Monitoring the Cold Spray Process: Real-time particle velocity monitoring through airborne acoustic emission analysis

S. Koufis, N. Eskue, D. Zarouchas, J.A. Pascoe

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Aerospace Structures & Materials
Faculty of Aerospace Engineering

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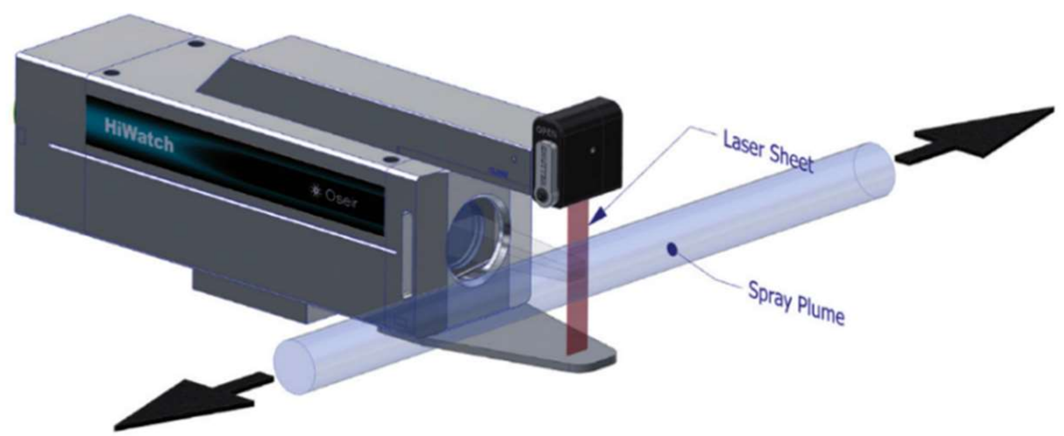
BRIGHTSKY

Process monitoring

Process monitoring

Particle velocimetry techniques

- Measure velocity, particle density
- Bulky equipment
- interrupt spray to measure → waste



Koivuluoto et al., *Coatings* (2020)

Airborne acoustic emission (AAE)

- Experienced operators can “hear” process anomalies → Information in sound
- Non-intrusive nature
- AAE has been used for other processes successfully
- Knowledge available for combining AAE with statistical and machine learning tools

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Experimental procedure

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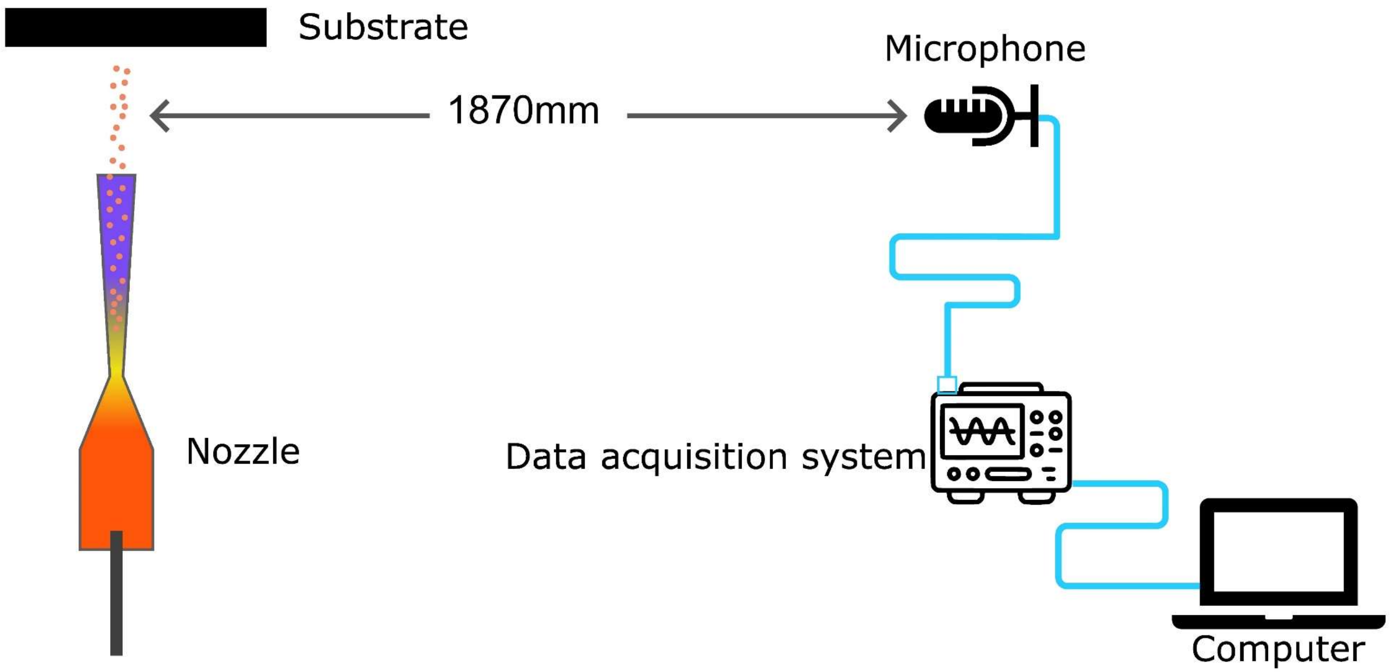
Experimental procedure

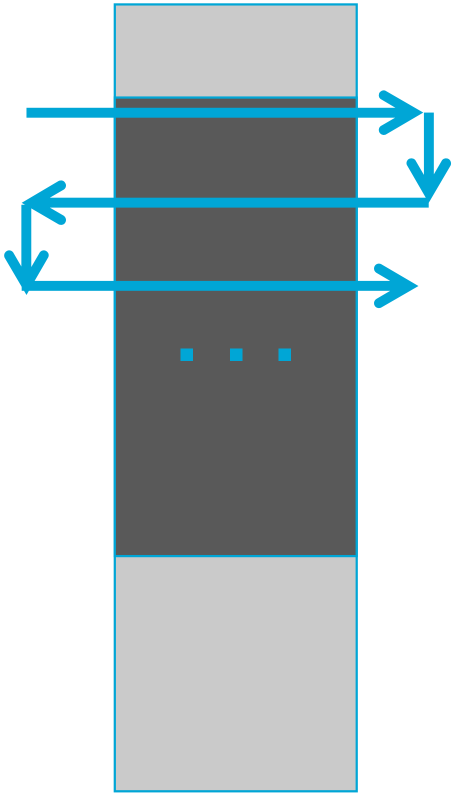


Experimental procedure

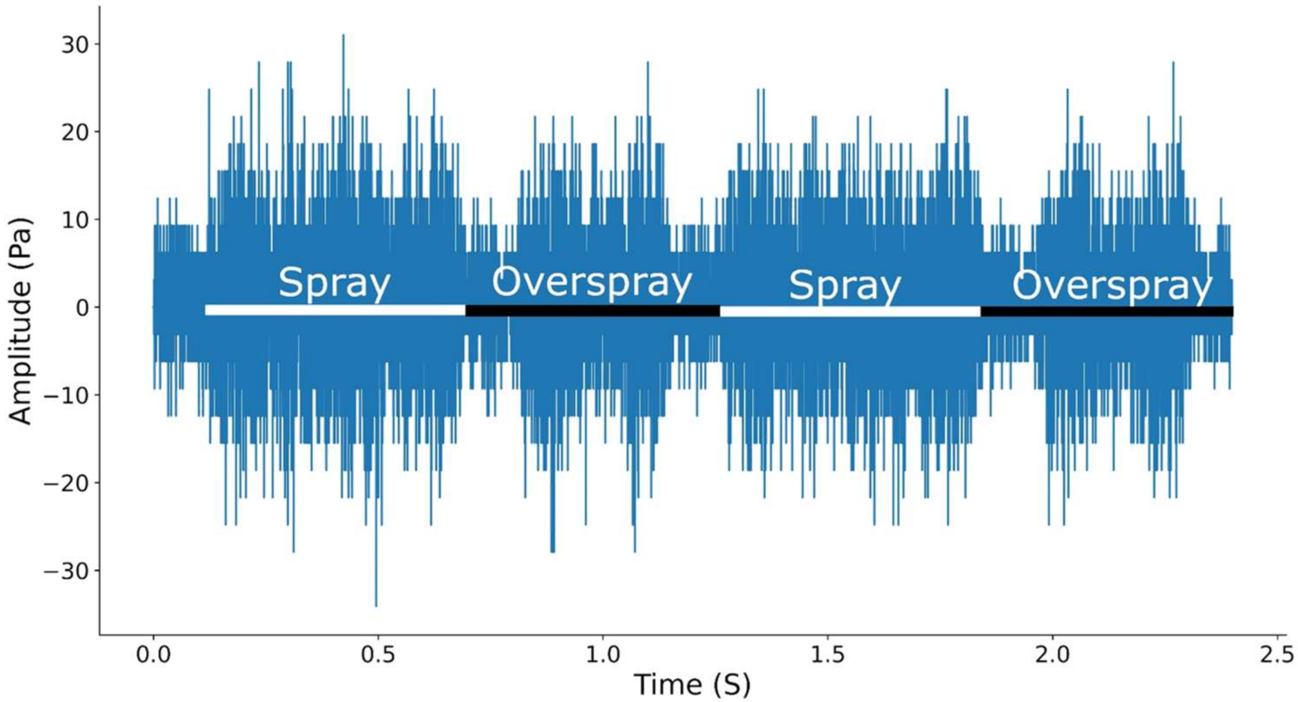
Test	Pressure (MPa)	Temperature (°C)	Average particle velocity (m/s)
1	6	600	670
2	4.5	600	625
3	7	600	690
4	5	500	620
5	3.5	600	580
6	5	400	600 (average)

Results and discussion

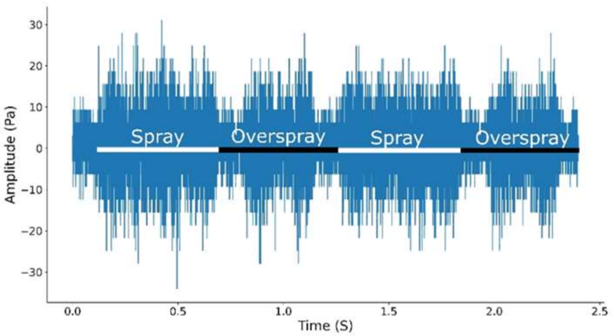
Results and discussion



3 layers – 20 passes



Results and discussion



Spray → Spray velocity

Overspray

- Spray - overspray separated manually
- Feature exploration performed to distinguish spray from overspray and diagnose velocity

Results and discussion
– Statistical analysis

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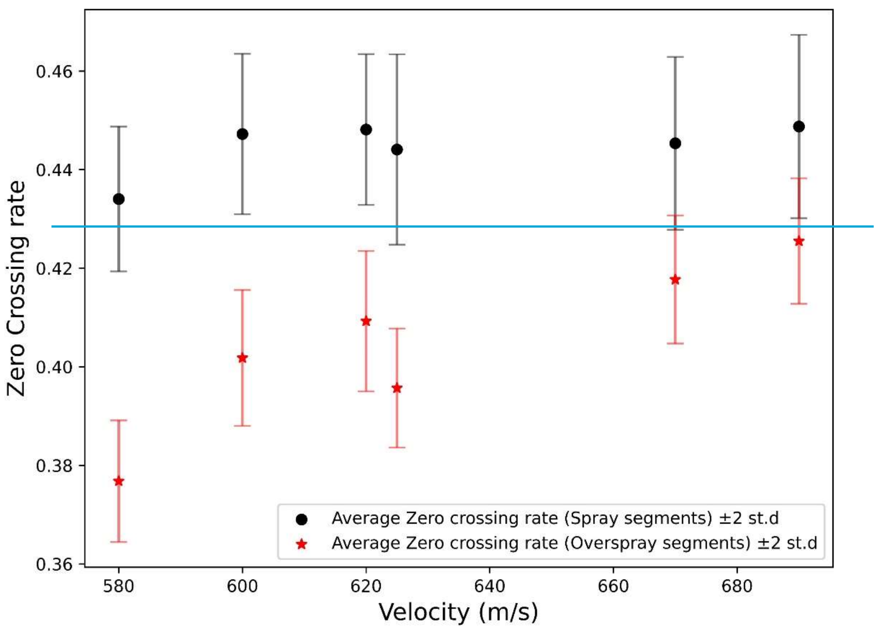
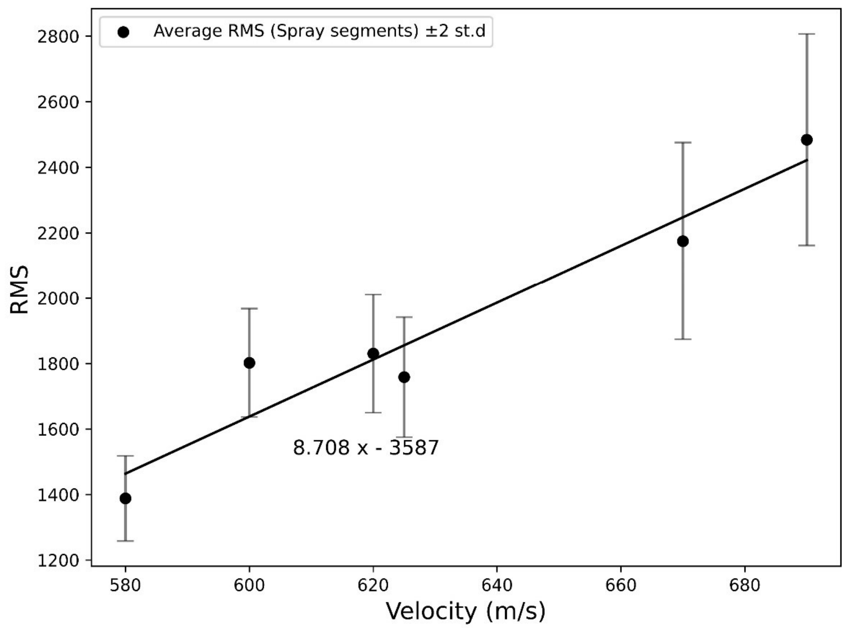
Results – Statistical analysis





- Zero crossing to separate spray from overspray
- RMS is almost linear with velocity (metric of power of the signal)
- St.D. of RMS too high for a rule-based model

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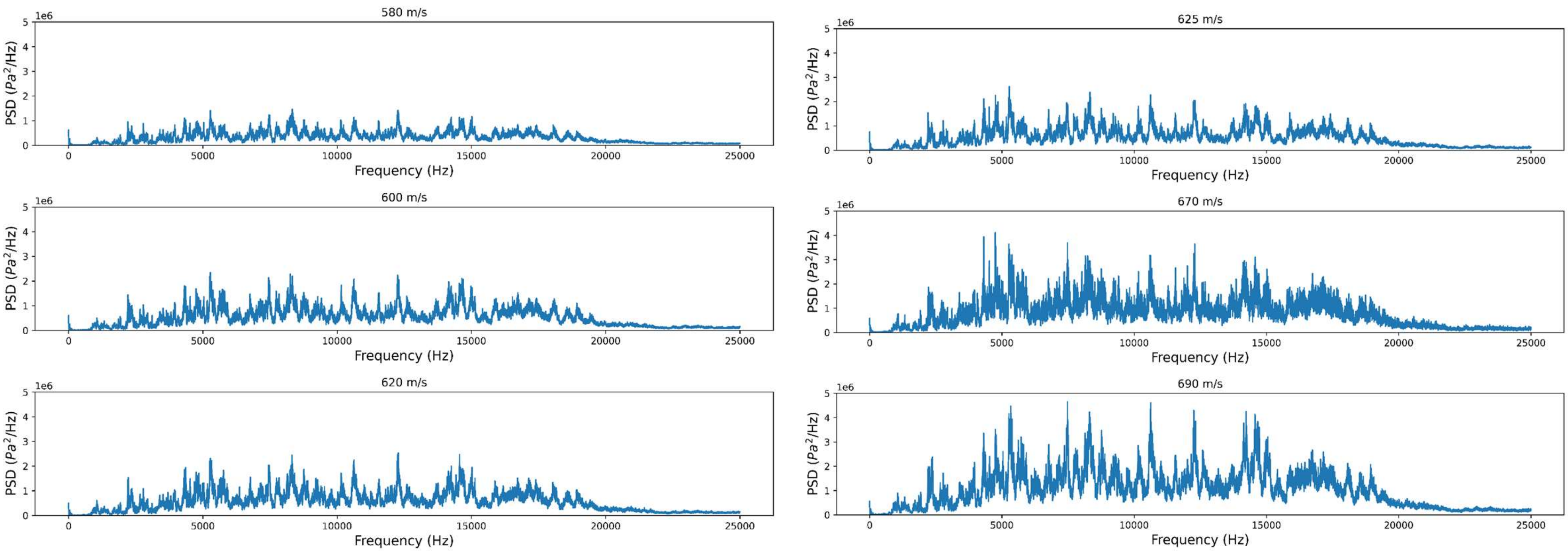
Results – Statistical analysis



- Average PSD
- Power increases with velocity
- No obvious frequency peak shifts

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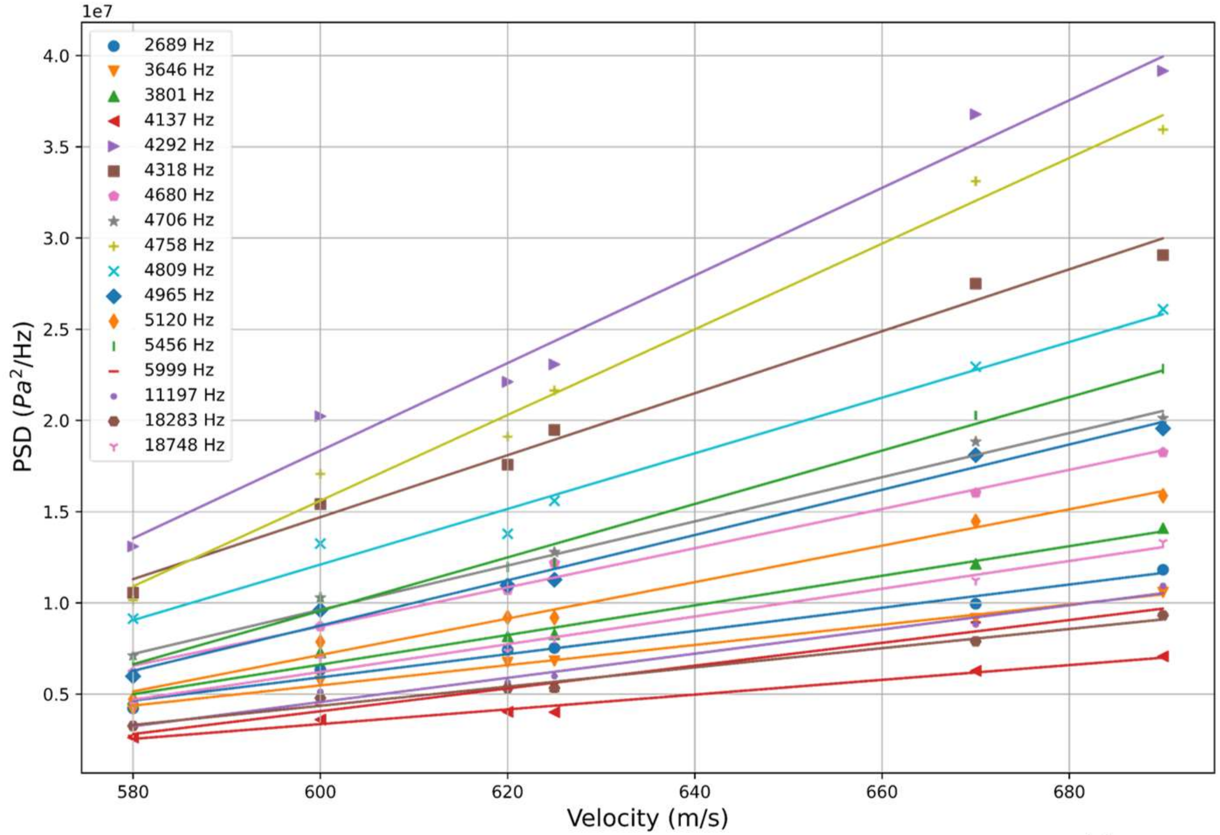
Results – Statistical analysis

- Pearson correlation:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

- 17 frequencies with score>0.99



Results – Statistical analysis

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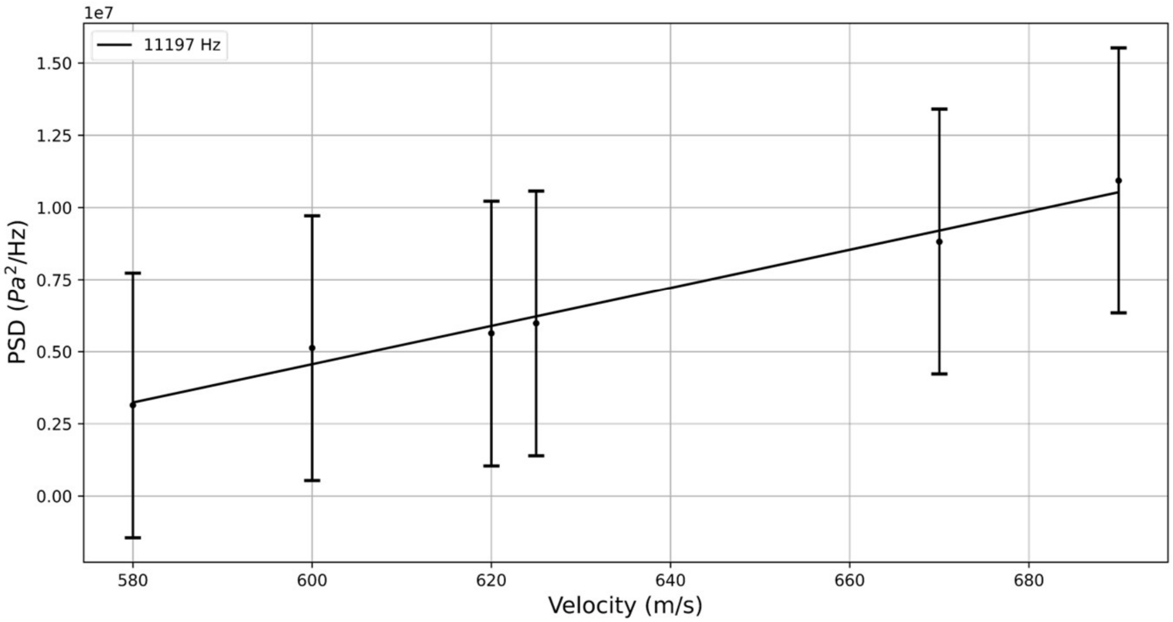

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Results – Statistical analysis

Test	Pressure (MPa)	Temperature (°C)	Average particle velocity (m/s)
2	4.5	600	625
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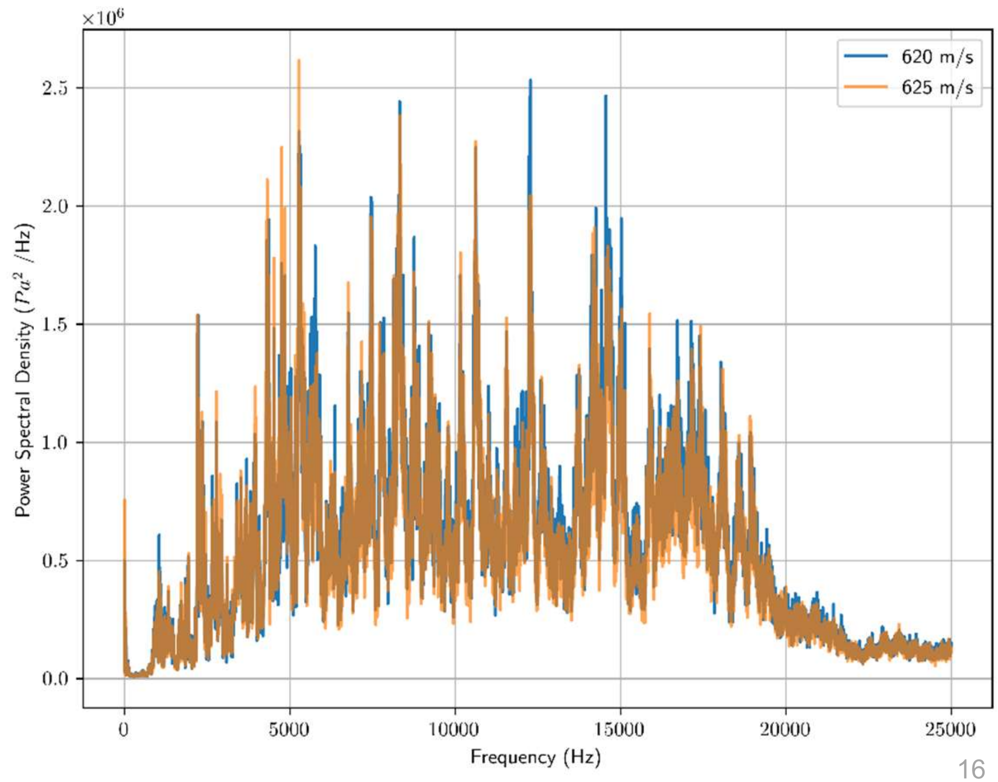

Results and discussion – Machine learning

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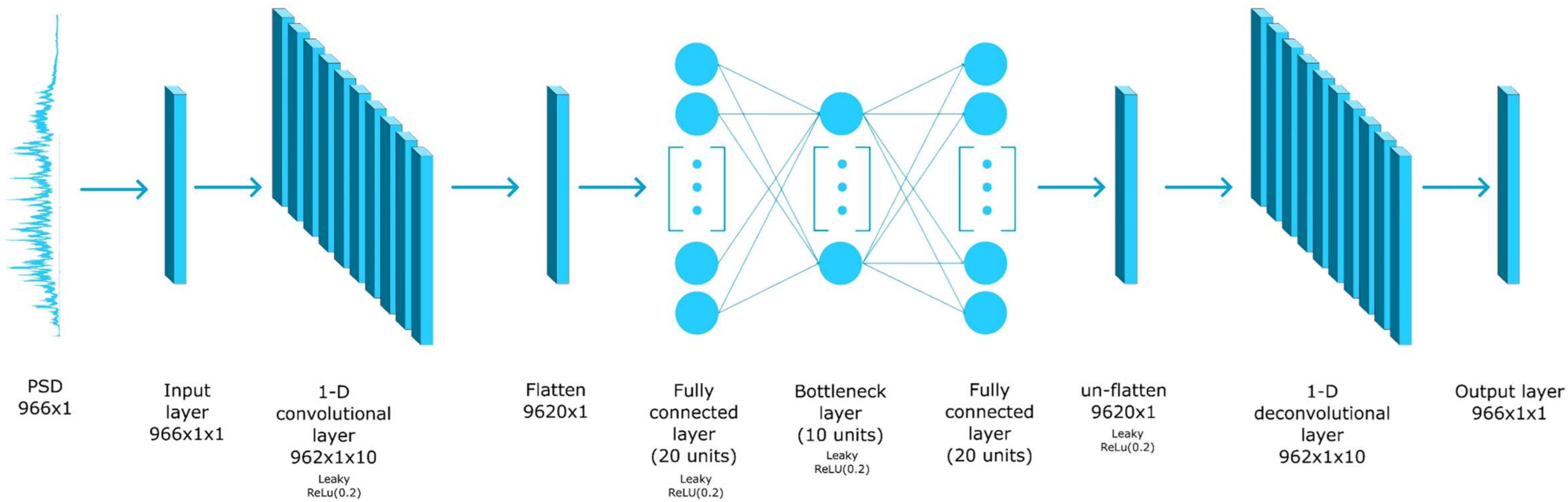
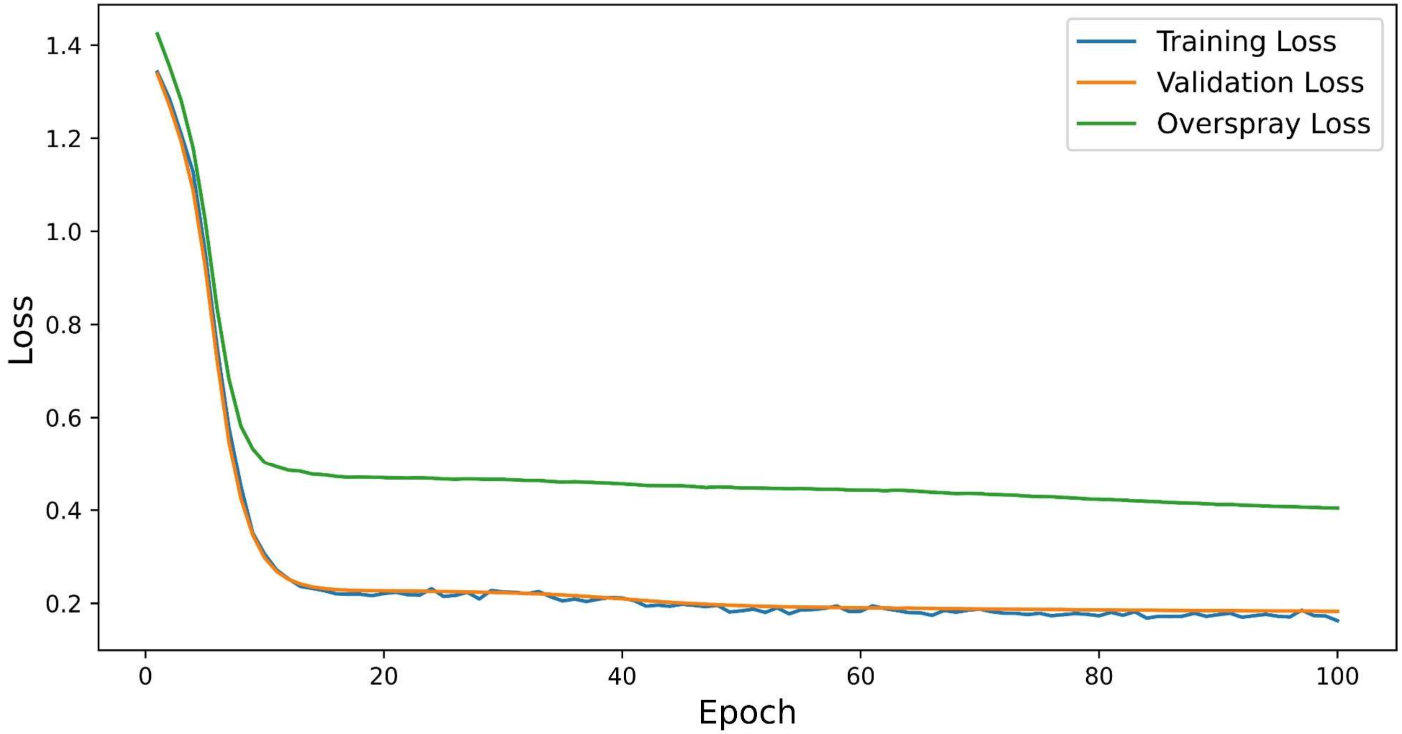


- Trained only with spray segments
- Aimed to minimise reconstruction error (RMSE)

Results – Machine learning



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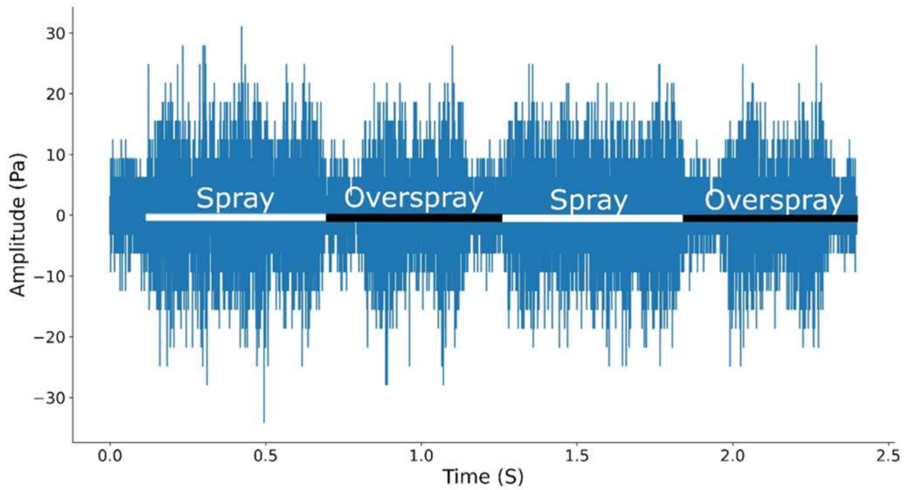
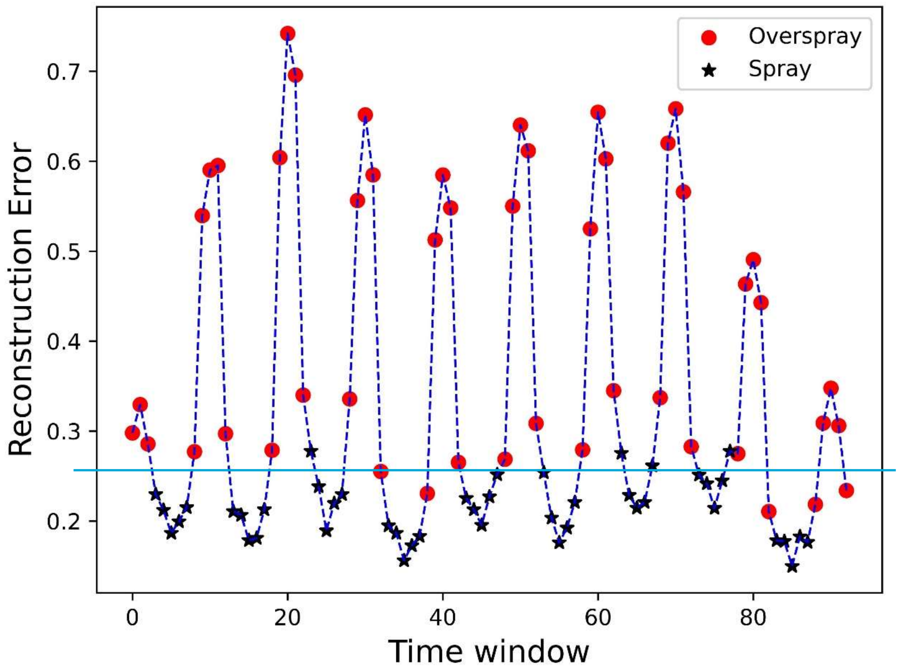
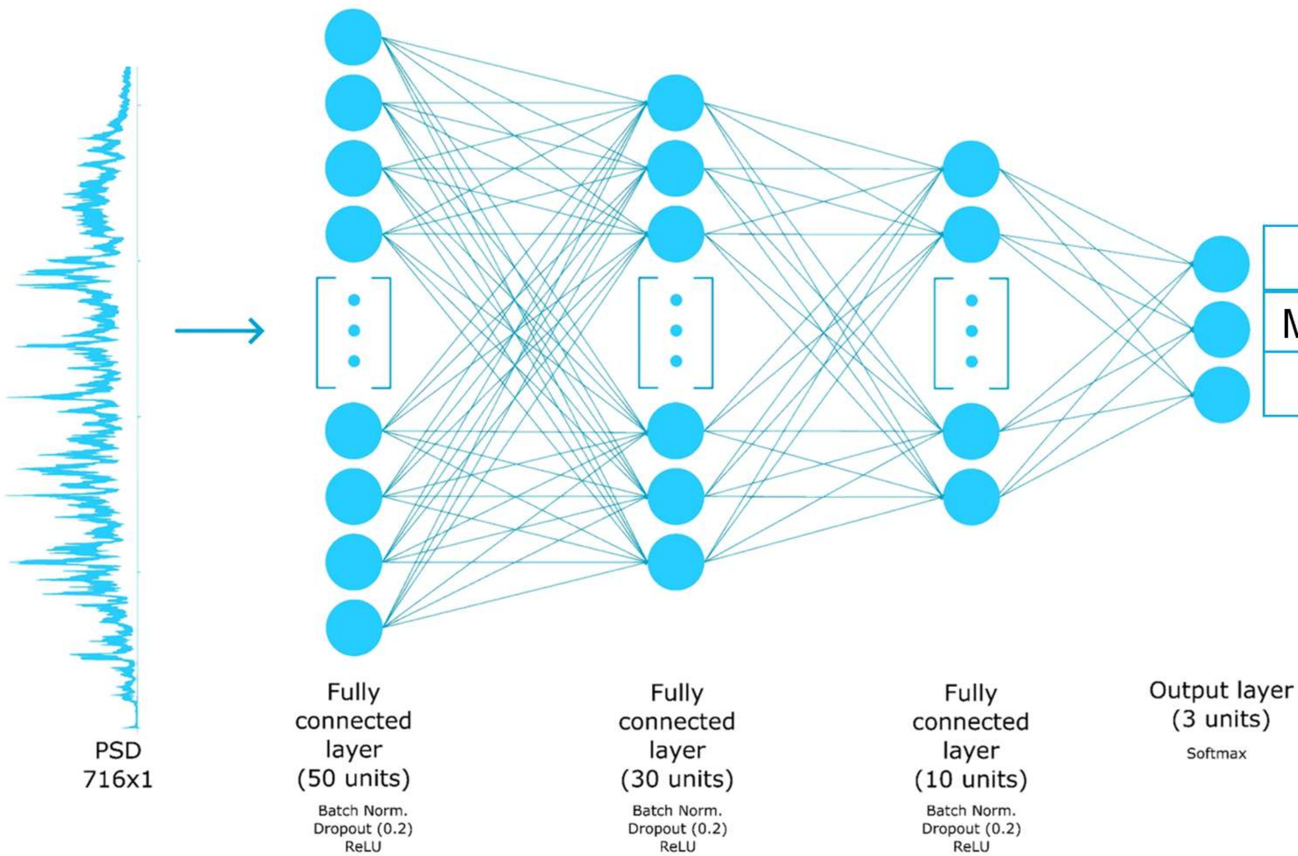
Results – Machine learning

- Threshold = test loss +2σ (agnostic of overspray)
- Accuracy 83.76%
- State transition is visible





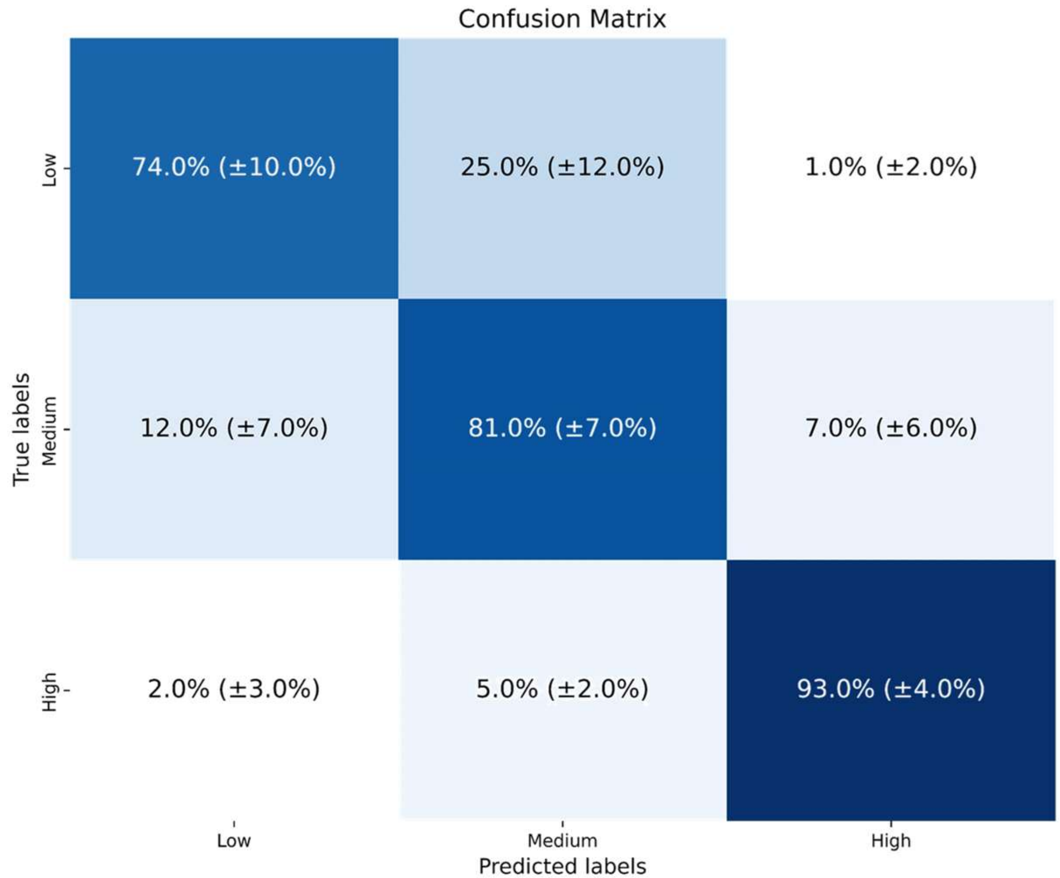
Results – Machine learning



Low → 580 - 600 m/s
Medium → 620 - 625 m/s
High →670 - 690 m/s

Results – Machine learning

- Very accurate on the third class
- Some confusion between low and medium classes, probably due to test 6.



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Conclusions

- The RMS is almost linear with spray velocity, and it can be used to identify permanent shifts
- PSD showed evidence of being agnostic of pressure and temperature combination used, reducing the experiments required
- Rule-based models are challenging to develop due to the high variability of the features examined.
- An autoencoder can identify the spray segments successfully
- An MLP performed well on diagnostics on the spray velocity. More experimental data is needed.
- Monitoring the cold spray process using AAE is feasible

Thank you

e.koufis@tudelf.nl