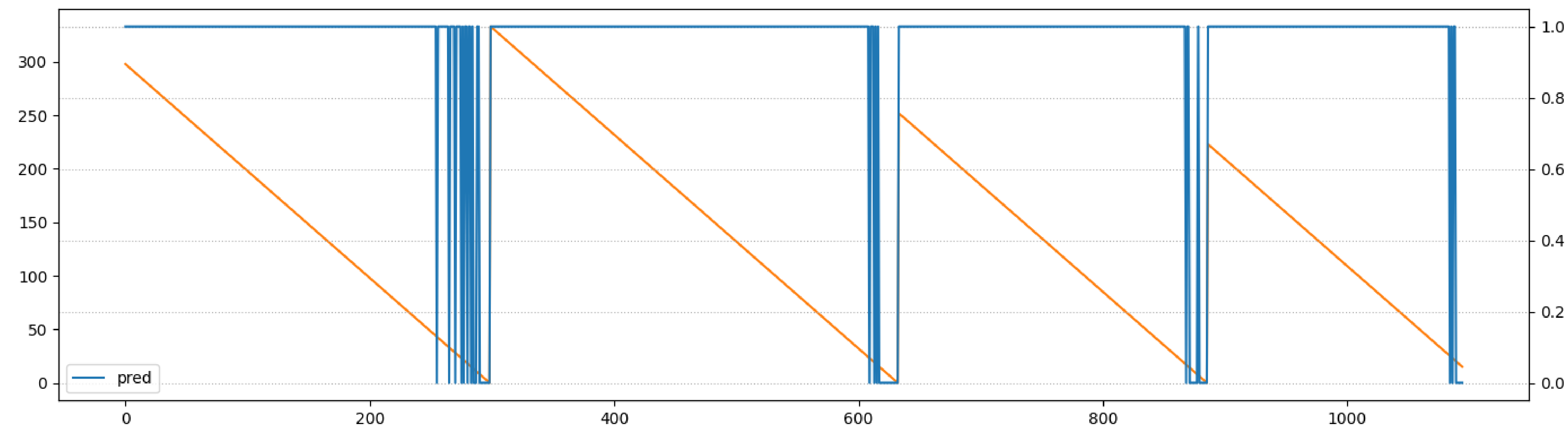



- Still, the behavior seems to be reasonable

# 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: -86.42 (training), -96.89 (test)
         Avg. fails: 0.00 (training), 0.00 (test)
         Avg. slack: 30.01 (training), 27.05 (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 $\theta$
- ...But here $\theta$ 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 $\theta$

The last point should be elaborated a bit more

## Taking a Step Back

**In the regression case, we are formally solving:**

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

$$\text{s.t.: } \theta^* = \operatorname*{argmin}_{\theta} L(f(x_k, \theta), \hat{y}_k)$$

- Where $\theta^*$ 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 $\varepsilon$ is chosen so as to minimize the cost

**This is a bilevel optimization problem**

- However, since $\theta$ 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:**

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

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

- 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 $\varepsilon$ appears in the loss function!

- This means we need to optimize $\varepsilon$ and $\theta$ at the same time

# Black Box Optimization

**Let's sketch a possible optimization approach**

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

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!