



Friedrich-Alexander-Universität
Erlangen-Nürnberg

Advanced Business Analytics Seminar
Winter Semester 23/24

Analysis of Continuous Manufacturing Sensor data with REHAU



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Analysis of continuous manufacturing polymer extrusion sensor data with REHAU

The shift towards Industry 4.0 entails a gradual rise in the intricacy of system operations and the management of production processes. Concurrently, emerging technologies present opportunities for enhancing services and cutting costs. With machines becoming more digitized, substantial amounts of data are now being collected. Utilizing data-driven methods becomes a viable solution to address the growing complexity and unlock potential benefits.

Objectives

- Identify polymer extrusion process dependencies and causalities.
- How do sensor parameters influence each other?
- Building data-driven process-model from data
- Model to simulate „what-if“ - scenarios



Figure only for representation

1. Data Overview & Initial Findings

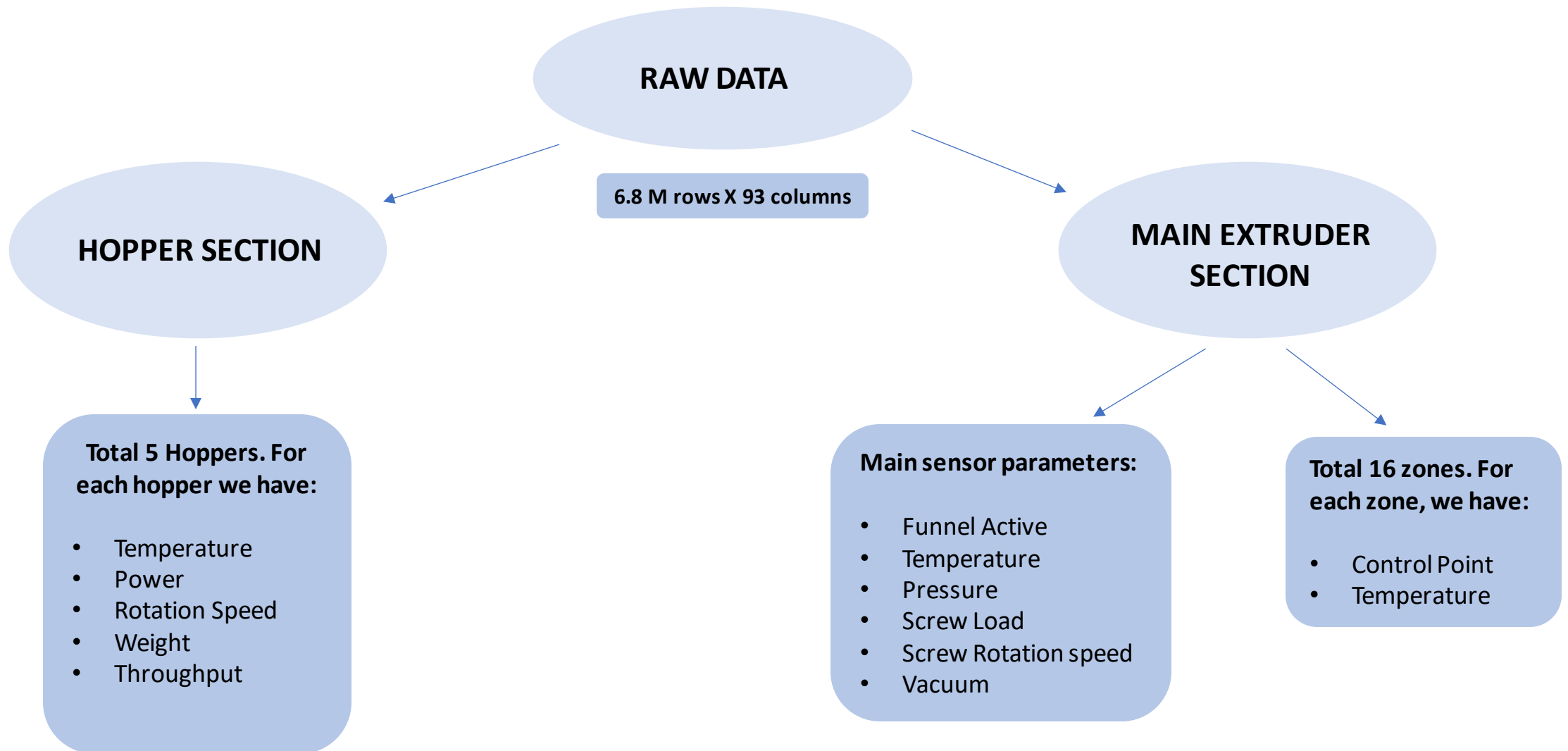
2. Hopper Section

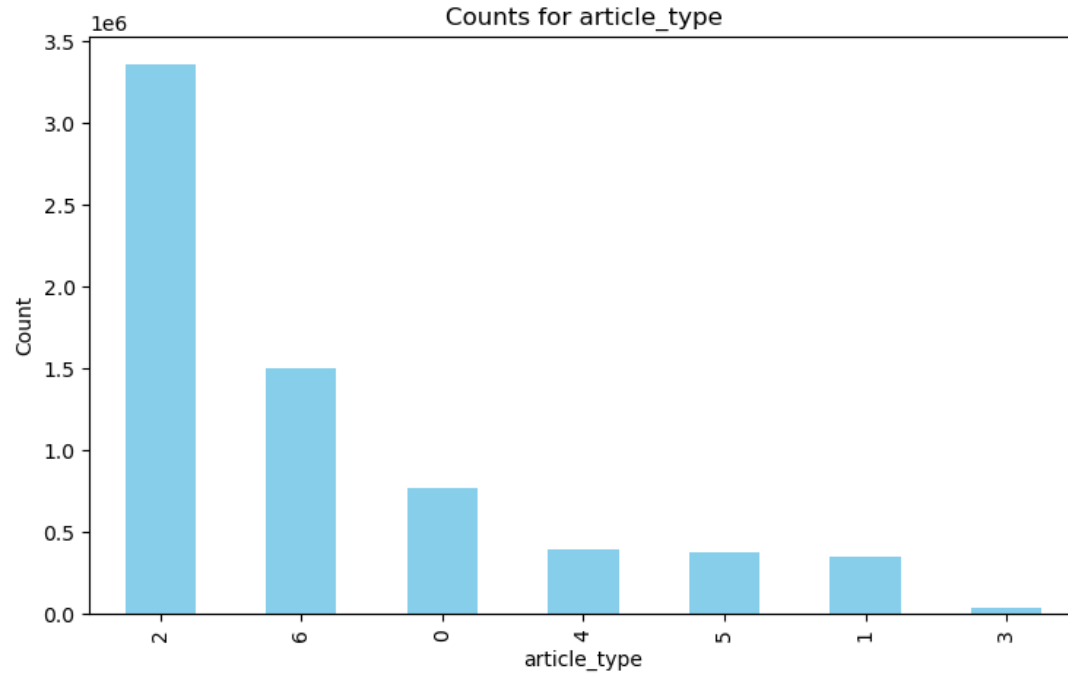
- I. Dependencies
- II. Model Building 1 & its What if Scenarios
- III. Model Building 2

3. Main Extruder

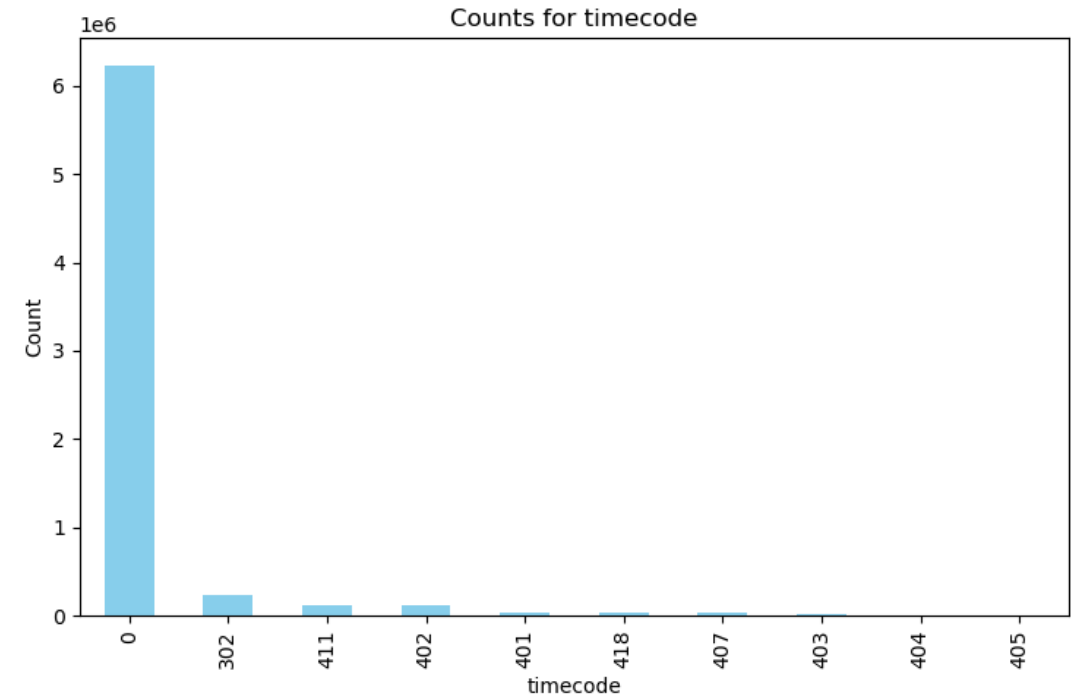
- I. Model Building 1 & What if Scenarios
- II. Dependencies
- III. Model Building 2
- IV. ADF Testing
- V. Granger Causality Test

4. Future Endeavours



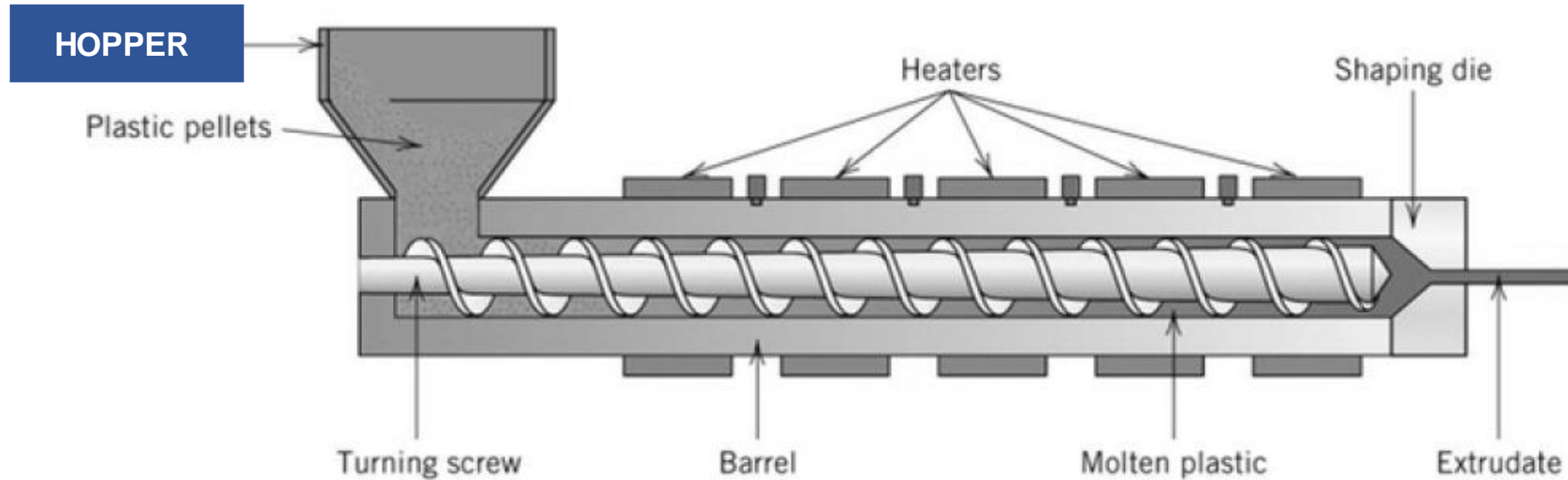


50% of the observations represent Article type 2.



Timecode 0 represents production time in line with specifications and others represent machine/article failure time.

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2. **Hopper Section**
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Strong Correlation	Weak Correlation	No Correlation
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Hopper 1-4	Temperature	Power / Throughput / Rotation speed	Weight
Temperature			
Power / Throughput / Rotation speed			
Weight			

- Hoppers 1-4 exhibit consistent correlation patterns among various sensor parameters.
- The high degree of similarity between Power, Throughput & Rotation speed suggests a cohesive behavior in the relationships between these sensors.

Hopper 5	Temperature	Power / Throughput / Rotation speed	Weight
Temperature			
Power / Throughput / Rotation speed			
Weight			

- Hopper 5 displays a slight deviation in correlation patterns compared to Hoppers 1-4.
- This distinct behavior in Hopper 5 may indicate unique operational characteristics or specific influences on the correlation between its sensor parameters.

Objective: Optimizing Hopper Parameter Coefficients for Precise Throughput Prediction

- Goal: Attain optimal coefficients for hopper parameters to predict throughput, closely aligning with predefined throughput standards.
- Striving for a model that ensures accurate throughput predictions based on specified hopper features.

Features and Target

- Parameters under consideration: Temperature, Power, Rotation Speed and Weight.
- Target variable for prediction: Throughput - the key performance indicator.

Model and Approach: Lasso Regression, but why Lasso?

- Lasso regression performs variable selection by imposing a penalty on the absolute size of the regression coefficients. This means that it tends to shrink the coefficients of less important variables towards zero, effectively selecting the most relevant variables. In the context of the hopper section, where various factors (e.g., temperature, pressure, screw speed) might affect the extrusion process, Lasso can help identify the most influential variables among a large set of potential predictors.
- Regularization: Lasso regression incorporates a regularization parameter that helps prevent overfitting by penalizing large coefficient values.

For simplicity of this presentation we have chosen Article Type 2 in this model since it covered 50% of the overall data.

Coefficients:

Feature 1: -0.0
Feature 2: -0.09
Feature 3: 0.33
Feature 4: 0.26
Feature 5: 0.09
Feature 6: 0.07
Feature 7: 0.12
Feature 8: -0.14
Feature 9: 0.0
Feature 10: 0.0
Feature 11: 0.04
Feature 12: -0.0
Feature 13: -0.0
Feature 14: 0.0
Feature 15: 0.13
Feature 16: -0.0
Feature 17: 0.38
Feature 18: 0.50
Feature 19: 0.08
Feature 20: 0.0004



Important Features and their Coefficients:

Hopper 1 Power: -0.09
Hopper 1 Rotation Speed: 0.33
Hopper 1 Weight: 0.26
Hopper 2 Temperature: 0.09
Hopper 2 Power: 0.07
Hopper 2 Rotation Speed: 0.12
Hopper 2 Weight: -0.14
Hopper 3 Rotation Speed: 0.04
Hopper 4 Rotation Speed: 0.13
Hopper 5 Temperature: 0.38
Hopper 5 Power: 0.50
Hopper 5 Rotation Speed: 0.08
Hopper 5 Weight: 0.0004

What does this coefficient signify?

Coefficient in a Machine Learning modelling represents the weight or magnitude of influence that a particular feature has on the predicted outcome.

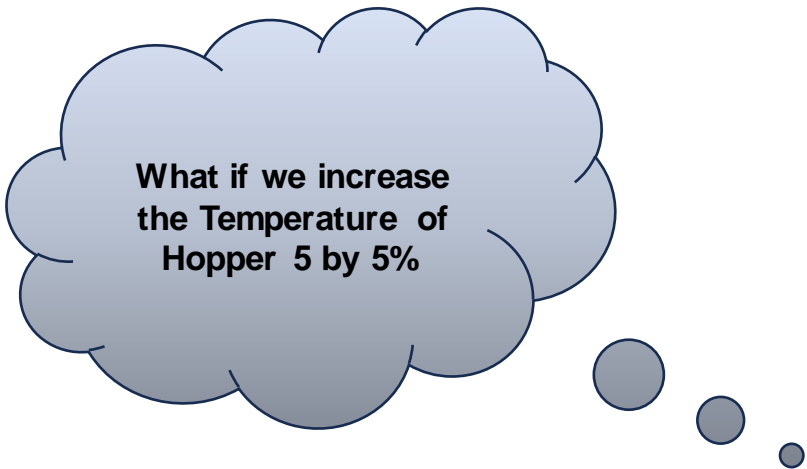
In Mathematical terms for a 2 feature model,

$y = m_1x_1 + m_2x_2 + b$, where:

y = predicted outcome

x_1, x_2 = input / feature values

m_1, m_2 = coefficients associated with inputs

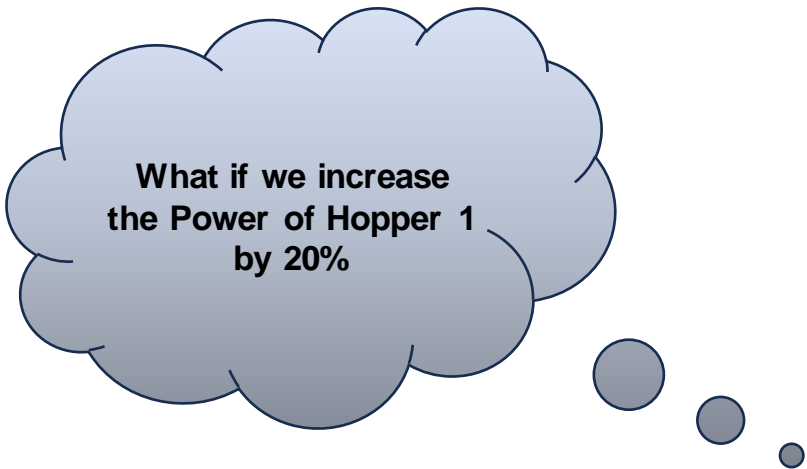


What if we increase
the Temperature of
Hopper 5 by 5%

Result: Observing a 4.66% increase in the model's throughput prediction with the implemented Hopper 5 Temperature adjustment.

Predicted output before increase : 124.39 kg/h
Predicted output after increase : 130.18 kg/h
Percentage Change: 4.66 %

Feature	Value
Hopper 1 Temp	24.06
Hopper 1 Power	70.9
Hopper 1 Rotation Speed	34.24
Hopper 1 Weight	6.52
Hopper 2 Temp	26.32
Hopper 2 Power	0
Hopper 2 Rotation Speed	0
Hopper 2 Weight	3.11
Hopper 3 Temp	23.29
Hopper 3 Power	0
Hopper 3 Rotation Speed	0
Hopper 3 Weight	3.86
Hopper 4 Temp	22.31
Hopper 4 Power	0
Hopper 4 Rotation Speed	0
Hopper 4 Weight	4.15
Hopper 5 Temp	304.55
Hopper 5 Power	0
Hopper 5 Rotation Speed	0
Hopper 5 Weight	8.09

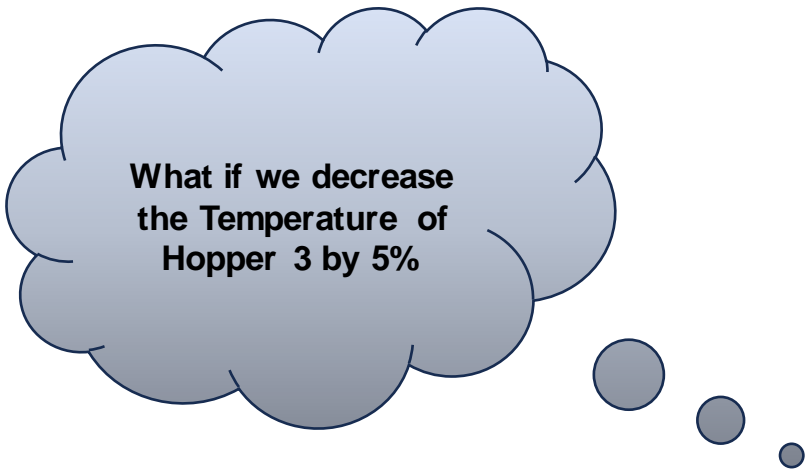


What if we increase
the Power of Hopper 1
by 20%

Result: Observing a 1.03% decrease in the model's throughput prediction with the implemented Hopper 1 Power adjustment.

Predicted output before increase: 124.38 kg/h
Predicted output after increase: 123.10 kg/h
Percentage change: -1.03%

Feature	Value
Hopper 1 Temp	24.06
Hopper 1 Power	70.9
Hopper 1 Rotation Speed	34.24
Hopper 1 Weight	6.52
Hopper 2 Temp	26.32
Hopper 2 Power	0
Hopper 2 Rotation Speed	0
Hopper 2 Weight	3.11
Hopper 3 Temp	23.29
Hopper 3 Power	0
Hopper 3 Rotation Speed	0
Hopper 3 Weight	3.86
Hopper 4 Temp	22.31
Hopper 4 Power	0
Hopper 4 Rotation Speed	0
Hopper 4 Weight	4.15
Hopper 5 Temp	304.55
Hopper 5 Power	0
Hopper 5 Rotation Speed	0
Hopper 5 Weight	8.09



What if we decrease
the Temperature of
Hopper 3 by 5%

Result: Observing a no significant change in the model's throughput prediction with the implemented Hopper 3 Temperature adjustment.

Predicted output before decrease: 124.38 kg/h
Predicted output after decrease: 124.38 kg/h
Percentage change: 0%

Feature	Value
Hopper 1 Temp	24.06
Hopper 1 Power	70.9
Hopper 1 Rotation Speed	34.24
Hopper 1 Weight	6.52
Hopper 2 Temp	26.32
Hopper 2 Power	0
Hopper 2 Rotation Speed	0
Hopper 2 Weight	3.11
Hopper 3 Temp	23.29
Hopper 3 Power	0
Hopper 3 Rotation Speed	0
Hopper 3 Weight	3.86
Hopper 4 Temp	22.31
Hopper 4 Power	0
Hopper 4 Rotation Speed	0
Hopper 4 Weight	4.15
Hopper 5 Temp	304.55
Hopper 5 Power	0
Hopper 5 Rotation Speed	0
Hopper 5 Weight	8.09

Objective: Optimizing Hopper Parameter Coefficients for Precise Throughput Prediction

- Goal: Observe mathematical relation between throughput of each individual hopper.
- Striving for a model that ensures accurate throughput predictions based on specified hopper throughputs.

Features and Target

- Parameters under consideration: Throughput act of each hopper.
- Target variable for prediction: Throughput set.

Model and Approach: Linear Regression

- Linear regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables by fitting a linear equation to observed data, aiming to predict the dependent variable's value based on the independent variable(s).

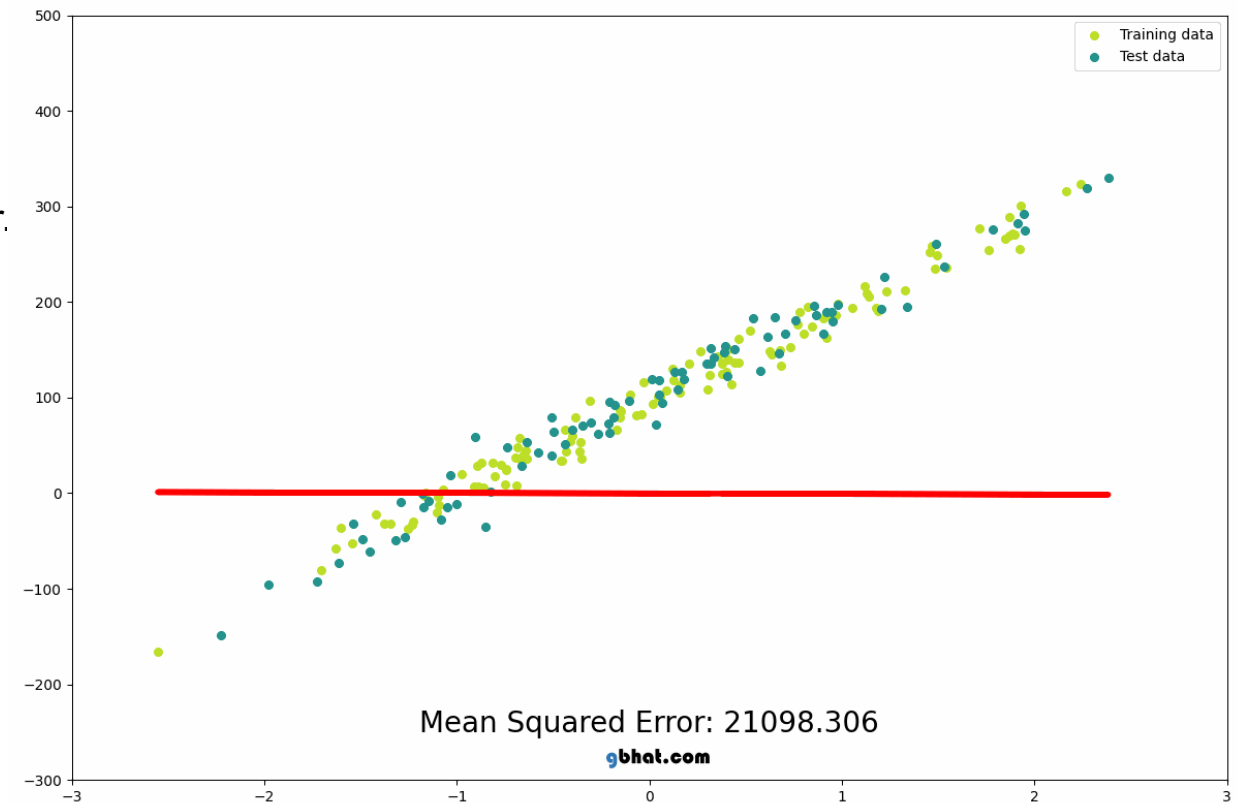


Figure only for representation

Contribution of each Hopper Throughput towards the Final Throughput for each Article type

Article Type 1 Features Coefficients

Hopper 4 Throughput:: 0.07

Article Type 0 has only
Hopper 4 contributing to
the final Throughput

Article type 2 Feature Coefficients

Hopper 1 Throughput:-0.03
Hopper 2 Throughput: 0.05
Hopper 3 Throughput: 0.01
Hopper 4 Throughput: 0.23
Hopper 5 Throughput: 0.01

Article 2 is the only
article type which has all
the Hoppers from 1 to 5
contributing towards the
final throughput.

Contribution of each Hopper Throughput towards the Final Throughput for each Article type

Article type 0 Feature Coefficients

Hopper 1 Throughput: 0.45
Hopper 2 Throughput: 3.23
Hopper 3 Throughput: 3.22
Hopper 5 Throughput: 0.10

Article Type 3 Features Coefficients

Hopper 1 Throughput: 0.05
Hopper 2 Throughput: 1.38
Hopper 3 Throughput: -0.08
Hopper 5 Throughput: -0.02

Article Type 4 Features Coefficients

Hopper 1 Throughput: 0.05
Hopper 2 Throughput: 2.77
Hopper 3 Throughput: 0.01
Hopper 5 Throughput: 0.08

Article Type 5 Features Coefficients

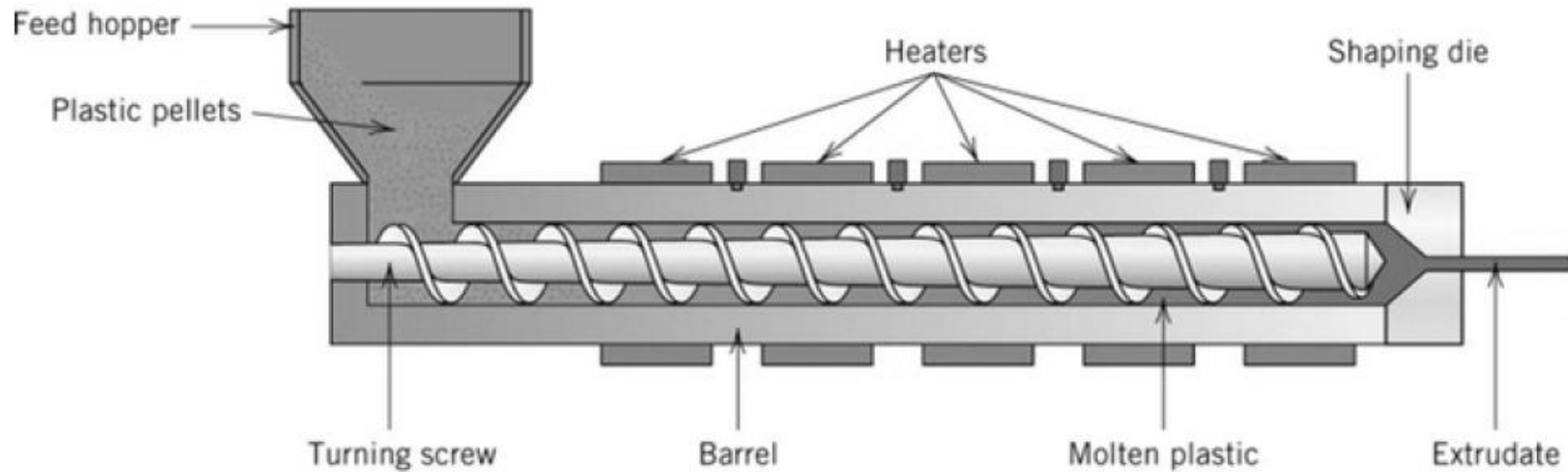
Hopper 1 Throughput: 0.26
Hopper 2 Throughput: 0.00
Hopper 3 Throughput: 0.18
Hopper 5 Throughput: 0.07

Article Type 6 Features Coefficients

Hopper 1 Throughput: 0.60
Hopper 2 Throughput: 1.03
Hopper 3 Throughput: 1.07
Hopper 5 Throughput: 0.03

Each of the article type here does not have the contribution of Hopper 4's Throughput towards the final Throughput.

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MAIN EXTRUDER

Objective: Optimizing Main extruder parameters Coefficients for Precise Throughput Prediction

Goal: To understand the mathematical relation between main extruder sensor parameters.

Features and Target

- Parameters under consideration : Input Throughput, Funnel Active, Melt Temperature, Screw Load, Screw Rotation Speed, Vacuum.
- Target variable for prediction : Melt Temperature & Pressure.

Model and Approach: Neural Network, but why?

- Neural networks are adept at capturing and modeling the intricate nonlinear relationships inherent in polymer extrusion processes.
- Main extruder portion data is highly complex and non-linear in nature so that regular linear/ridge/lasso is not a good fit for this scenario. So in order to increase the model accuracy neural net is a good choice.

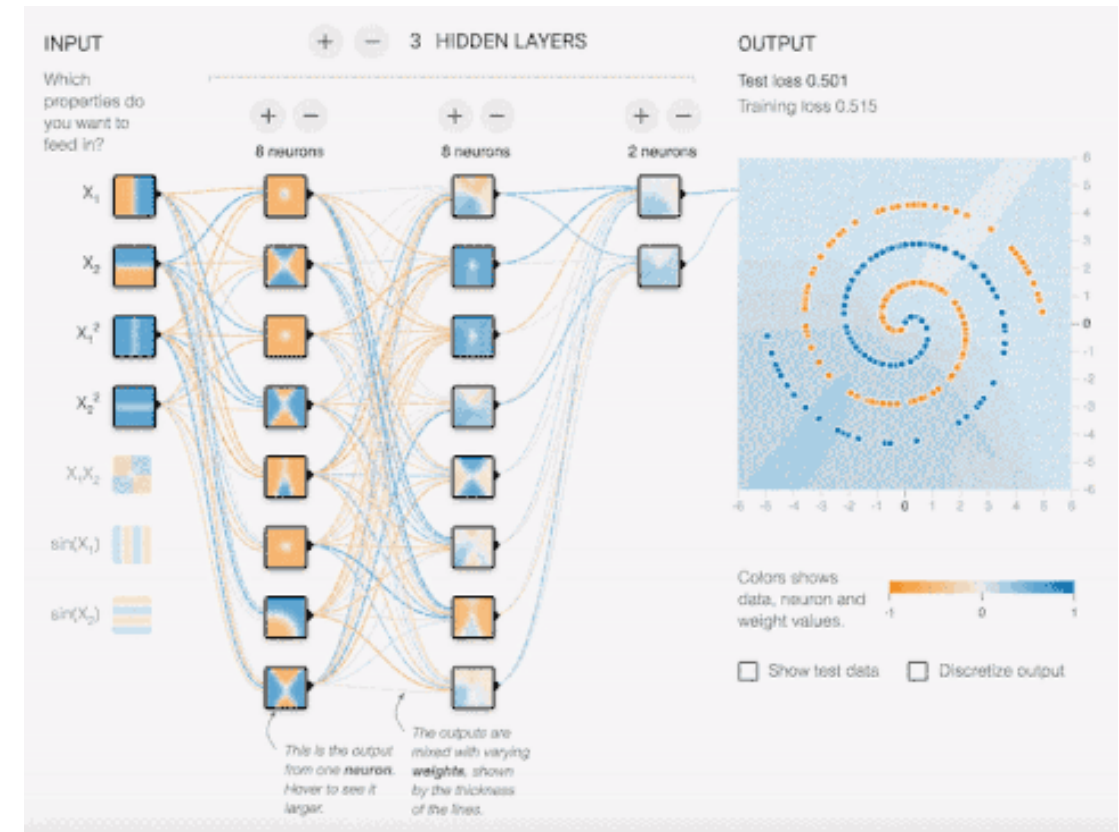
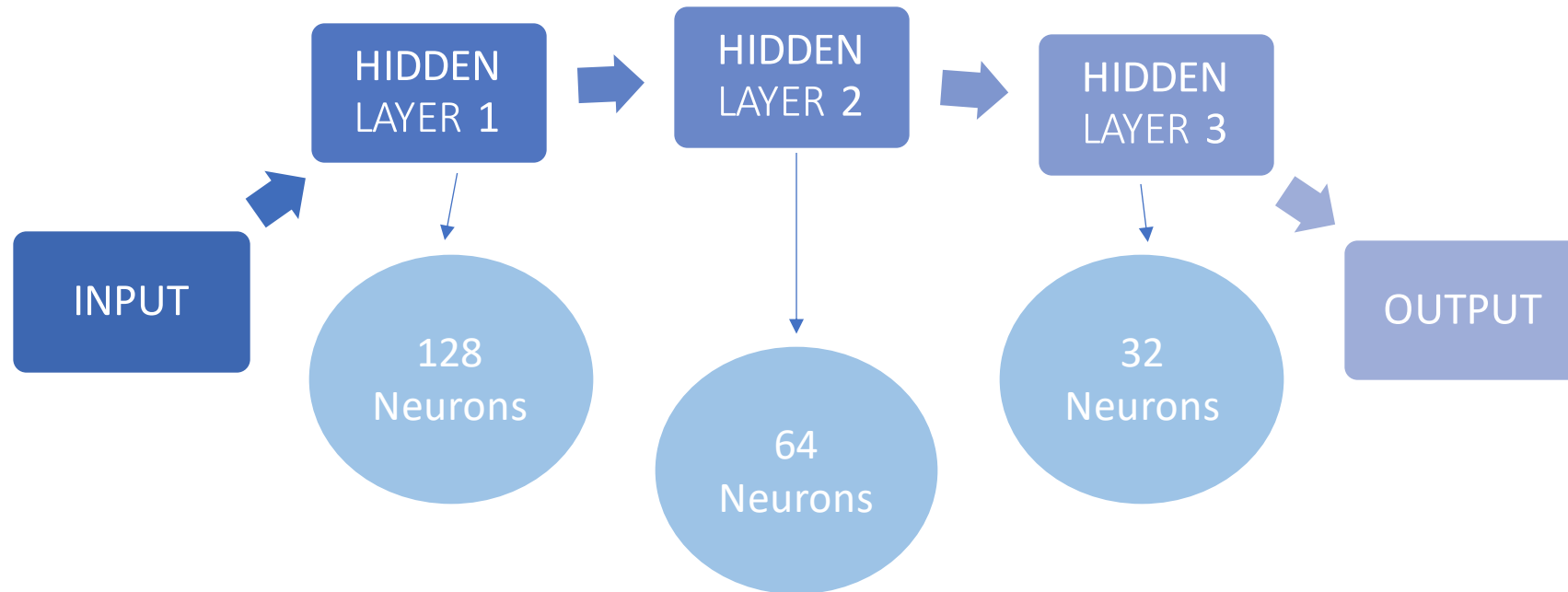


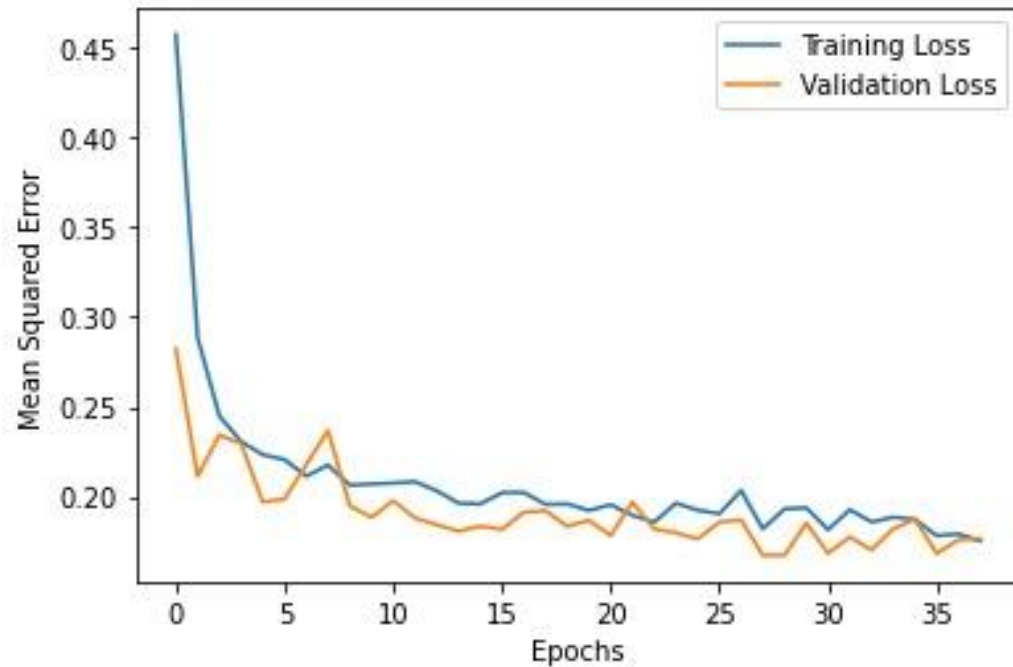
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Neural Network Architecture

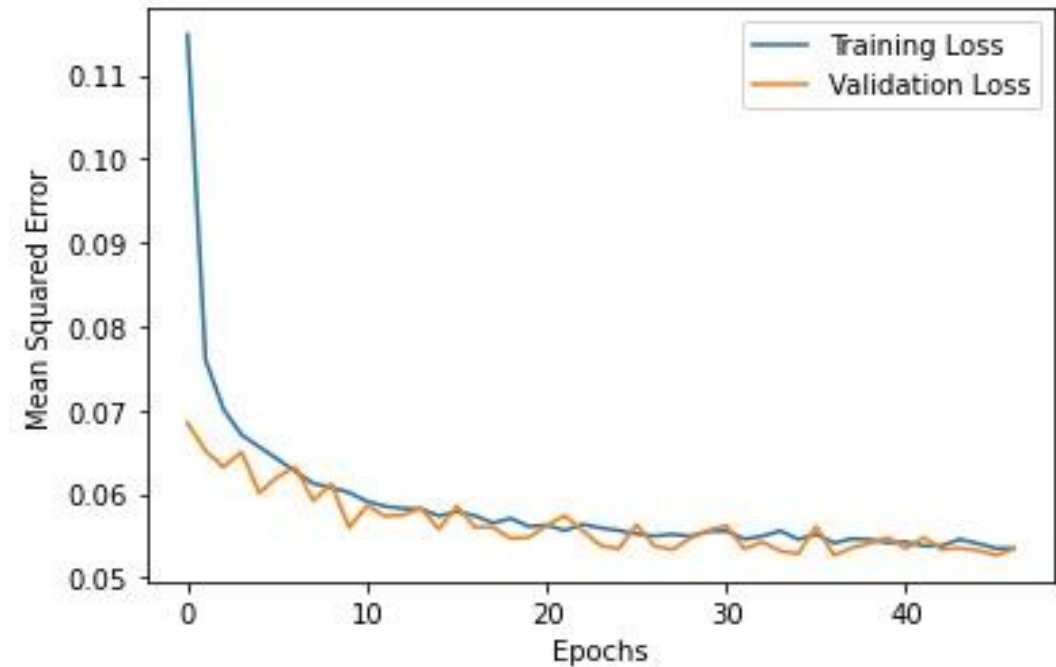


- We have passed the main extruder features to the input layer and then output is passed through the following consecutive hidden layers and finally output layer is responsible for the desired prediction.
- As we proceed through the hidden layers our model learns more abstract features gradually leading to a trustworthy accurate output.

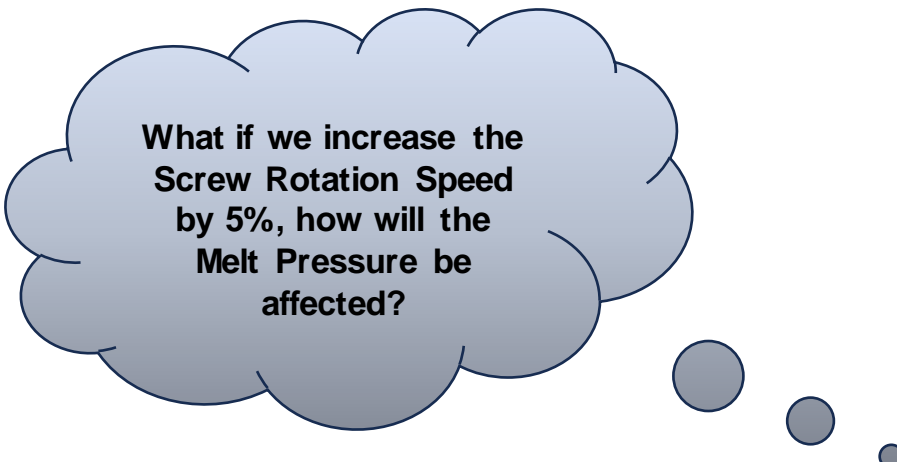
Neural Network Training Visualization :



Loss curve for temperature as target column



Loss curve for pressure as target column

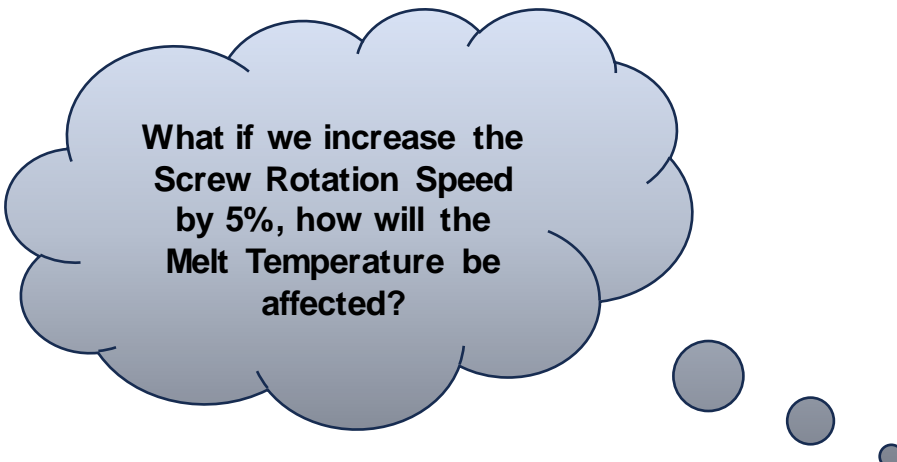


What if we increase the
Screw Rotation Speed
by 5%, how will the
Melt Pressure be
affected?

Feature	Standardized Value
Total Throughput	0.13
Funnel Active	0
Melt Temperature	0.65
Screw Load	2.37
Screw Rotation Speed	0.24
Vacuum	-0.12

Result: Observing a 1.37% decrease in the model's Melt Pressure with the implemented Screw Rotation Speed adjustment.

Predicted output before increase (Standardized): 0.51 bar
Predicted output after increase (Standardized): 0.50 bar
Percentage Change: -1.37 %



What if we increase the Screw Rotation Speed by 5%, how will the Melt Temperature be affected?

Feature	Standardized Value
Total Throughput	0.13
Funnel Active	0
Melt Pressure	-0.03
Screw Load	2.37
Screw Rotation Speed	0.24
Vacuum	-0.12

Result: Observing a 0.11% increase in the model's Melt Temperature with the implemented Screw Rotation Speed adjustment.

Predicted output before increase (Standardized): 1.256
Predicted output after increase (Standardized): 1.257
Percentage Change: 0.11 %

MAIN EXTRUDER ZONES 1-16 : DEPENDENCIES

Strong Correlation	Moderate Correlation	No Correlation
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Zones 1-16	Temp Zones 1-12 & 15-16	Temp Zone 13	Temp Zone 14
Temp Zones 1-12 & 15-16	Strong Correlation	No Correlation	Moderate Correlation
Temp Zone 13	No Correlation	Strong Correlation	Moderate Correlation
Temp Zone 14	Moderate Correlation	Moderate Correlation	Strong Correlation

- Zones 1-12 & 15-16 exhibit consistent strong correlation patterns among each other.
- Zone 13 has almost no correlation with other zones.
- Zone 14 has a moderate correlation with other zones.

Objective: Optimizing Zonal Parameter Coefficients for main extruder parameters prediction

- Goal: To understand the mathematical relation between main extruder and heating power & temperature zones 1 -16.
- Striving for a model that ensures accurate main extruder parameters prediction based on specific zonal features.

Features and Target

- Parameters under consideration : Temperature & Control point.
- Target variable for prediction : Melt Temperature, Melt Pressure, Screw Load, Screw Rotation Speed, Vacuum.

Model and Approach: Lasso Regression, but why Lasso?

- Lasso regression performs variable selection by imposing a penalty on the absolute size of the regression coefficients. This means that it tends to shrink the coefficients of less important variables towards zero, effectively selecting the most relevant variables. In the context of the hopper section, where various factors (e.g., temperature, pressure, screw speed) might affect the extrusion process, Lasso can help identify the most influential variables among a large set of potential predictors.
- Regularization: Lasso regression incorporates a regularization parameter that helps prevent overfitting by penalizing large coefficient values.

Contribution of each Zones to Main extruder parameters

Screw Load Feature Coefficients

Zone 5 Temperature : 2.01
Zone 7 Temperature : -0.56
Zone 9 Temperature : -0.52

Zone 2 Ctrl Point : -0.02
Zone 3 Ctrl Point : -0.23
Zone 4 Ctrl Point : -0.19
Zone 5 Ctrl Point : -0.81
Zone 8 Ctrl Point : 0.07
Zone 12 Ctrl Point: 0.006

Temp Zone 5 and Control Zone 5
contributes the most towards Screw
Load positively and negatively based
on the coefficient values.

Pressure Feature Coefficients

Zone 1 Temperature : 0.61
Zone 3 Temperature : 0.02
Zone 4 Temperature : 0.21
Zone 7 Temperature : 0.006
Zone 10 Temperature : 0.13

Zone 3 Ctrl Point : 0.05
Zone 4 Ctrl Point : 0.02
Zone 5 Ctrl Point : -0.95
Zone 8 Ctrl Point : 0.04
Zone 12 Ctrl Point : 0.005

Temp Zone 1 and Control Zone 5
contributes the most towards Pressure
positively and negatively based on the
coefficient values.

Contribution of each Zones to Main extruder parameters

Temperature Feature Coefficients

Zone 1 Temperature : 0.81
Zone 2 Temperature : 0.004
Zone 5 Temperature : 0.17

Zone 1 Ctrl Point : 0.05
Zone 4 Ctrl Point : -0.02
Zone 5 Ctrl Point : -0.85
Zone 8 Ctrl Point : 0.009
Zone 10 Ctrl Point : 0.03
Zone 11 Ctrl Point : 0.004
Zone 12 Ctrl Point : 0.046

Temp Zone 1 and Control Zone 5 contributes the most towards Temperature positively and negatively based on the coefficient values.

Screw Rotation speed Feature Coefficients

Zone 1 Temperature : 0.96
Zone 2 Temperature : 0.0009
Zone 4 Temperature : 0.0001
Zone 5 Temperature : 0.03

Zone 1 Ctrl Point : 0.05
Zone 4 Ctrl Point : -0.005
Zone 5 Ctrl Point : -0.86
Zone 8 Ctrl Point : 0.01
Zone 10 Ctrl Point : 0.04
Zone 12 Ctrl Point : 0.05

Temp Zone 1 and Control Zone 5 contributes the most towards Screw Rotation Speed positively and negatively based on the coefficient values.

Vacuum Feature Coefficients

Zone 1 Temperature : 0.59
Zone 4 Temperature : 0.08
Zone 5 Temperature : 0.17
Zone 7 Temperature : 0.05
Zone 14 Temperature : 0.06

Zone 1 Ctrl Point : 0.03
Zone 4 Ctrl Point : -0.03
Zone 5 Ctrl Point : -0.85
Zone 10 Ctrl Point : 0.03
Zone 11 Ctrl Point : 0.01
Zone 12 Ctrl Point : 0.02

Temp Zone 1 and Control Zone 5 contributes the most towards Vacuum positively and negatively based on the coefficient values.

Why ADF Testing?

ADF test is a valuable tool for analyzing time series data, providing insights into the underlying properties of the data and guiding the selection of appropriate modeling techniques.

Stationary data refers to a time series dataset whose statistical properties such as mean, variance, and autocovariance remain constant over time.

Benefits:

- **Detection of Structural Changes:** Changes in the statistical properties of time series data, such as shifts in mean or variance, can signal structural changes in regulations or consumer preferences.
- **Causal Inference:** ADF testing can be used in conjunction with other econometric techniques to explore causal relationships between variables.
- **Improved Decision-Making:** Stationary time series data provides a stable foundation for analyzing historical trends and making informed decisions.

Melt Pressure:

ADF Statistic: -7.55, p-value: 3.22e-11

Conclusion: Reject the null hypothesis, the time series is likely stationary.

Melt Temperature:

ADF Statistic: -8.33, p-value: 3.30e-13

Conclusion: Reject the null hypothesis, the time series is likely stationary.

Screw Load:

ADF Statistic: -7.17, p-value: 2.78e-10

Conclusion: Reject the null hypothesis, the time series is likely stationary.

Vacuum:

ADF Statistic: -12.17, p-value: 1.41e-22

Conclusion: Reject the null hypothesis, the time series is likely stationary.

Screw Rotation Speed:

ADF Statistic: -6.87, p-value: 1.53e-09

Conclusion: Reject the null hypothesis, the time series is likely stationary.

Objective

The main purpose of the Granger causality test is to determine whether one time series variable can reliably predict future values of another time series variable.

Approach

- We have taken 3 time lags here.
- "lag" refers to the number of past observations of a variable that are included in the model to predict the current value of another variable.
- Sensory data that are included in the test are Temperature, Pressure, Screw Load and Screw Rotation speed

Melt Pressure

- Temperature causes changes in 'Pressure' at all tested lag lengths.
- Screw Load causes changes in 'Pressure' at all tested lag lengths.
- Screw Rotation speed does not Granger cause changes in 'Pressure' at lag lengths 1 and 2, but it does at lag length 3.

Temperature

- Pressure does not Granger cause changes in 'Temperature'.
- Both screw load and screw rotation speed do have a Granger causality relationship with Temperature.

Screw Load

- Both Temperature and screw rotation speed Granger cause changes in screw load, whereas pressure only shows significant evidence of causing changes in screw load at lag 2 and 3.

Screw Rotation Speed

- Pressure Granger cause changes in Screw rotation speed at lag 2 and 3.
- Temperature Granger cause changes in Screw rotation speed at all lag lengths.
- Screw Load influence changes in Screw rotation speed at lag 2 and 3.

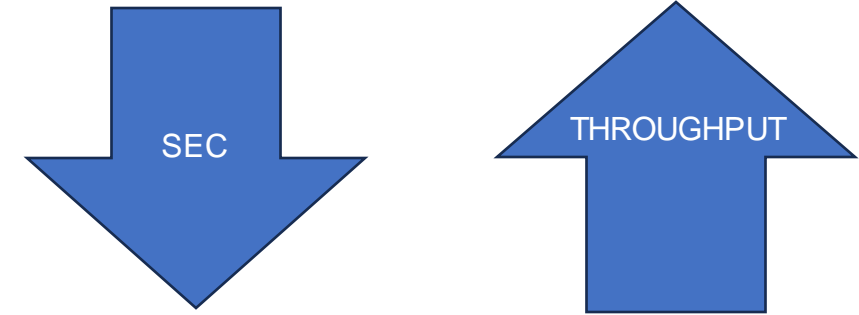
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Specific energy consumption (SEC) of a hopper = $\text{power(kw)} / \text{throughput(kg/h)}$

Objective : Minimizing the SEC while maximizing throughput

Problem Statement : Multi objective optimization problem

Probable Solution : To solve a multi-objective optimization problem where we aim to minimize energy consumption while maximizing throughput, you can use techniques like Pareto optimization. One common approach is to use multi-objective evolutionary algorithms (MOEAs) such as [NSGA-II \(Non-dominated Sorting Genetic Algorithm II\)](#) or [SPEA2 \(Strength Pareto Evolutionary Algorithm\)](#).



Business Outcome

Cost Reduction: Optimizing energy consumption and maximizing throughput leads to lower operational expenses and increased profitability.

Increased Productivity: Maximizing throughput enables the business to produce more units in the same timeframe, enhancing overall productivity and output capacity.

Competitive Advantage: Efficiency improvements resulting from optimization provide a competitive edge, allowing the business to offer more competitive pricing or higher-quality products.



THANK
YOU!