IMPROVE USAGE OF UNSUPERVISED DATA FOR DEFINITION OF RUL-BASED MANTEINANCE POLICIES

Giorgia Pavani,
Livia Del Gaudio,
Alessandro Pasi

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AI IN INDUSTRY EXAM

Project

We will run multiple experiments on C-MAPSS dataset, to analyse the benefits of domain knowledge injection to improve the usage of unsupervised data.

Task 1

Experiments with different ratios of supervised data.

Task 2

Experiments with different ratios of unsupervised data.

Task 3

Experiments with different ratios of both supervised and unsupervised data.

Task 4

Introduce a static regularizer to enforce the model to learn strictly positive RUL values.

Task 5

Develop a Lagrangian based approach to dynalically maximize the weight of the regularizer.

Project Pipeline

01 **Dataset Inspection**

02 **Task 1:** supervised experiments

03 **Task 2:** unsupervised experiments

04 **Task 3**: mixed experiments

05 **Task 4:** positivity constraint

06 **Task 5:** Lagrangian approach

07 **Results and future work**

Dataset inspection

This project is developed using NASA Commercial Modular Aero-Propulsion System Simulation (**C-MAPSS**): a simulator for turbofan engines.

We will focus on **FD004** dataset, which works under 6 operating condition and 2 falut modes. It is composed by the following attributes:

- ***src*** (FD004)
- *machine*
- *cycle*
- *p1, p2, p3* (controlled parameters)
- *s1..s21* (sensors)
- *RUL*

Data preprocessing and models setup

1. **Standardize** data, so that it has 0 mean and 1 standard deviation.

2. **Split the machines** for train, validation and test. Then take different **train ratios** depending on the Task.

3. For *unsupervised* setting: **remove RUL** and **truncate** machines series in order to simulate non supervised experiments.

4. Define a baseline, namely an **MLP Regressor** with two hidden layers with 32 units each. The **loss** definition is task-dependent.

5. Run all the experiments with 30 seeds and for 15 epochs, in order to ensure robustness of the results.

Task 1:
fully supervised experiments

EXPECTATIONS:

- higher percentages of supervised data will yelds better performances.
- possible overfitting due to simplistic models.
- model will learn the decreasing RUL trend and the failure accurately.
- approximately correct predictions of initial and final RUL values.

1.1 100% of supervised data

1.2 75% of supervised data

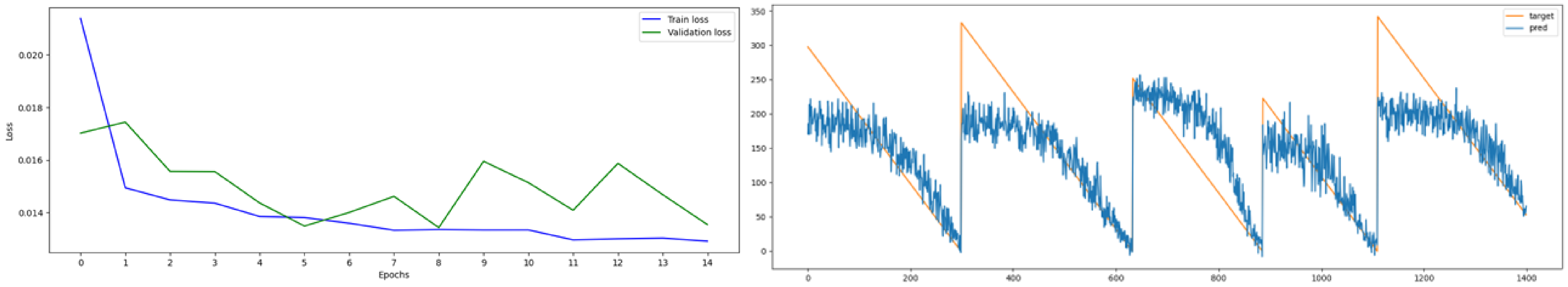
1.3 50% of supervised data

Task 1: results

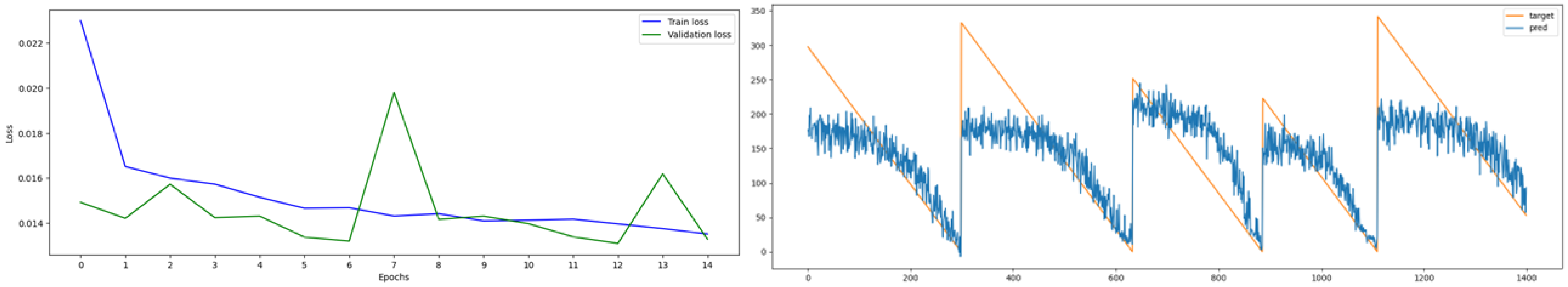
The loss for Task 1 is Mean Squared Error (**MSE**), computed between the true and predicted RUL values.

	MSE mean	Standard deviation
Task 1.1	0.0123038	0.000977068
Task 1.2	0.0125143	0.000928641
Task 1.3	0.0128224	0.00103055

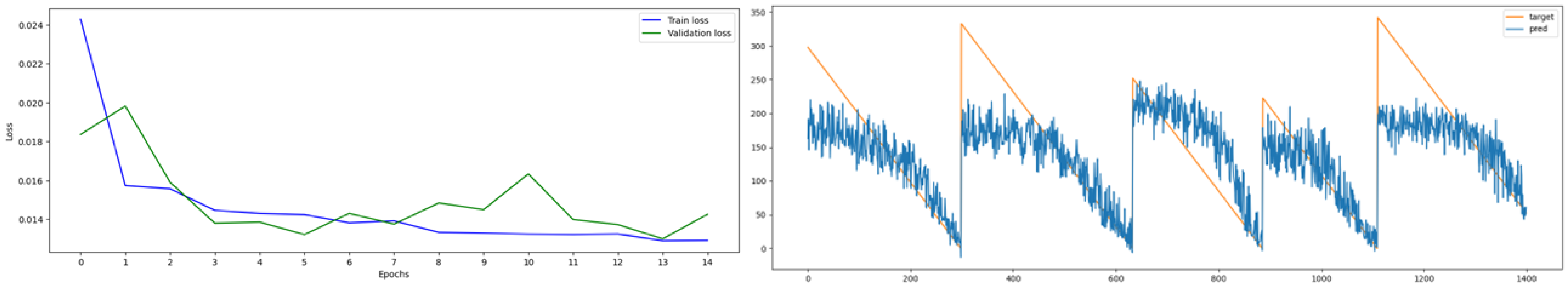
Task 1.1



Task 1.2



Task 1.3



Task 1 - comments

As expected the model learns the decreasing RUL trend.

Differently from what we expected, the model struggles in identifying the initial value, resulting in an underextimation of the true initial RUL.

The regressor gets quite accuratley the lower value, but it happens that it predicts negative RUL values, that are not allowed as they’re not realistic.

Task 2:
fully unsupervised experiments

EXPECTATIONS:

- learns the decreasing trend of the RUL.
- struggles in predicting the initial and final RUL values of the serie.
- lower performances with respect to experiments with only supervised data (Task 1).

2.1 100% of unsupervised data

2.2 75% of unsupervised data

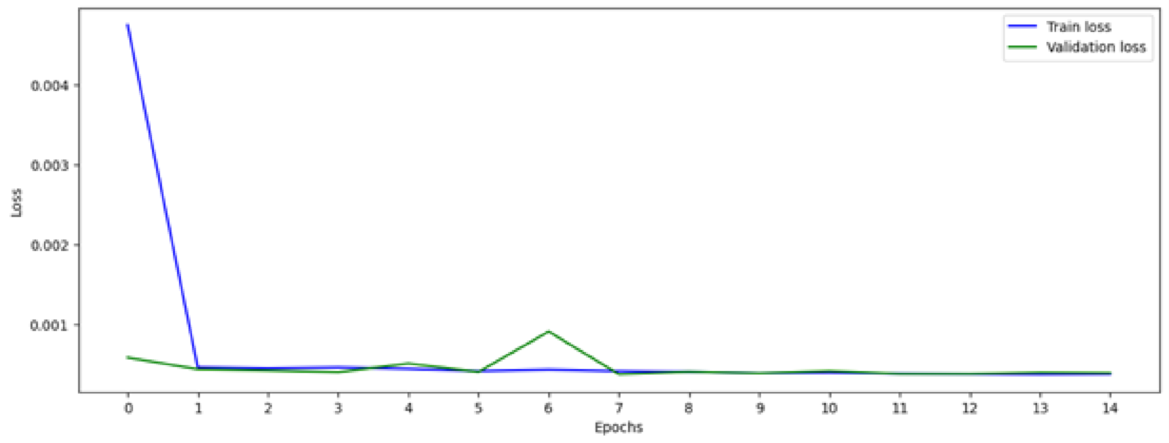
2.3 50% of unsupervised data

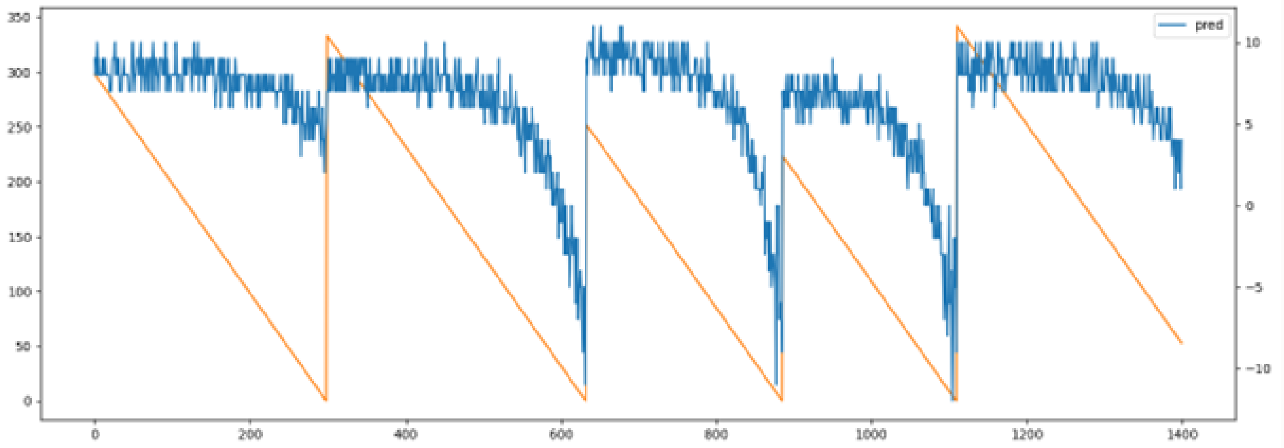
Task 2: results

The loss for Task 2 is **CST** loss, measured on the decreasing RUL constraint. We cannot compute the MSE because RUL values are not available.

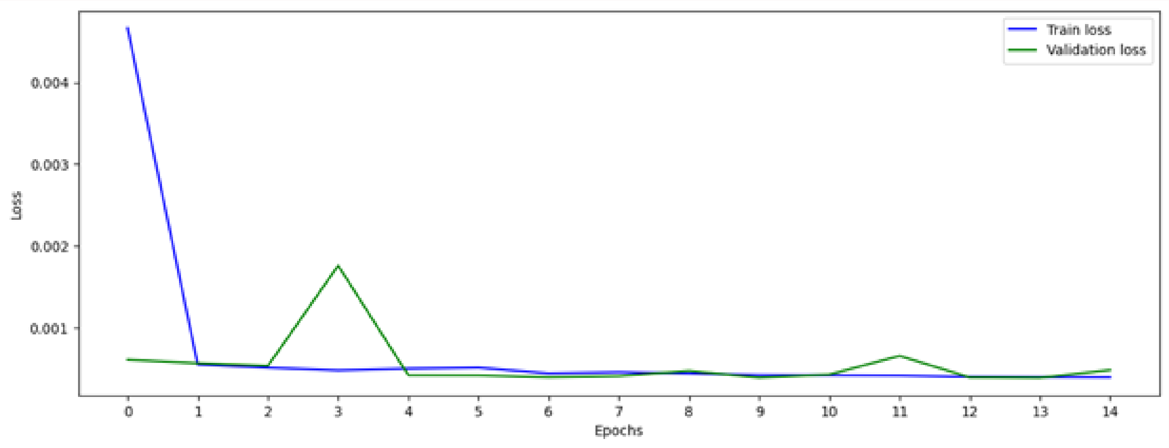
	MSE mean	Standard deviation
Task 2.1	0.0843178	0.0110605
Task 2.2	0.0841617	0.0145537
Task 2.3	0.0936787	0.0636977

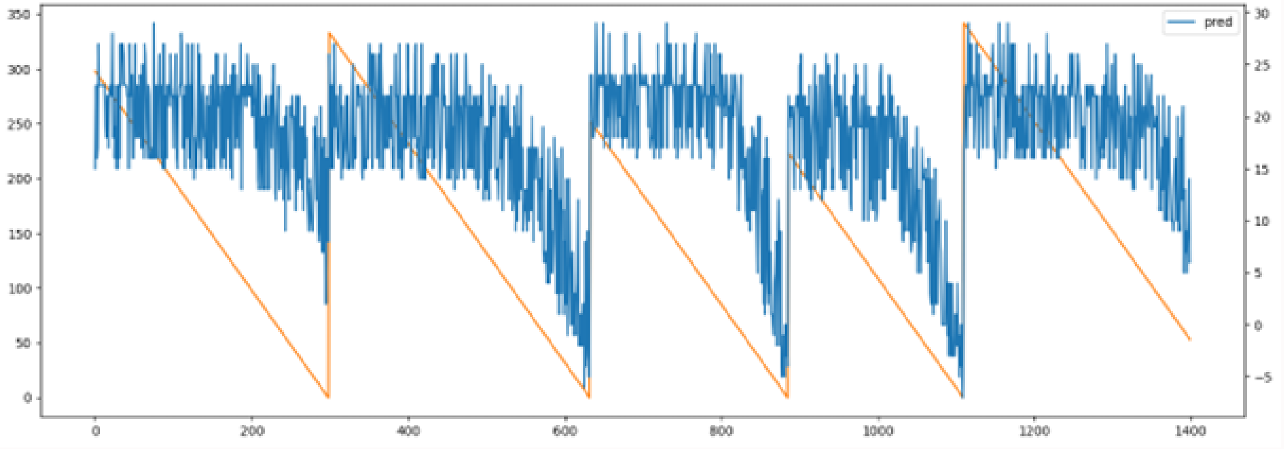
Task 2.1



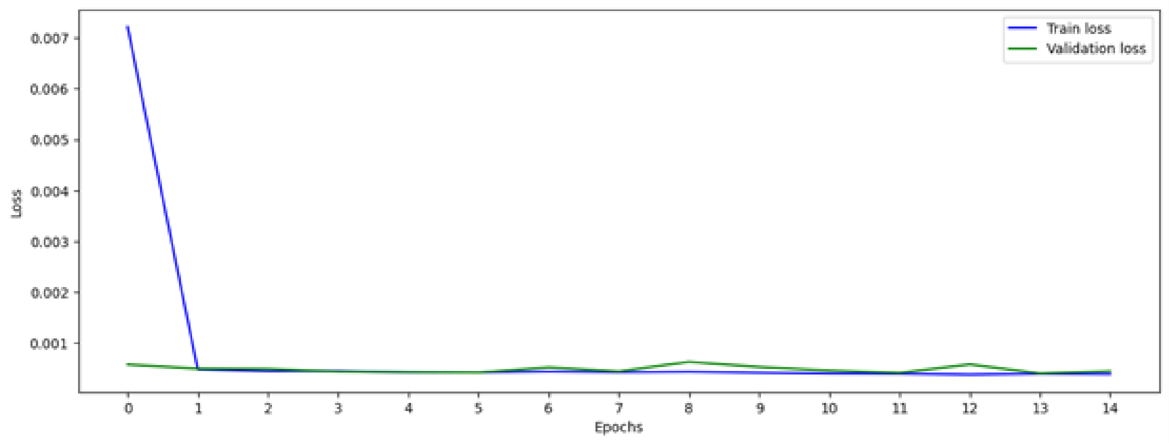


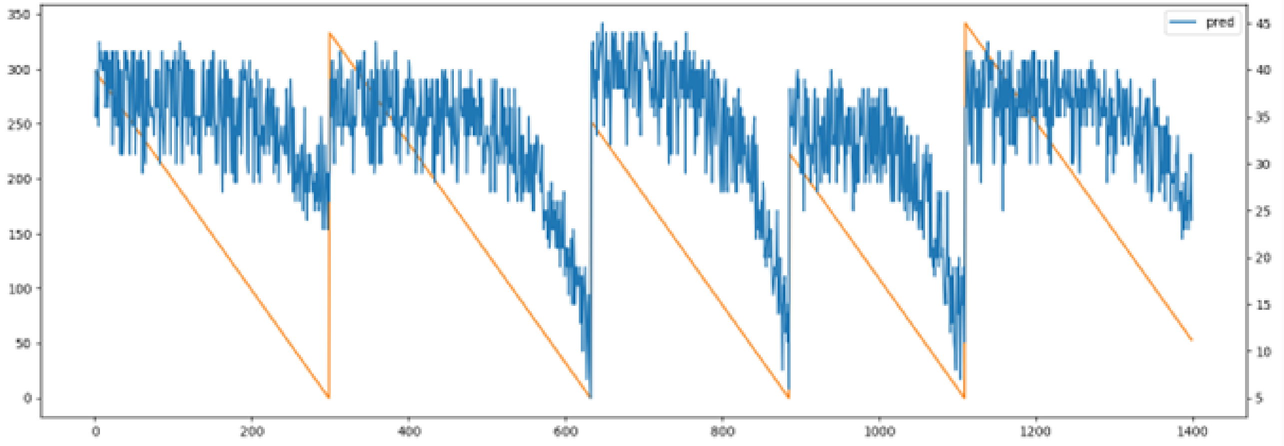
Task 2.2





Task 2.3





Task 2 - comments

As expected, the model struggles in learning the initial and final values of the remaining useful life of the machines, but it is able to guess the right decreasing trend.

Comparing the results with ***Task 1***, as expected, we have worse performances:

- *initial RUL values* of Task 1 are higher than those of Task 2: for the first the values are more closer to the right initial RUL (near 200), for the second they are far more different, as the maximum initial value is around 50.
- *final RUL values* of Task 1 are closer to 0 than those of Task 2.
- Task 2 has a lot more negative RUL values and rarely ends with a 0.

Task 3:

mixed supervised and unsupervised experiments

EXPECTATIONS:

- increasing supervised samples while keeping unsupervised fixed, improves performances.
- increasing unsupervised samples while keeping supervised fixed, worsen the performaces.
- higher number of supervised samples with respect to unsupervised data will lead to greater results.
- we expect that the performances will lay in between those of Task 1 and Task 2.

16 combinations of both supervised and unsupervised data were studied, changing their ratio considering the following percentages of data

- 100%
- 75%
- 50%
- 25%

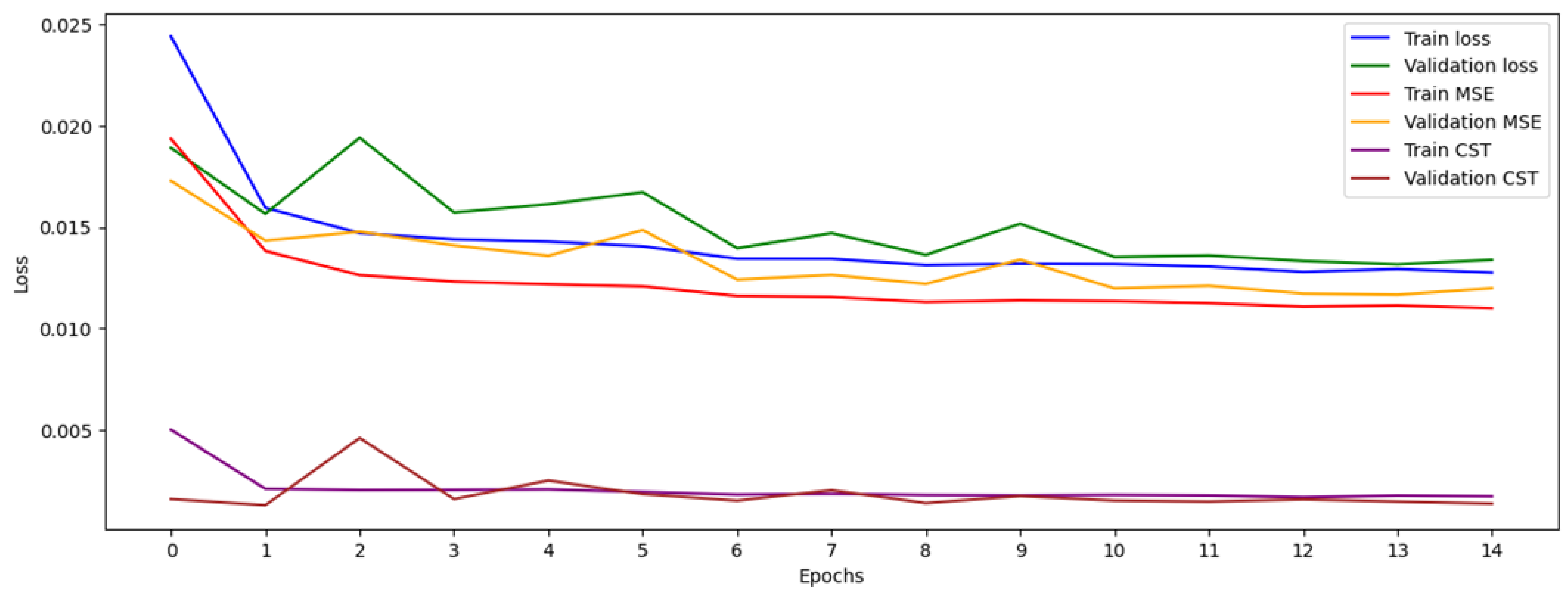
Task 3: results

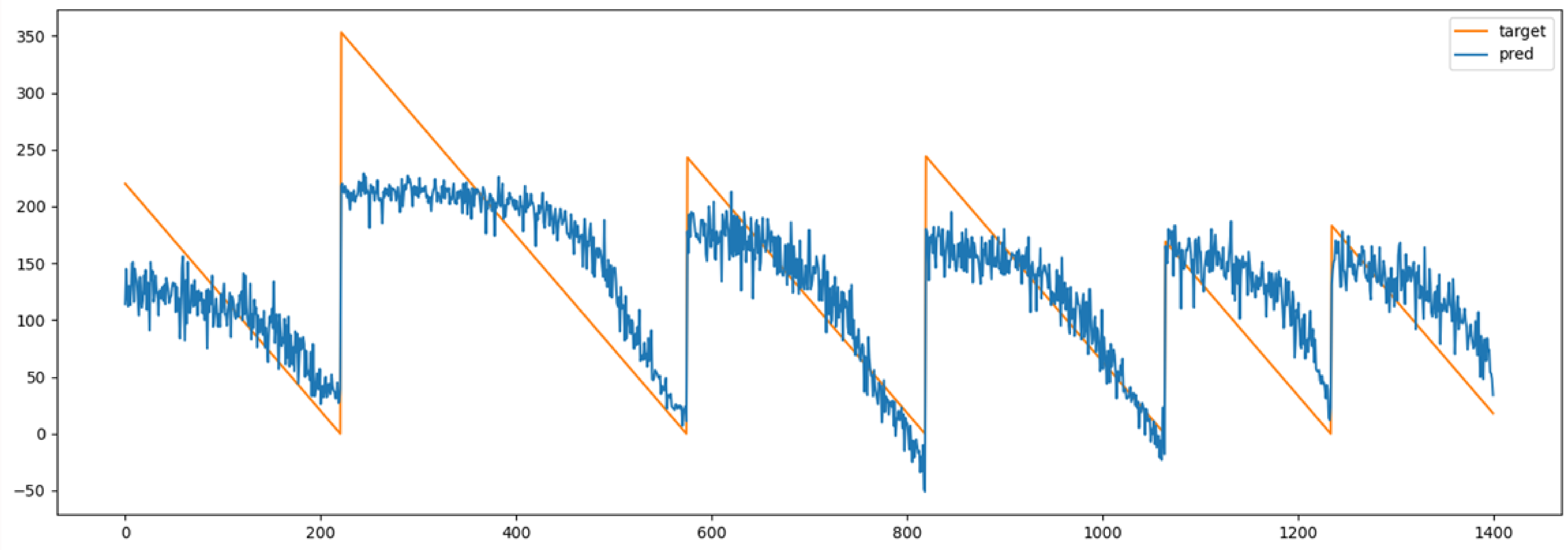
The total loss used for Task 3 is the **sum** of both MSE and CST losses. The reason behid this is to take into account the influence of both supervised and unsupervised data.

Task	Percentages	Mean	Std
Task 3.1	100 u, 100 s	0,010972	0,000815
Task 3.2	100 u, 75 s	0,010904	0,000474
Task 3.3	100 u, 50 s	0,012487	0,000795
Task 3.4	100 u, 25 s	0,014843	0,000869
Task 3.5	50 u, 100 s	0,010645	0,000598
Task 3.6	75 u, 100 s	0,01057	0,000463
Task 3.7	25 u, 100 s	0,010676	0,000545
Task 3.8	75 u, 75 s	0,011209	0,000915
Task 3.9	75 u, 50 s	0,011457	0,000933
Task 3.10	75 u, 25 s	0,012425	0,001151
Task 3.11	50 u, 75 s	0,011414	0,001067
Task 3.12	50 u, 50 s	0,011593	0,00079
Task 3.13	50 u, 25 s	0,012445	0,00093
Task 3.14	25 u, 75 s	0,011179	0,001023
Task 3.15	25 u, 50 s	0,011903	0,001301
Task 3.16	25 u, 25 s	0,012051	0,000879

Task 3: results

Best performing setup, among all 16 combinations tested, is the one used in **Task 3.6.**
It is composed by 100% supervised and 75% unsupervised samples.





Task 3 - comments

According to our hypothesis, performance improves when when keeping fixed unsupervised data and increasing supervised data ratio. However, the opposite statement does not hold.

Performance does not fall between Tasks 1 and 2 as we wrongly expected. This suggests that using mixed data allows better extraction of characteristics, by keeping good points from both supervised and unsupervised paradigms.

As expected, better performance is observed when the supervised samples exceeds the unsupervised counterpart, while higher unsupervised data tends to yield inferior performance.

Task 4:

positivity constraint

EXPECTATIONS:

- significantly enhance model's performance by enforcing the model to predict strictrly positive RUL values.

4.1 The positivity constraint is implemented by adding a **positivity regularizer** to the loss.

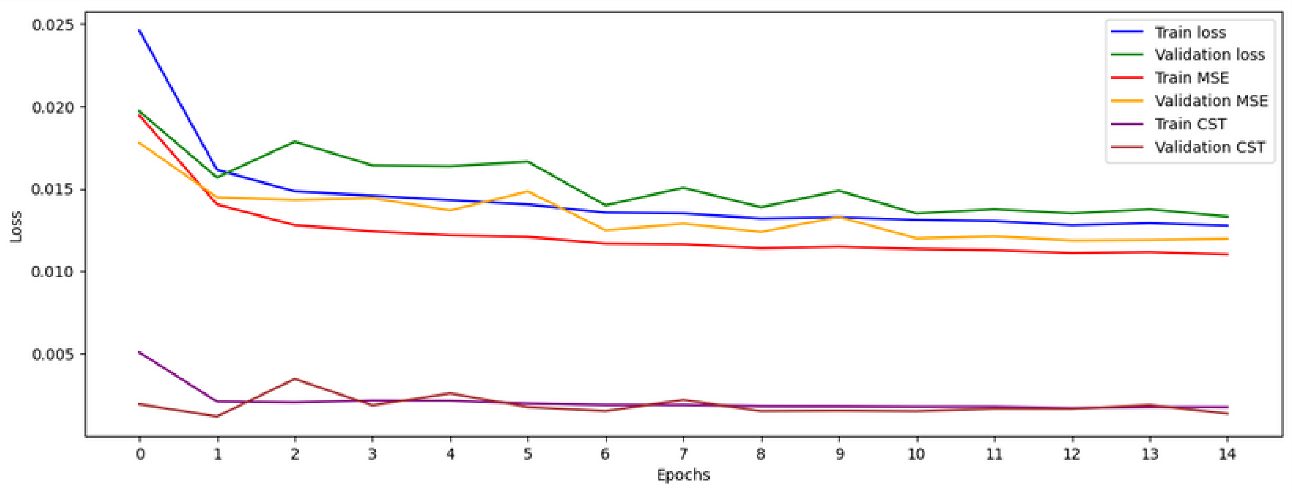
4.2 Add a final **exponential layer** to our network, so that it learns the logarithm of the predictions (by definition strictly positive).

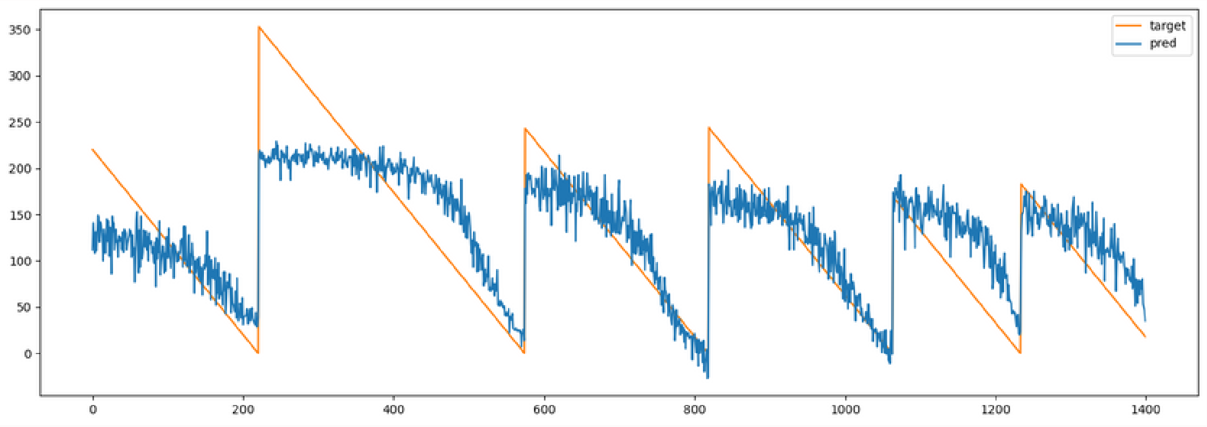
Task 4: results

The total loss used for Task 4.2 is the sum of both MSE and CST losses. Instead, the loss for Task 4.1 additionaly takes into account the positivity regularizer value during its computation.

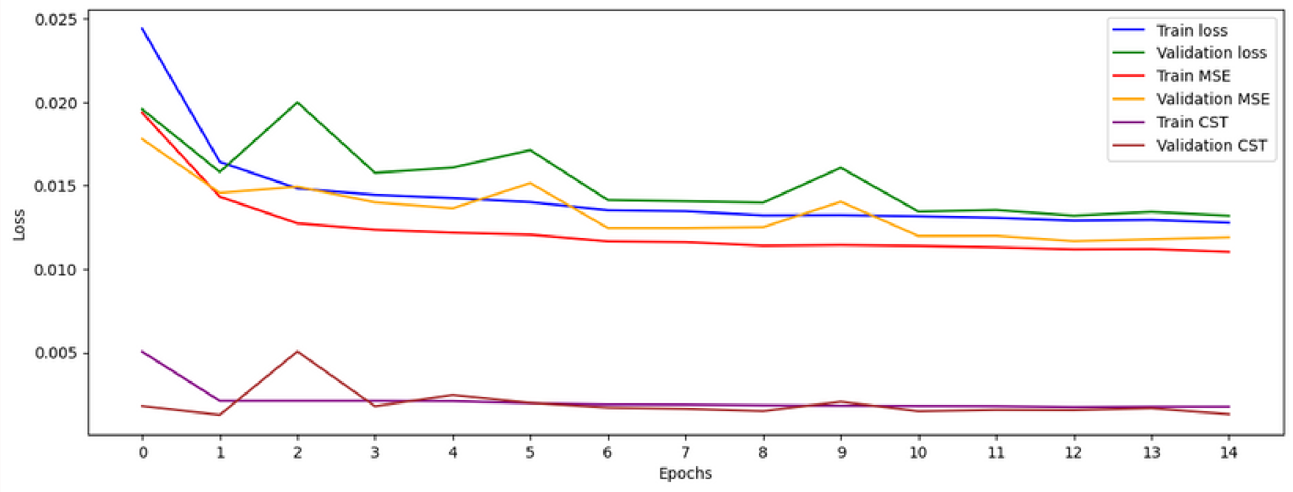
	MSE mean	Standard deviation
Task 4.1	0.0105681	0.000425142
Task 4.2	0.0105701	0.000500566

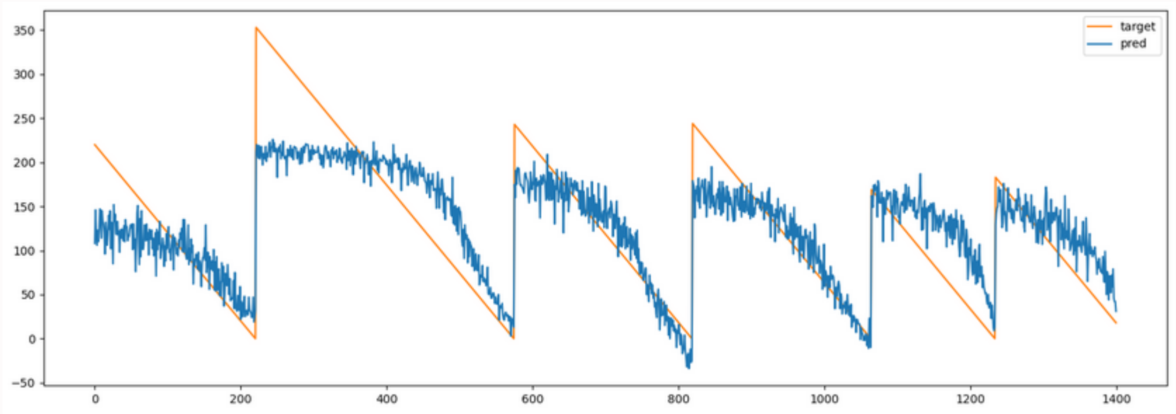
Task 4.1





Task 4.2





Task 4 - comments

Contrarily to our suppositions, for Task 4 there is a slightly improvement from Task 3.6 and not remarkable. This is due to the fact that the model was trained with greater number of supervised samples with respect to the unsupervised ones. Therefore, with this dataset the effects of positivity regularizer are not very visible.

To concretely investigate on the effects of the positivity constraint, we analyzed the effects of this constraint on *fully unsupervised dataset*. As expected, the results show high enhancement of the performances: the loss value halves with the adding of this regularizer.

Task 5:

Lagrangian approach

EXPECTATIONS:

- positive impact on model performances
- there might be conflicts during the computation of the total loss when we also have the positivity regularizer, which could introduce complexities and affect the explainability.

5.1 dynamic weight of *cst* on model in Task 3.6

5.2 dynamic weight of *cst* on model in Task 4

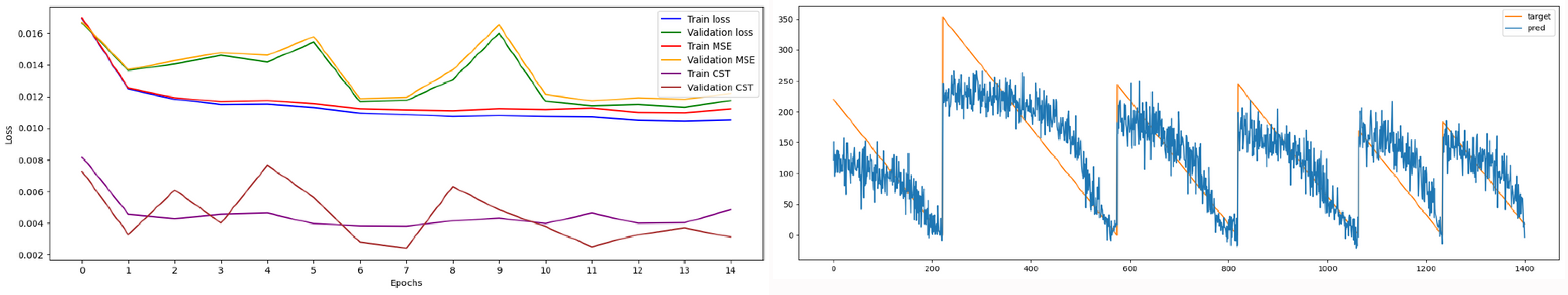
5.3 dynamic weight of *cst* and *positivity regularizer* on model in Task 4

Task 5: results

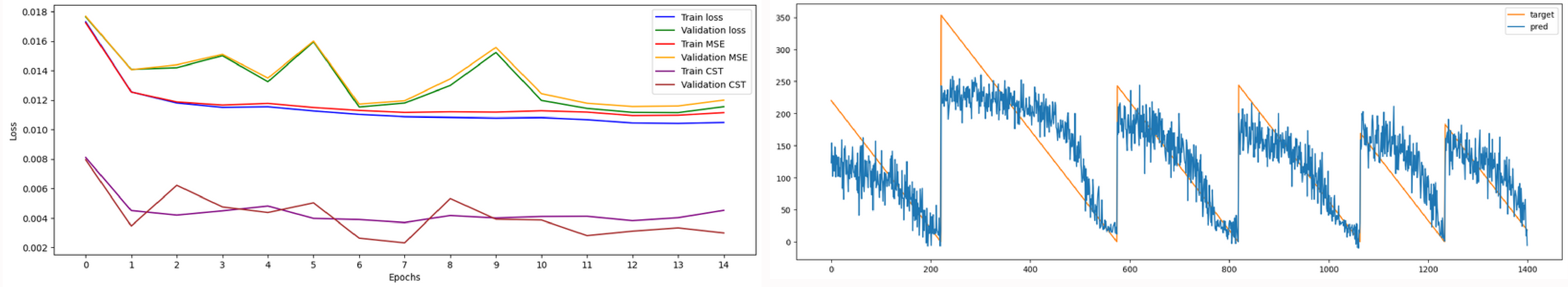
The loss for Task 5 is the combined loss given by the sum of MSE and CST losses also taking into account the dynamic Lagragian weight. Additionally, in Tasks 5.2 and 5.3 the total loss is also influenced by the positivity regularizer.

	MSE mean	Standard deviation
Task 5.1	0.0109465	0.0009015
Task 5.2	0.0110581	0.0008015
Task 5.3	0.0109223	0.00082183

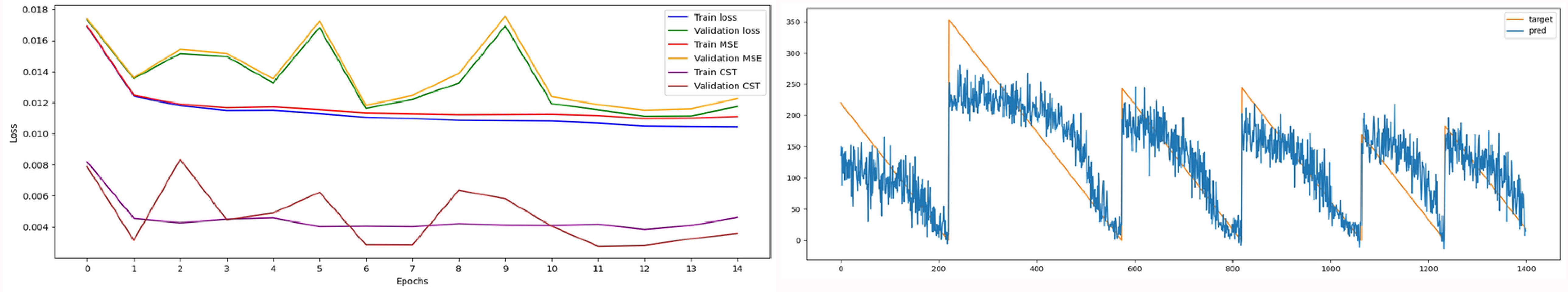
Task 5.1



Task 5.2



Task 5.3



Task 5 - comments

Contrarily from expectations:

- All models tested in Tasks 5 show a degradation of performance with respect to the relative benchmark (Task 3.6 and Task 4).
- Task 5.3 yields the best results, suggesting that having also a gamma dynamically learnt positively impacts the performance.

As expected, since results of Task 5.2 are worse than in Task 5.1, the possibility of a conflict between the lagrangian multiplier and static positivity regularizer seems to hold.

We strongly believe that, similarly to Task 4, using an higher ratio of unsupervised data than supervised samples will lead to a greater improvement of the performances.

Final observations

Models trained on both supervised and unsupervised data outperform those trained solely on supervised or unsupervised data. As mixed datasets enable models to learn both the monotonically decreasing trend from unsupervised data and the bound values for predictions from supervised data, our initial expectations are challenged.

Attempts to enhance the best model's performance with positivity regularization or dynamic weight for the CST loss were not as effective as expected. However, this does not mean that these techniques useless; they may be more suitable for datasets dominated by unsupervised data.

Future work

We could repeat the last tests on Task 4 and Task 5 with fully unsupervised data or mixed data where unsupervised samples are much greater than the supervised ones, in order to replicate our experiments in a more realistic setup.

It is possible to test Task 5 using the model proposed in Task 4.2, where the positivity RUL constraint is implemented adding a final exponential layer to the regressor model.

Lastly we could also try to improve performances by implenting a more complex network, possibly by adding hidden layers or changing network structure.

THANKS FOR ATTENTION