Smart DRB Factory

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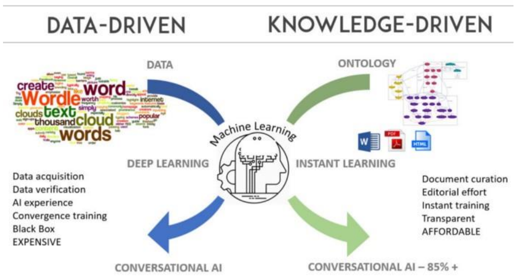
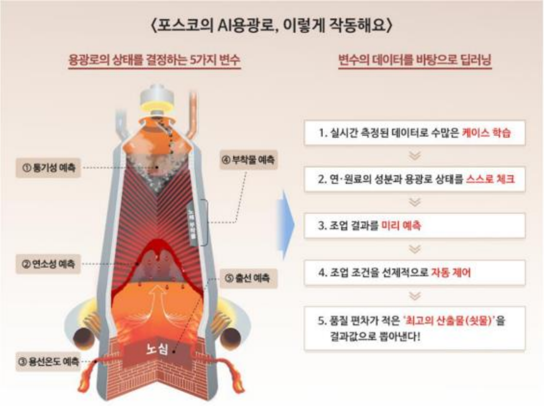
Data driven approach

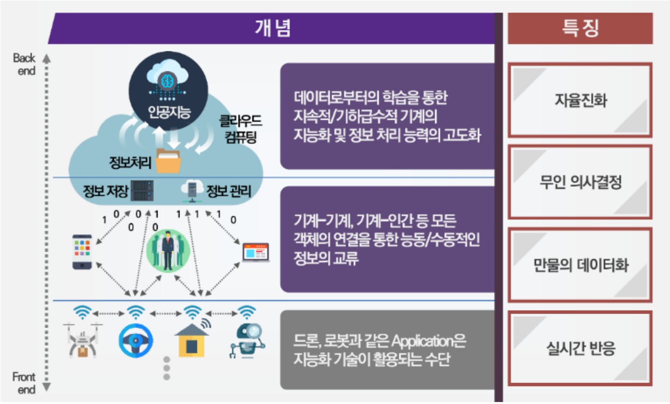
- Data resistant (데이터를 중요하게 생각)
  - Make data as a priority
- Data aware (데이터의 가치를 인식하는)
  - Data being generated
  - Realize the value of data
- Data guided (데이터 분석에 대해 관심 가지기 시작)
  - Focus on data analysis
  - Realize tactical value of data
- Data savvy (데이터에 대한 요령)
  - Realize the strategic value of data
  - Self-service data science
- Data driven (데이터가 곧 경쟁력)
  - Data is made available to all
  - Every major decision is made completely backed by data evidence
  - Data becomes the language of conversation between teams

By dataQraft, 2020.09

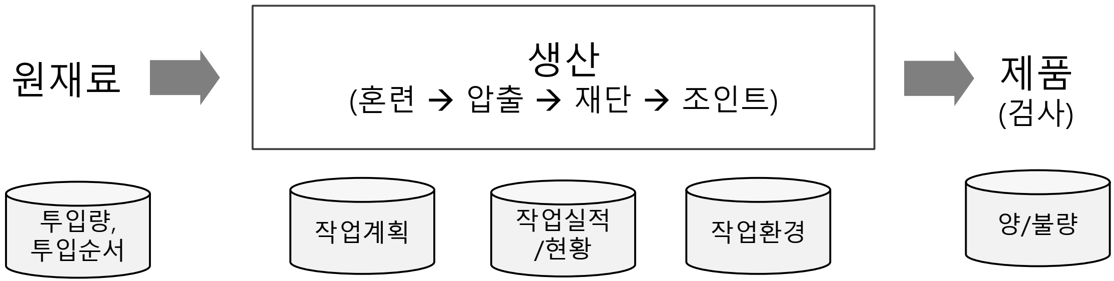


Data driven approach

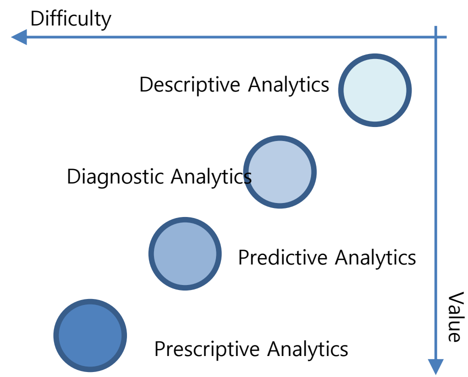




데이터 기반 접근법의 단계



작업현황	**1. Monitoring**
작업이상상황	**2. Detection**
불량의 원인	**4. Diagnosis**
작업완료시간	**3. Prediction**
작업의사결정	**5. Auto control**



압출 단면을 이용한 불량 검출

1. Monitoring

2. Detection

4. Diagnosis

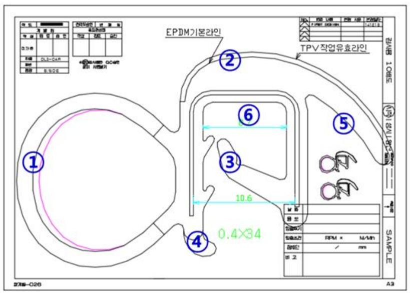
3. Prediction

5. Auto control

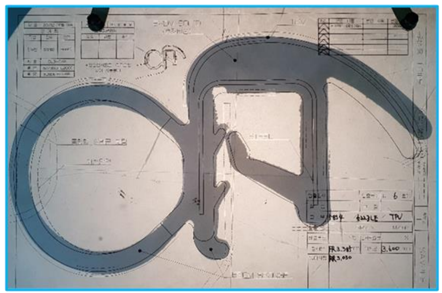
Not data driven

1. 형상 불량 발생 유형 및 주요 제어 조건

▷ 형상 검사 기준



▷ 10배 투영 검사 결과 : 한도견본 수립후 육안검사

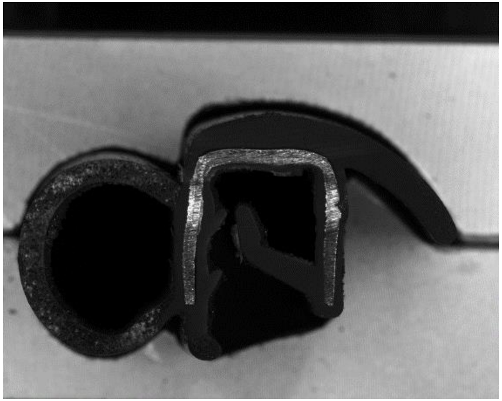


주요 관리 부위	불량 유형	주요 제어 조건	사용원재료
① 튜브	튜브 형상 크기/두께 산포, 튜브 상/하단부 변형	AIR 주입 압력, 스폰지 발포, 가이드롤 부착위치	스폰지고무(발포)
② 케리어 상단	두께 산포, 내부 철심금 위치 산포	압출구금 마모, 압출기 스크류 RPM, 프리포밍각도	솔리드고무
③ 그리프	두께/길이 산포, 끝단부 상/하 각도 산포	압출기 스크류 RPM, 단면 이송용 지지롤 간섭,엠보롤간섭	
④ 수밀립	두께/길이/각도 산포	오븐벨트 속도	
⑤ 트림립	두께/길이 산포, 끝단부 상/하 각도 산포	엠보롤 간섭, 가이드롤 부착위치, 압출고무 무늬	
⑥ 벤딩 내폭	내폭 산포	사이드 벤딩롤 세팅 간격	

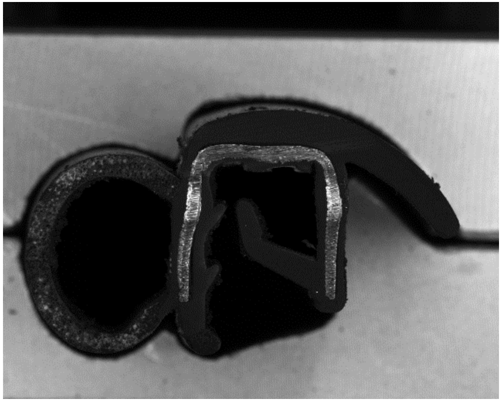
부산대학교 PUSAN NATIONAL UNIVERSITY BAE Lab Bigdata Analytics & Engineering

Data Set

- Data set size
  - Image size: 1280 x 1024 x 3
  - Set size
    - OK: 127
    - NG: 333
  - 별도의 측정없이 시각적으로 단순 분류 어려움

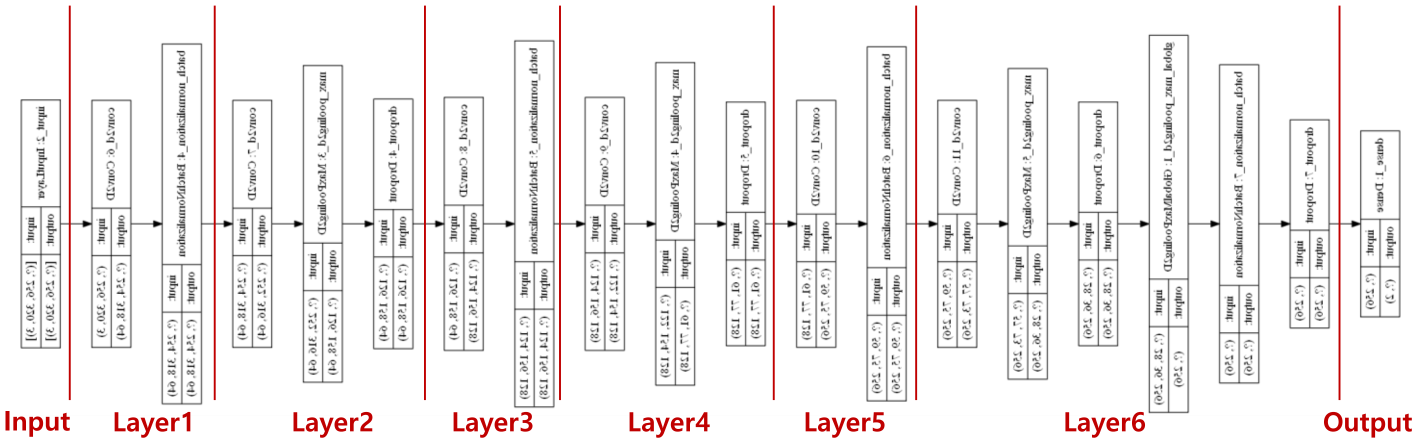


<OK>



<NG>

[M1] Simple CNN



[M1] Simple CNN

- Data set
  - Image Size: 320 x 256 x 3
  - Total: OK-127 NG-333
  - Train: OK-83(65%) NG-123
  - Test:: OK-44(35%) NG-210
- Validation
  - Sensitivity(NG): 57.6%
  - Sensitivity(OK): 84.1%

# Labels	Input Dim.	Train set Acc.	Test set Acc.
2	(320, 256, 3)	80.1%	62.2%

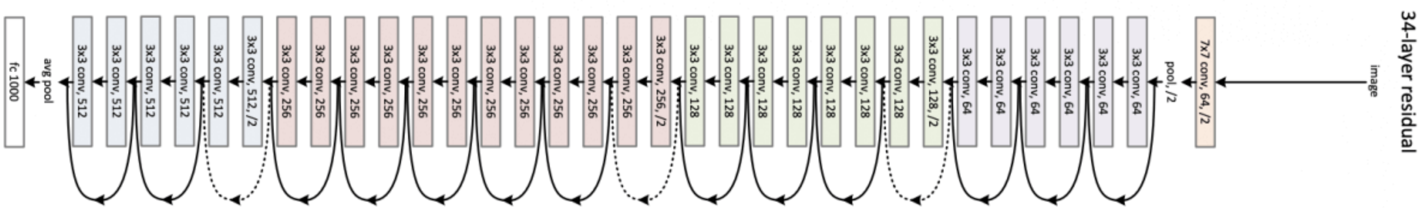
Train		Pred	
		NG	OK
Real	NG	83	40
	OK	1	82

Test		Pred	
		NG	OK
Real	NG	121	89
	OK	7	37

오판정 목록: test_wrong_result_training_simpleCNN.csv

[M2] ResNet50

- 50 Layer로 구성된 Neural Network



출처: He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.

[M2] ResNet50

- Data set
  - Image Size: 320 x 256 x 3
  - Total: OK-127 NG-333
  - Train: OK-83(65%) NG-123
  - Test:: OK-44(35%) NG-210
- Validation
  - Sensitivity(NG): 97.6%
  - Sensitivity(OK): 100%

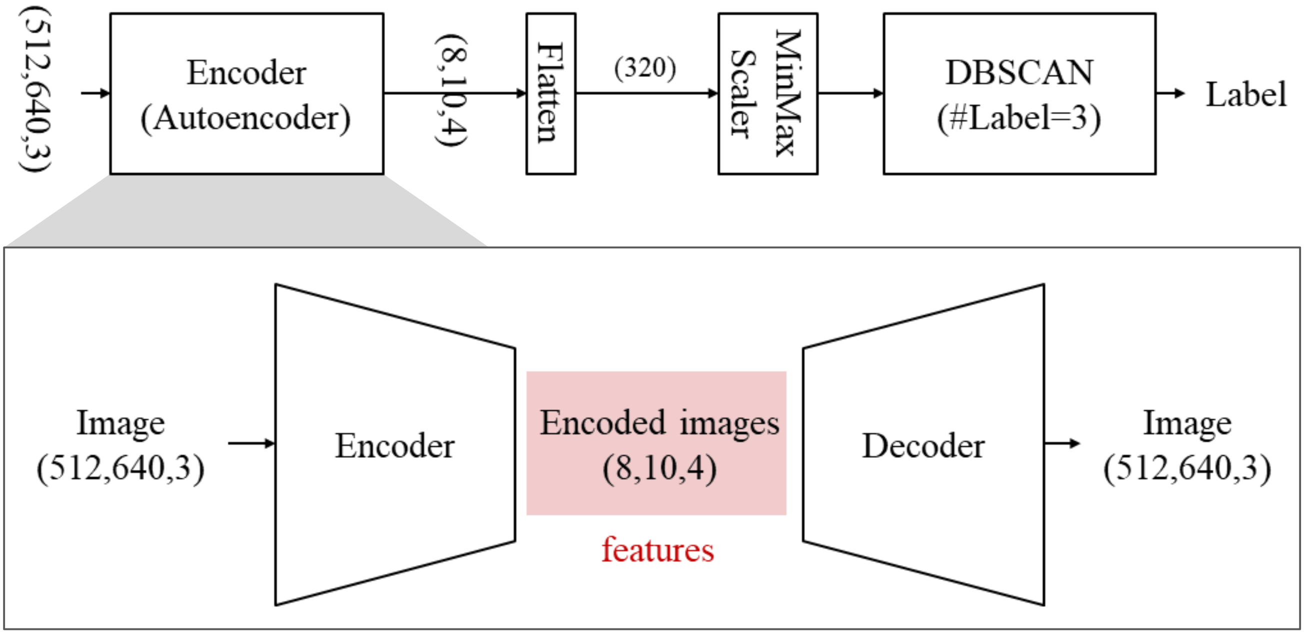
# Labels	Input Dim.	Train set Acc.	Test set Acc.
2	(320, 256, 3)	100%	98.03%

Train		Pred	
		NG	OK
Real	NG	123	0
	OK	0	83

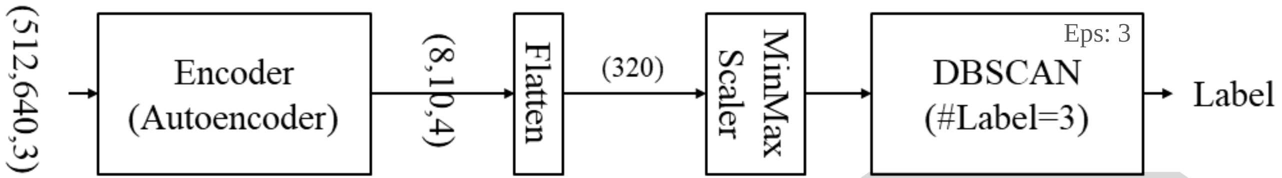
Test		Pred	
		NG	OK
Real	NG	205	5
	OK	0	44

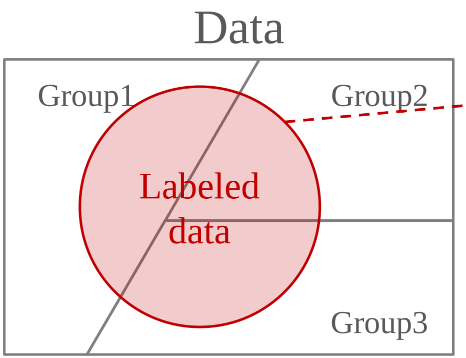
[M3] DBSCAN with autoencoder

For RGB (Exp1)



[M3] DBSCAN with autoencoder





(ex) Group2 Labeling

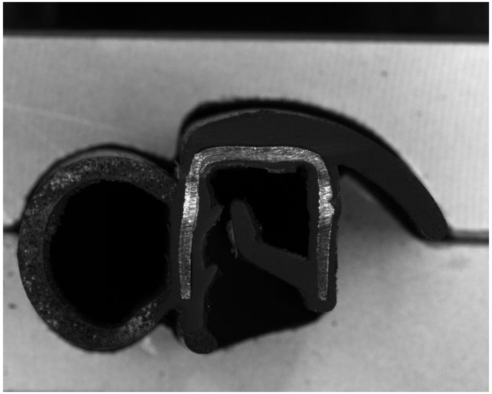
Group2 중 Labeled data만 활용

- OK Labeled data: 70%
- NG Labeled data: 30%

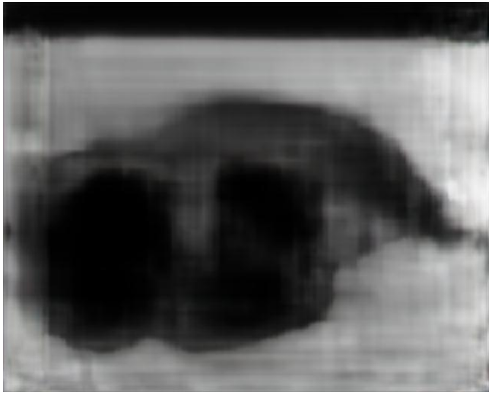
→ Group2의 Label: OK

[M3] DBSCAN with autoencoder

- Original Image size: (1280 x 1024 x 3)
- Exp.1 (RGB)
  - Resized Image: (640 x 512 x 3)
- Example of Input image and Decoded image
  - 선명하게 복원되지 않음



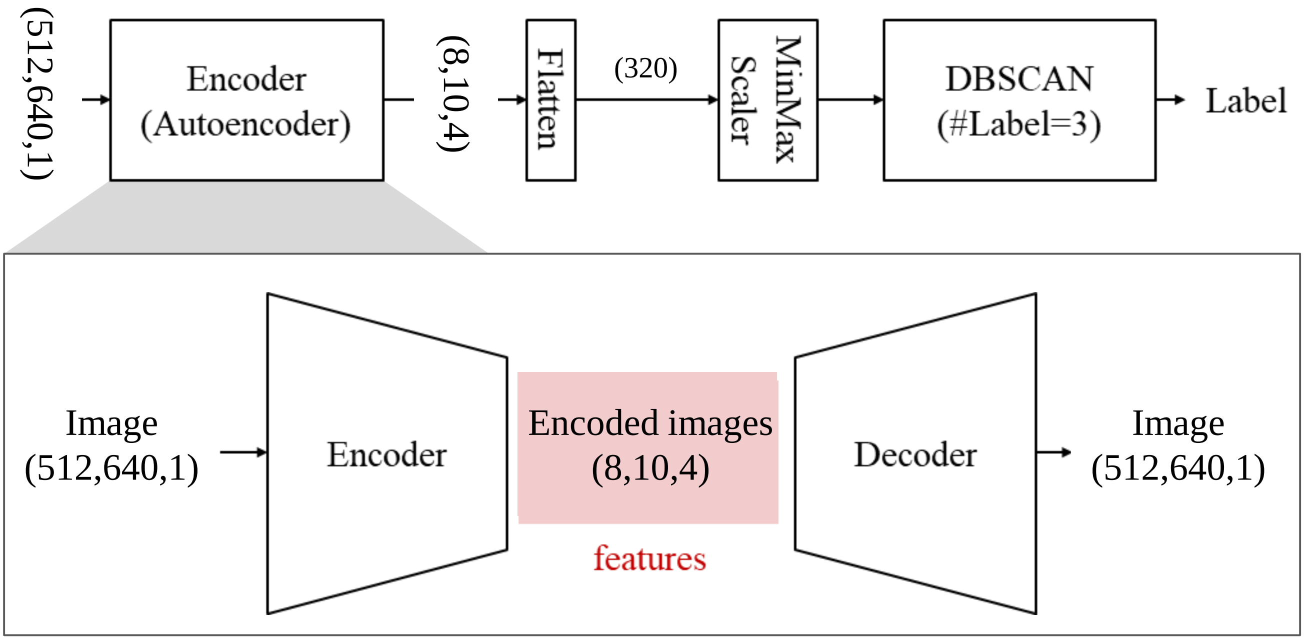
<Input image>



<Decoded image>

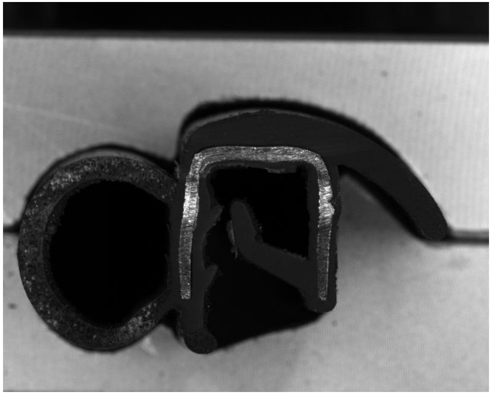
[M3] DBSCAN with autoencoder

For Grayscale image (Exp2)

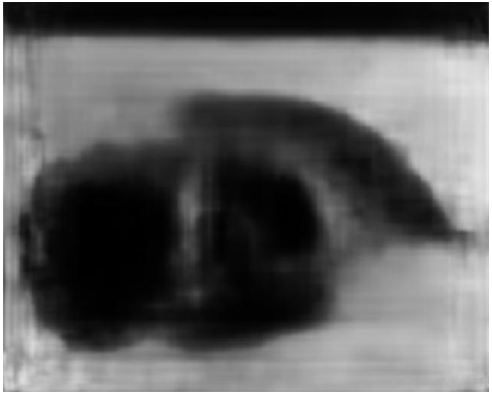


[M3] DBSCAN with autoencoder

- Original Image size: (1280 x 1024 x 3)
- Exp.2 (Grayscale)
  – Resized Image: (640 x 512 x 1)
- Example of Input image and Decoded image
    - RGB 보다는 선명하나, 선명하게 복원되지 않음



<Input image>



<Decoded image>

[M3] DBSCAN with autoencoder

- Results
  - Exp1: RGB
    - Acc: 95%
    - Sensitivity(NG): 94.6%
    - Sensitivity(OK): 96.1%
  - Exp2: Gray scale
    - Acc: 95%
    - Sensitivity(NG): 94.6%
    - Sensitivity(OK): 96.1%
  - 주어진 이미지에서 RGB와 Gray scale은 성능의 차이가 없음

		Pred	
		NG	OK
Real	NG	315	18
	OK	5	122

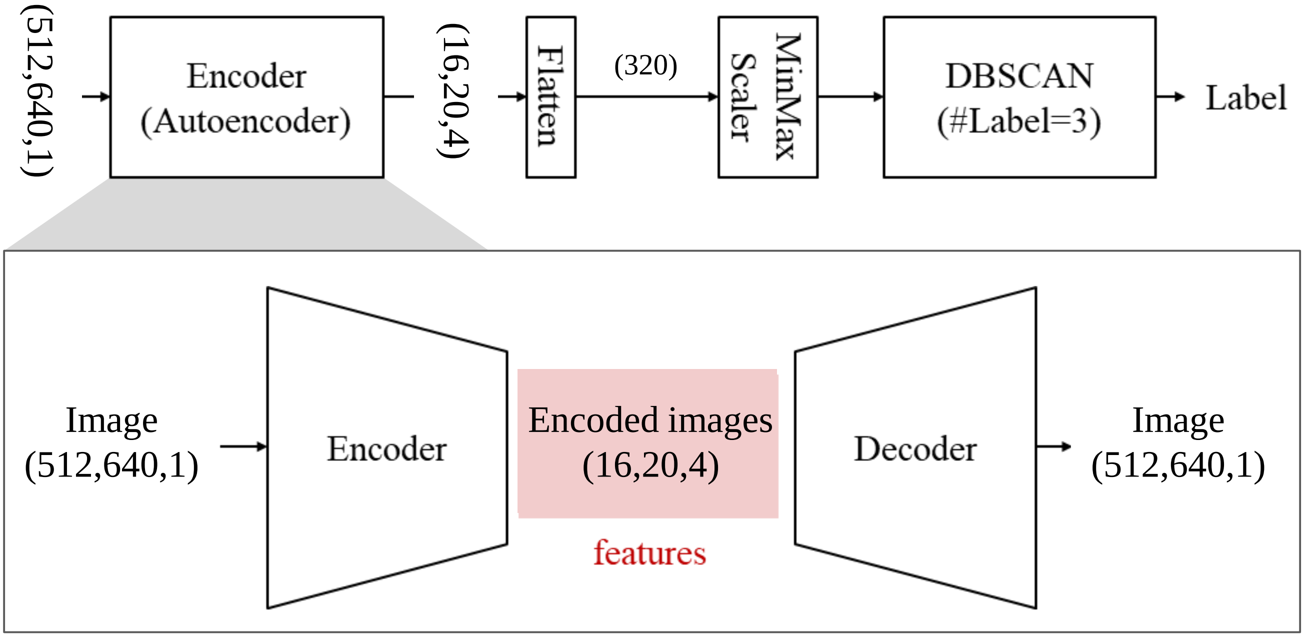
<RGB>

		Pred	
		NG	OK
Real	NG	315	18
	OK	5	122

<Gray scale>

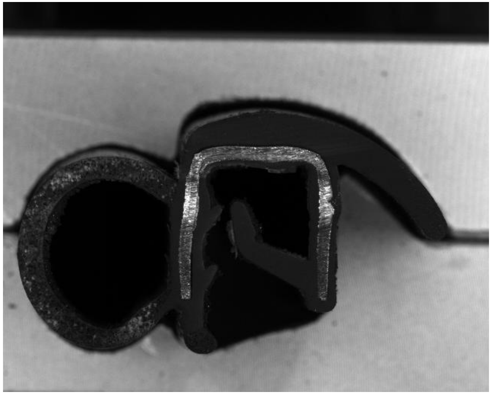
[M3] DBSCAN with autoencoder

For Grayscale image with simpler model (Exp3)

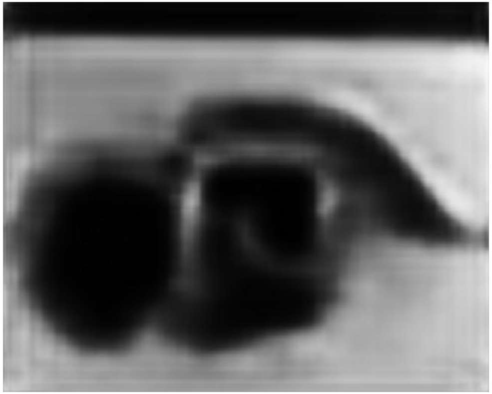


[M3] DBSCAN with autoencoder

- Original Image size: (1280 x 1024 x 3)
- Exp.3 (Grayscale)
  - Resized Image: (640 x 512 x 1)
  - Revised model: Feature size (16 x 20 x 4)
- Example of Input image and Decoded image
  - 더 Deep한 모델보다 선명하게 복원됨



<Input image>



<Exp3>

[M3] DBSCAN with autoencoder

- Results
  - Exp1: RGB
    - Acc: 95%
    - Sensitivity(NG): 94.6%
    - Sensitivity(OK): 96.1%
  - Exp3: Gray scale with simpler model
    - Acc: 92.4%
    - Sensitivity(NG): 94.6%
    - Sensitivity(OK): 86.6%
  - 모델을 축소한 경우, 복원은 더 잘 되지만 클러스터링 성능은 떨어짐(feature의 수 증가)

		Pred	
		NG	OK
Real	NG	315	18
	OK	5	122

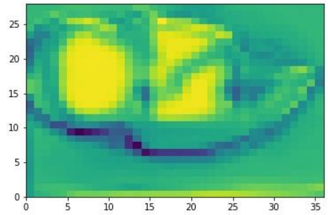
<RGB % Gray Scale>

		Pred	
		NG	OK
Real	NG	315	18
	OK	17	110

<Exp3>

Future work

- 모델의 현장 적용
  - 현장에서 실시간으로 얻어지는 데이터에 활용할 수 있는 방법론 개발
    (+) 이미지 분류 모델 성능 고도화
    - 예: 이미지 기반 불량 원인 도출
      - 이미지 내 각 pixel이 특정 Label(OK, NG)로 판단될 확률
        (색이 밝을수록 높은 확률)
      - 불량 원인이 되는 부분에 확률이 높게 나타날 것으로 기대



NG로 판단할 확률

Yun, Sangdoo, et al. "Re-labeling imagenet: from single to multi-labels, from global to localized labels." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021.

  - 수집 장비 등의 문제로 이미지 상태 변화에도 대응할 수 있는 방법론 개발
    - Online learning

품질 예측

1. Monitoring
2. Detection
4. Diagnosis
3. Prediction
5. Auto control

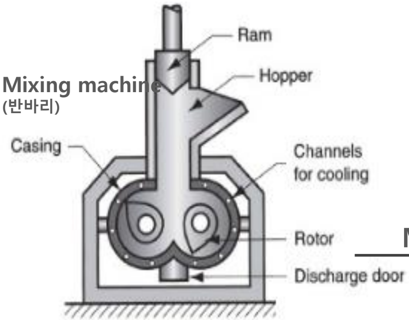
INTRODUCTION

- **Mixing machine process for rubber belt**

Ingredient

by product recipe

Mixing machine
(반바리)



Mid product (Rubber sheet)

Properties analysis

INTRODUCTION

To ensure that machines perform to their full potential, comprehensive analysis is required.

Monitoring, prediction, and classification of machine performance can be beneficial in improving decision making in industrial management.

Machine learning is one of solution, it will analyze and learn to gain knowledge and even predict information based on data

INTRODUCTION

- **Problems**
  - › The features generated from machine are minimal and log-oriented
  - › The machine normally produces a good product rather than a non-good product
- **Solutions**
  - › We propose feature engineering method formulated based on data generated by machine
  - › We implement Synthetic Minority Oversampling Technique (SMOTE) to overcome imbalance data
- **Necessities and Expectancy effects**
  - › Enable to no inspection or sample inspection instead of total inspection for mid-product of rubber belt
  - › Enable to optimize the process by simulation for improving the quality of mid-product or for reducing OPEX

INSIGHT ABOUT FEATURE ENGINEERING

- **Explicit feature engineering**
  - › Explicit feature engineering applies mathematical model functions to the transformation of a features
- **Implicit feature engineering**
  - › Implicit feature engineering applies dimensionality reduction of the data.
- **Knowledge-and-human-learning-guided feature engineering**
  - › Knowledge and human learning are acquired through experience and exploration.

DATA Structure

- Relational DB structure

Relations to be analyzed

1st Relation **Mixing recipe** "recipe".csv
Mix_ID
EquipID
MixTime
MixActCode
Addressname
Seq
Mater_Code
MatWeight
MatWeight
MaterAllow

2nd Relation **Real time sensing data** "PO No.-BATCH No".csv
PONO-BATCH No.
SeqNo
Ptime
Temp
Voltage
Ram
M1T10
M1T90
M1ML
M1MH
D2MN
Hard

Key value

3rd Relation **Inspection result** "result".csv
PONO
BATCHNO
Equipment
PDATE
M1T10
M1T90
M1ML
M1MH
D2MN
Hard
T10RE
T90RE
D2RE
HARDRE
RESULT

Labels

4th Relation **Standard range of properties** "result".csv
Hardness
S.G
Mooney viscosity
T10
T90

EXPLORATORY DATA ANALYSIS

- 2nd Relation : Real time sensing data (with 638 files which have the name of PO No.-BATCH No.)

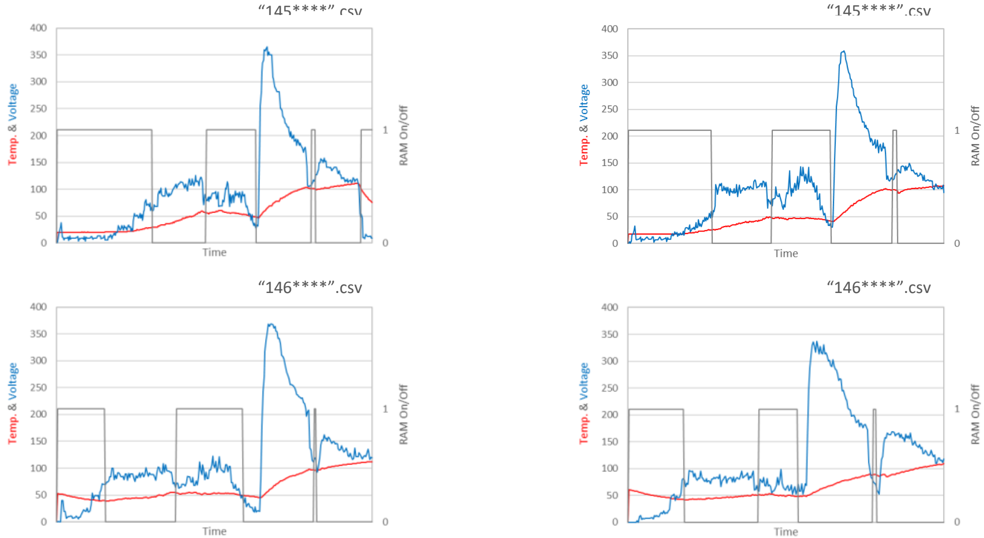
11 Attributes available

SeqNo (INT)	Ptime (MM:SS)	Temp (REAL)	Voltage (INT)	Ram (BN)	M1T10 (MM:SS)	M1T90 (MM:SS)	M1ML (REAL)	M1MH (REAL)	D2MN (REAL)	Hard (INT)
0	00:00.0	0	0	0	4:21	11:52	2.54	23.19	72.5	78
1	04:00.0	20.3	1	1						
2	04:00.9	20.3	1	1						
3	04:01.9	20.2	1	1						
4	04:02.8	20.2	1	1						
5	04:03.8	20.2	4	1						
6	04:04.7	20.2	5	1						
7	04:05.7	20.2	0	1						
8	04:06.6	20.2	2	1						
9	04:07.6	20.1	2	1						
10	04:08.5	20.1	1	1						
11	04:09.4	20.1	1	1						

"M1T10/M1T90/M1ML/M1MH": Rheological properties
"D2MN": Mooney viscosity
"Hard": Hardness

EXPLORATORY DATA ANALYSIS

- Samples of Real time sensing data



EXPLORATORY DATA ANALYSIS

- 3rd Relation : Inspection result

15 Attributes available

PONO (INT)	BATCHNO (INT)	Equipment (INT)	PDATE (YYYY/MM/DD)	M1T10 (MM:SS)	M1T90 (MM:SS)	M1ML (REAL)	M1MH (REAL)	D2MN (REAL)	Hard (INT)	T10RE (BN)	T90RE (BN)	D2RE (BN)	HardRE (BN)	Result (BN)
14689524	1	3	2021-03-25	4:36	11:36	2.73	23.28	83.9	80	OK	OK	OK	OK	OK
14689524	3	3	2021-03-25	4:41	11:33	2.95	23.82	88	79	OK	OK	OK	OK	OK
14689524	6	3	2021-03-25	4:39	11:28	3.07	24.72	89.3	80	OK	OK	OK	OK	OK
14689524	9	3	2021-03-25	4:31	11:20	3.26	25.14	88.4	79	OK	OK	OK	OK	OK
14689524	12	3	2021-03-25					86.9	80			OK	OK	OK
14689524	15	3	2021-03-25	4:20	11:27	3.38	25.53	90.7	81	OK	OK	OK	OK	OK
14688369	1	3	2021-03-23					83.8	79			OK	OK	OK
14688369	3	3	2021-03-23					85.6	78			OK	OK	OK
14688369	6	3	2021-03-23					87.6	78			OK	OK	OK
14688369	9	3	2021-03-23					88.4	79			OK	OK	OK
14688369	12	3	2021-03-23					90.5	80			OK	OK	OK
14688369	15	3	2021-03-23					86.4	80	OK	OK	OK	OK	OK
14685154	1	3	2021-03-19	4:24	11:42	2.91	23.23	85.7	80	OK	OK	OK	OK	OK
14685154	3	3	2021-03-19	4:33	11:39	3.44	25.62	91.4	81	OK	OK	OK	OK	OK

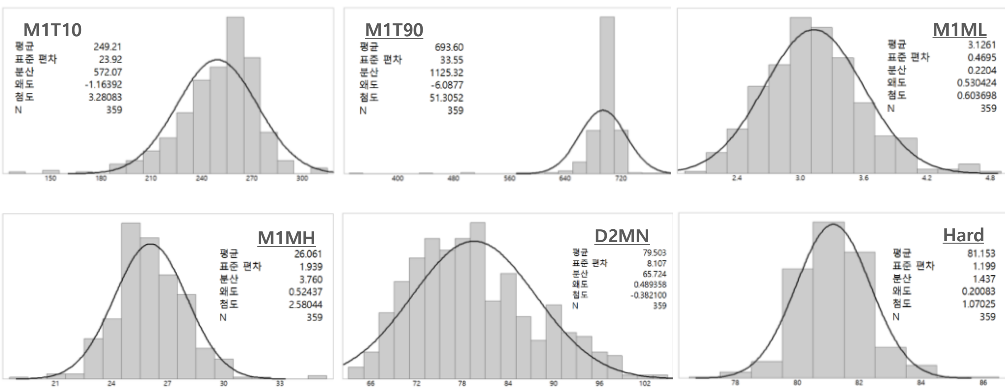
EXPLORATORY DATA ANALYSIS

- **Range of OK properties**

4 Attributes available

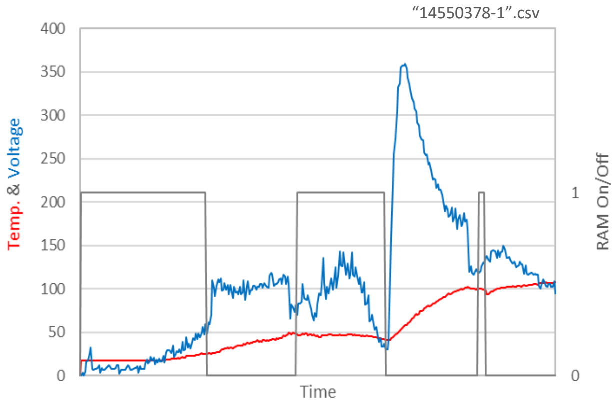
Hardness	D2MN	M1T10	M1T90
80 ± 3	85 ± 10	4:10 ± 00:40	11:10 ± 00:80

- **Histogram for 6 kinds of label data**



DATA PROCESSING

- **Explicit Feature engineering**



Regarding RAM

(1) "# of RAM closed": count{continuous interval for RAM value '0'}
(2) "Total time of RAM closed" : sum{Cumulated time for RAM value '0'}
(3) "Total time of RAM open" : sum{Cumulated time for RAM value '1'}
(4) "Max time among each RAM closed": Max{Each cumulated time for RAM value '0'}
(5) "Max time among each RAM open": Max{Each cumulated time for RAM value '1'}

Regarding Temp.

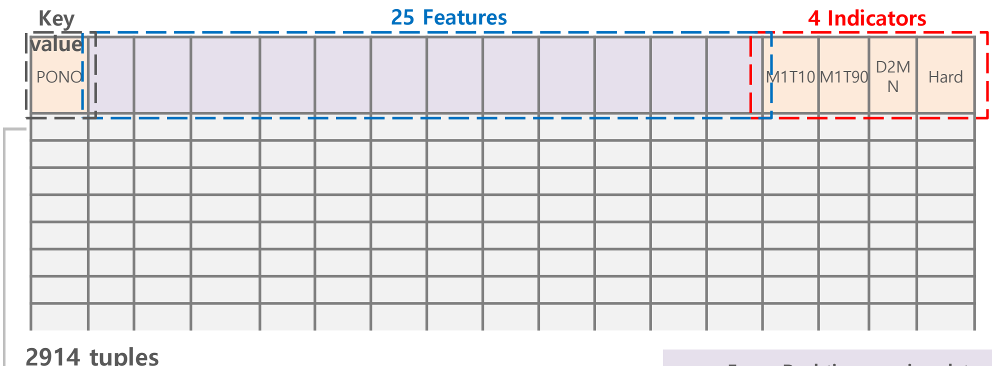
(6) "Ave. Temp.": average{All time Temp.}
(7) "Ave. Temp. during RAM closed": average{Temp. when RAM value '0'}
(8) "Ave. Temp. during RAM open": average{Temp. when RAM value '1'}
(9) "Max. Temp. during RAM closed": max{All Temp. when RAM value '0'}
(10) "Max. Temp. during RAM open": max{All Temp. when RAM value '1'}
(11) "Difference Max-Min of temperature during RAM closed": Tmax – Tmin when RAM value'0'
(12) "Ave. Variation rate of Temp. during RAM closed": average{(xi+1-x1)/xi, when RAM value '0'}
(13) "Max. Variation rate of Temp. during RAM closed": max{(xi+1-x1)/xi, when RAM value '0'}
(14) "Heat flux": sum{time*each Temp value}
(15) "Heat flux during RAM closed": sum{time*each Temp value when RAM value '0'}
(16) "Heat flux during RAM open": sum{time*each Temp value when RAM value '1'}

Regarding Volt.

(17) "Ave. Volt." : average{All Volt.}
(18) "Ave. Volt. during RAM closed": average{All Volt. when RAM value '0'}
(19) "Ave. Volt. during RAM open": average{All Volt. when RAM value '1'}
(20) "Max. Volt. during RAM closed": max{All Volt. when RAM value '0'}
(21) "Max. Volt. during RAM open": max{All Volt. when RAM value '1'}
(22) "Difference Max-Min of voltage during RAM closed": Vmax – Vmin when RAM value '0'
(23) "Physics flux": sum{time*each Volt value}
(24) "Physics flux during RAM closed": sum{time*each Volt. value when RAM value '0'}
(25) "Physics flux during RAM open": sum{time*each Volt. value when RAM value '1'}

DATA PROCESSING

- **Restructure of RDB**



*Note
- "Results" data was based on 4 indicators.
- The rows which have null value of variables were deleted.
- SMOTE is applied in the restructure of RDB for comparison purpose.

From: Real time sensing data

From: Inspection result

Build a Model

- **Machine Learning Random Forest Classifier**
  - › 10 Depth
  - › 100 Number of Trees
  - › 70% Data Training 30% Data Testing
  - › App.: Python SKLEARN

Result Random Forest

Technique	Accuracy	Sensitivity	Specificity	F1_Score
Without Feature Engineering	87.31	85.62	89.06	87.29
Without Feature Engineering + SMOTE	88.00	86.52	89.53	88.00
Proposed Feature Engineering	**90.40**	**87.64**	**93.25**	**90.28**
Proposed Feature Engineering + SMOTE	90.06	87.64	92.42	89.97

BUILD A MODEL

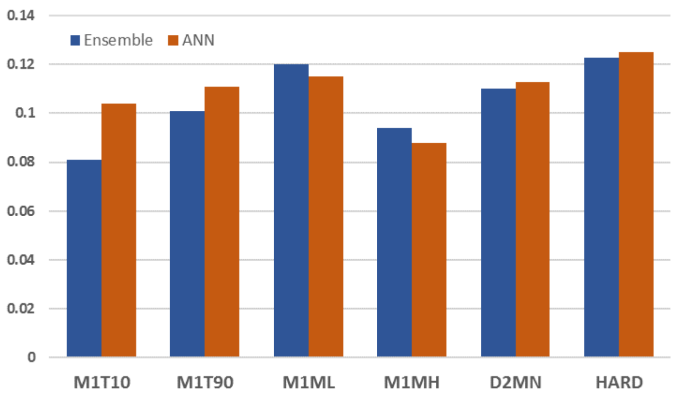
- **Machine Learning XGBoost Classifier**
  - › 10 Depth
  - › 100 Number of Trees
  - › 70% Data Training 30% Data Testing
  - › App.: Python SKLEARN

Result XGBoost

Technique	Accuracy	Sensitivity	Specificity	F1_Score
Without Feature Engineering	87.66	86.52	88.83	87.70
Without Feature Engineering + SMOTE	86.97	85.39	88.60	86.96
Proposed Feature Engineering	90.29	87.42	93.25	90.15
Proposed Feature Engineering + SMOTE	**90.51**	**87.64**	**93.48**	**90.38**

The reason why we didn't use NN

- **Performance for Regressor**
  - › RMSE of Ensemble and ANN Regressor



Conclusions

- Proposed feature engineering improves the classification results significantly.

- Based on the research results, all evaluation metrics such as accuracy, sensitivity, specificity, and F1-score, increased by 2-3% in XGBoost and Random Forest classification

- In overcoming dataset imbalance, the implementation of SMOTE does not provide substantial results.

이상 공정 탐색

1. Monitoring
2. Detection
4. Diagnosis
3. Prediction
5. Auto control

Project Purpose and Expected Benefits

Purpose & Expected Benefits

▣ Real-time Signal monitoring & prediction of the Roll-mixing process

1.Real-time monitoring application

2. Process cycle time control

3. Reduce costly expenses for unexpected events

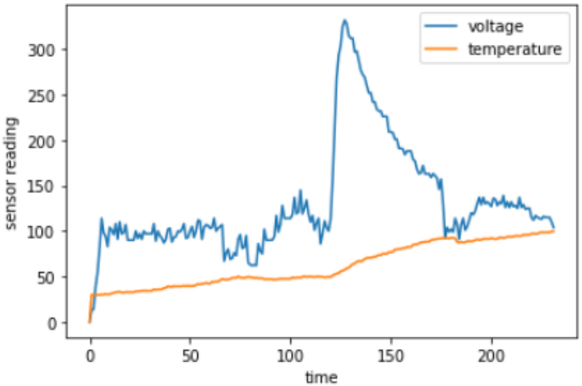
4. Increasing product reliability

Dataset Overview

Data of Real-time signals

Batch:
Dataset consist of 446 csv files,
each csv file represents a batch of wo
rking process of roll mixing

Signal:
Real-time attributes of machine
(voltage & temperature)



- The production time of each batch was around 300 seconds.
- Each batch has two(2) main real-time signals. Power(Voltage) and Temperature.

Questions arise from the Data

For Real-time Signal monitoring & prediction:

Q1. How to monitor the production signal ?

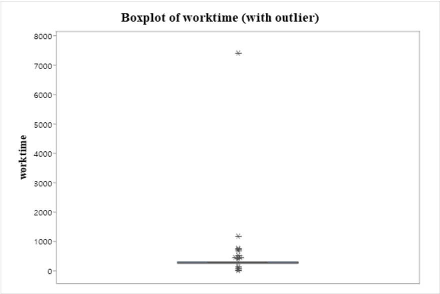
Q2. How to predict the production signal in future for early warning syste m?

Q3. If we don't know the batches are good or not (un-supervised), how to monitor the production signal?

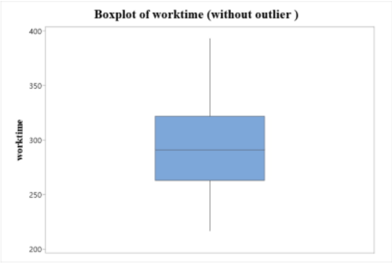
Data Preprocessing (Deletion of Outlier)

Implementation of Pre-treatment (Deletion of Outlier) from Given Database (From DRB)

	Given Database	Pre-treatment
No. of Batch	458 ea.	446 ea.
Worktime	15 ~ 7,417 seconds	230 ~ 393 seconds



No of Batch	458	Standard	337
Means	329	Range	7,402



No of Batch	446	Standard	26
Means	308	Range	163

Data Preprocessing

All 446 batches transformed to have same production time(300 sec).
Including 288 good batches, and 158 bad batches.(35% bad batches)
The batch quality standard is given in dataset.

There were 5 main quality evaluation criteria of each batch.

Batch quality standard table

Hard	Gravity	D2MNRE	T10	T90
80 ± 3	1.37 ± 0.05	85 ± 10	4:10 ± 40	11:10 ± 80

If all these criteria were satisfied, the batch will be "Good Batch".

Hard	Gravity	D2MNRE	T10	T90	Result
OK	OK	OK	OK	OK	OK
OK	OK	OK	OK	NG	NG

OK= "good batch"
NG="not good batch"

Data Preprocessing

Batch Quality Criteria

RESULT	PONO	Equipment	MIXNO	PDATE	M1T10	T10RE	M1T90	T90RE	D2MN	D2MNRE	Hard	HardRE	Gravity
OK	14689524	3	K-RECU-2	2021-03-25	276	OK	696	OK	83.9	OK	80	OK	
OK	14689524	3	K-RECU-2	2021-03-25	281	OK	693	OK	88	OK	79	OK	
OK	14689524	3	K-RECU-2	2021-03-25	279	OK	688	OK	89.3	OK	80	OK	
OK	14689524	3	K-RECU-2	2021-03-25	271	OK	680	OK	88.4	OK	79	OK	
OK	14689524	3	K-RECU-2	2021-03-25	0		0		86.9	OK	80	OK	
OK	14689524	3	K-RECU-2	2021-03-25	260	OK	687	OK	90.7	OK	81	OK	1.39
OK	14688369	3	K-RECU-2	2021-03-23	0		0		83.8	OK	79	OK	
OK	14688369	3	K-RECU-2	2021-03-23	0		0		85.6	OK	78	OK	
NG	14683623	3	K-RECU-2	2021-03-23	270	OK	712	OK	95.2	NG	80	OK	

Out of standard

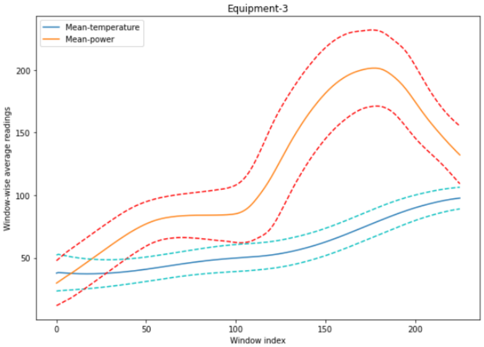
Batch quality standard table				
Hard	Gravity	D2MNRE	T10	T90
80 ± 3	1.37 ± 0.05	85 ± 10	4:10 ± 40	11:10 ± 80

Real Time Production Monitoring Model

Assumptions

1. Real-time signals (Temperature and Voltage) have an impact on the Product Quality.
2. "Good" batches have more stable signals flows than "bad" batches.
3. We can build a control chart to check the signal flow is stable or not.

Control Chart (example)



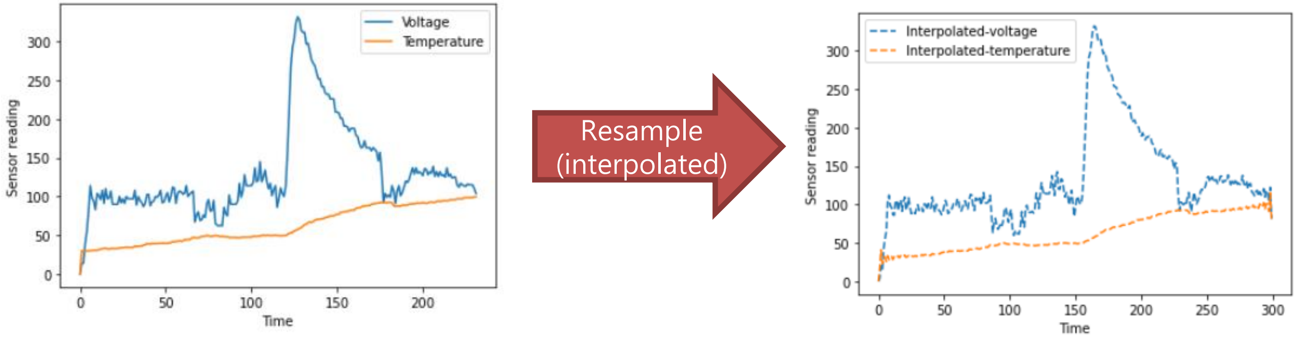
Overview - Constructing a Window-based Signal Control Chart Model

- Our model is constructed using a window based-signal control chart which utilize the following:
  - Data Interpolation/Resampling and Window based statistics:
    - Mean
    - Standard Deviation
  - Average the training batches statistics to create an overall control chart
  - Create a N-step ahead signal prediction model to provide an early warning system using a Seq2Seq LSTM.

Data Resampling

Data Resampling

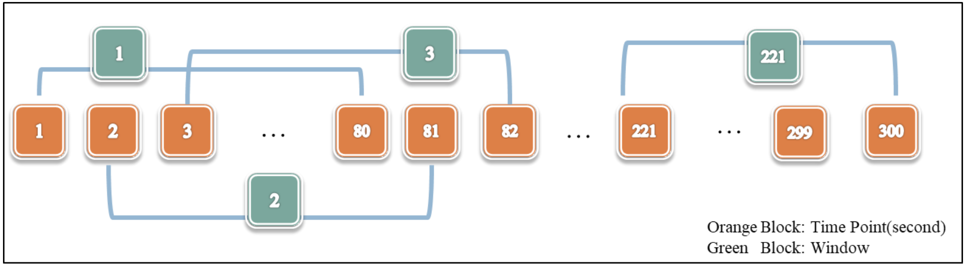
1. The change of signals (temperature and voltage) from each batch has a similar trend/patterns.
2. We want to check the trend of different batches.
3. The production times of batches are different.
4. To offset the influence of production times on the trend, **Resample Algorithm** is used to unify the production time.



Window Based Statistics

Modeling: Window-based Signal Control Chart

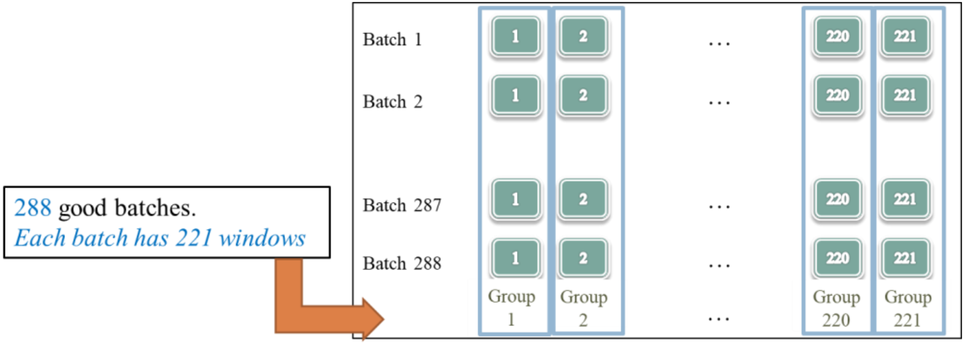
Window : A (Short) production signal time period.
Separate each batch into several windows.
The size of windows are the same. Each batch has same number of windows.



- The batch production time =300 second.
- Size of each window =80. (221 windows are constructed)

Averaging windows over all Batches

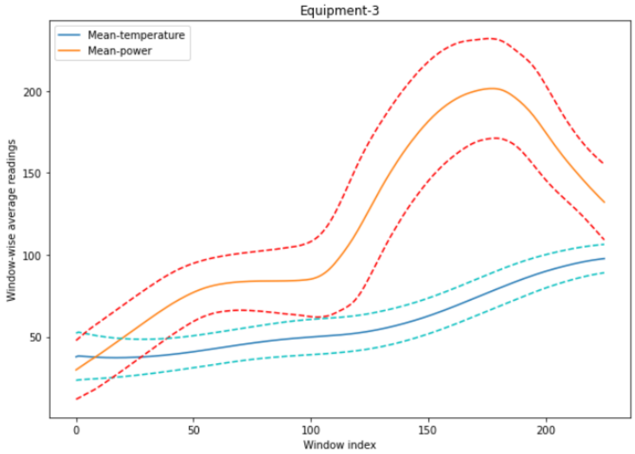
Window-based Signal Control Chart



Step 1: Input all good batches, each batch has a same size (221) of windows.
Step 2: Combine windows have same time into groups. *(221 groups)*
Step 3: Calculate the means and standard of each group. *(221 means and standard collected)*
Step 4: Connecting each mean and standard point of different group.

Window-based Signal Control Chart Model

Control Charts – Control Standard: 1.5σ



Red: Voltage Control upper/lower bound

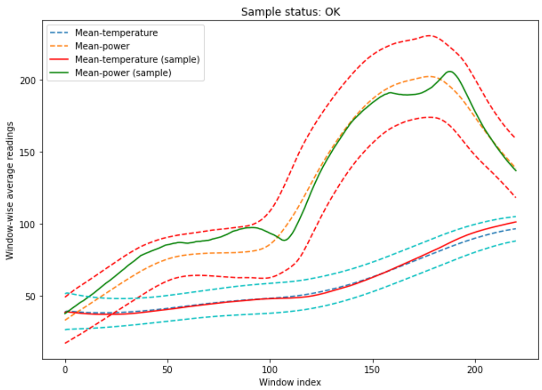
Orange: Voltage Center line

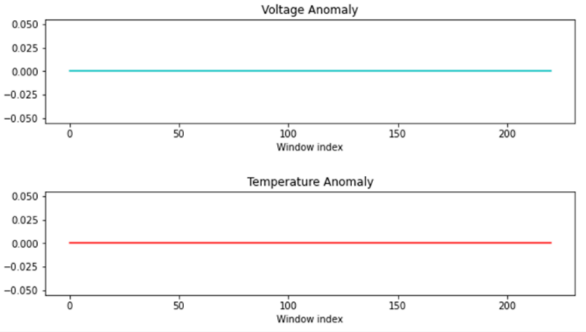
Cyan: Temperature Control upper/lower bound

Blue : Temperature Center line

Window-based Signal Control Chart

Modeling: Control Charts – Control Standard: 1.5σ

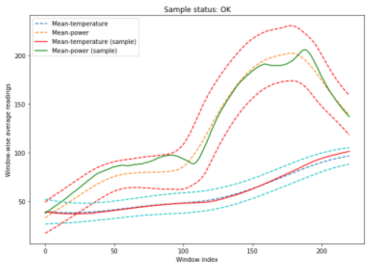


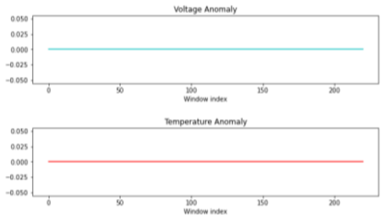


This example is from good batch in 1.5σ control level.
we see that the whole production process is under control.

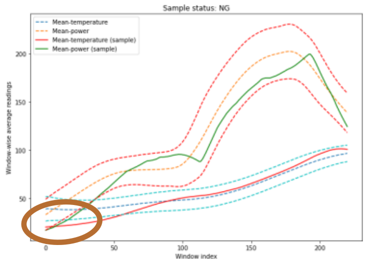
Window-based Signal Control Chart

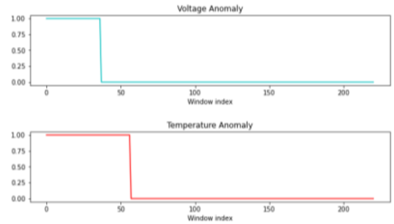
Modeling: Control Charts – Control Standard: 1.5σ





Good Batch (OK):
all signals are in control.

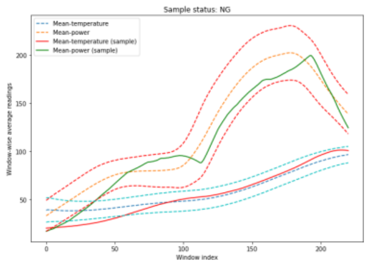


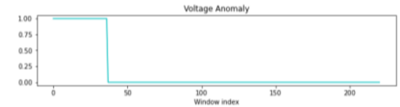


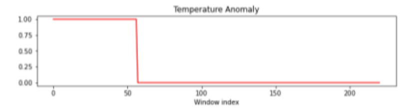
Not Good Batch (NG):
some signals are over contro
l bound

Window-based Signal Control Chart

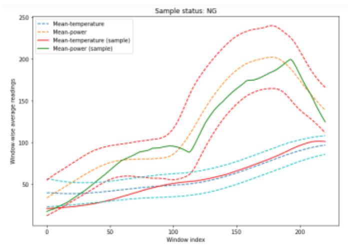
Modeling: Control Charts – Control standards: 1.5σ & 2σ

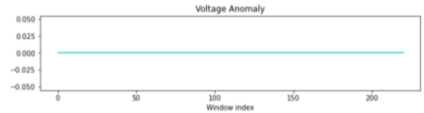


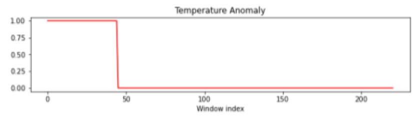




Control Standard = 1.5 σ







Control Standard = 2σ

Result Analysis

Result Analysis – different sigma level

Over Control Rate (OCR) : control level standard.

$$\text{Over Control Rate} = \frac{\text{Number of Over Control Windows}}{\text{Number of All Windows}}$$

Low OCR means control well. Less anormal signal existed.

The over control rate (OCR) of Good/No Good batches - sigma level = 1.5

Sigma level = 1.5	Good Batch OCR	No Good Batch OCR
Voltage OCR	9.041%	15.915%
Temperature OCR	9.626%	15.991%
average OCR	9.333%	15.953%

The over control rate (OCR) of Good/No Good batches - Sigma level = 2

Sigma level = 2	Good Batch OCR	No Good Batch OCR
Voltage OCR	2.460%	7.103%
Temperature OCR	2.921%	5.518%
average OCR	2.690%	6.311%

No good batches have low control level than good batches significantly.

Result Analysis

Window Size =50	Good Batch OCR	No Good Batch OCR
Voltage OCR	8.755%	18.050%
Temperature OCR	10.907%	18.968%
average OCR	9.831%	18.509%

Window Size =80	Good Batch OCR	No Good Batch OCR
Voltage OCR	9.333%	15.915%
Temperature OCR	9.626%	15.991%
average OCR	9.041%	15.953%

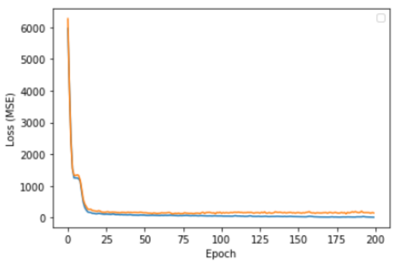
Window Size =100	Good Batch OCR	No Good Batch OCR
Voltage OCR	9.333%	14.042%
Temperature OCR	9.626%	14.006%
average OCR	9.041%	14.024%

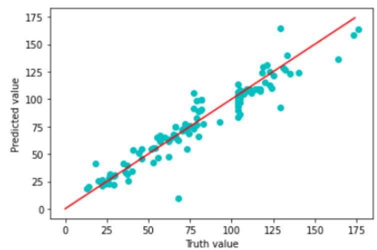
No good batches have low control level than good batches significantly.

Finish Time Prediction

Used to estimate the finish time in order to utilize resampling accordingly in real time

1. The length of our control chart is fixed. However, we do not know when the actual production time will be finish.
2. First 200 seconds of signals were selected to predict the end time of production.
3. The LSTM algorithm can predict the remaining production time. (*r value= 90.4%)*
4. use Resample to stretch control chart to match the predicted finish time.

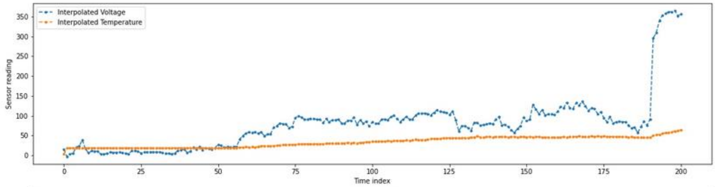




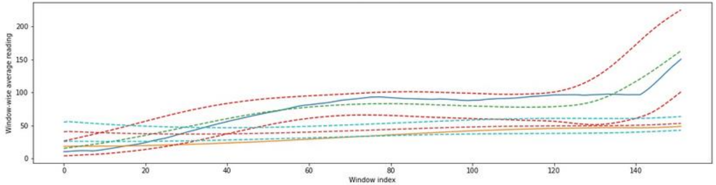
Real Time Monitoring Algorithm

Monitoring Simulation: Prediction of Finish Time

- After we predict the production time, we use Resample to stretch/interpolate the size of signal to match the predicted finish time.
- Then, continue monitoring the production process until finished.



Real-time Production Process signal



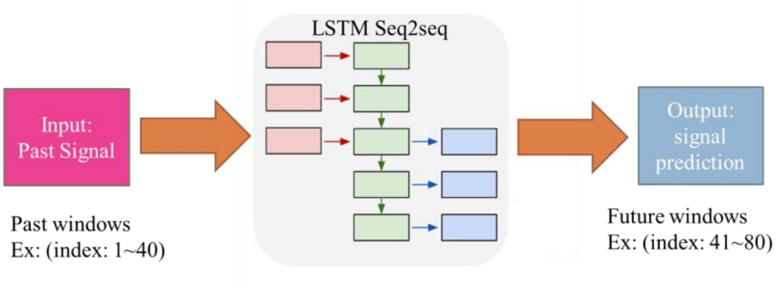
Window-based Production Monitorin
g

Early Warning Prediction Model

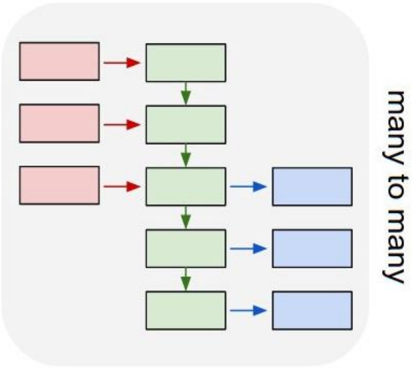
LTSM N-step Prediction

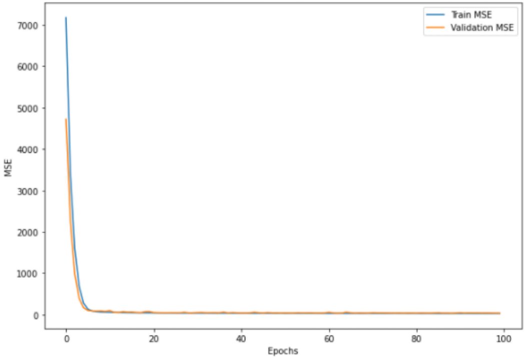
We perform N-step ahead Prediction as an early warning system by predicting if signal will be out of boundary in the future.

- LSTM seq2seq model can perform a real-time N-step signal window prediction.
- By input the past signal windows to the LSTM model, the future signal windows can be predicted in real time.



Seq2Seq Training (LSTM N-Step Prediction)

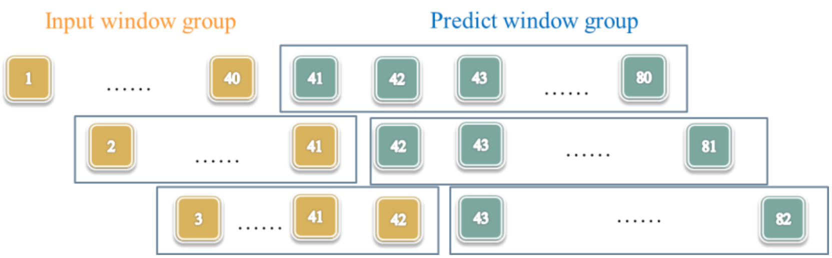




Test_error	Voltage	Temperature
RMSE	10.755	2.225
MSE	115.673	4.952

Production Process Signal Prediction - Real Time Implementation

LSTM N-step Prediction

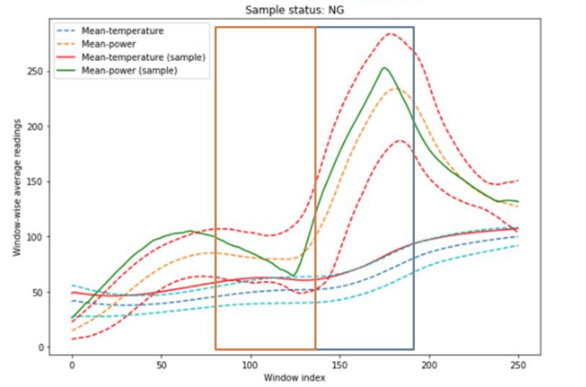


Each input window group will get it's predict window group.
The prediction will be overlap.
However, we only use the results of the current state as the prediction results.

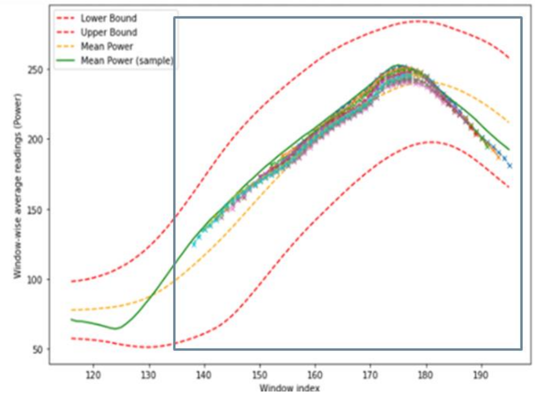
Production Process Signal Prediction - Real Time Implementation

LSTM N-Step Prediction

Input Predict

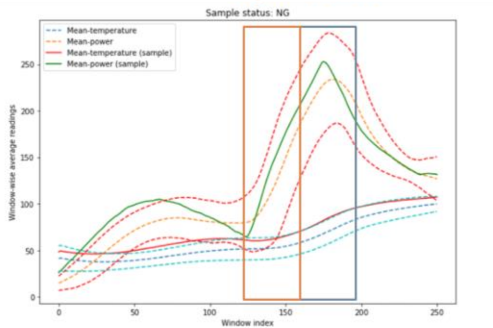


Example: Power Prediction



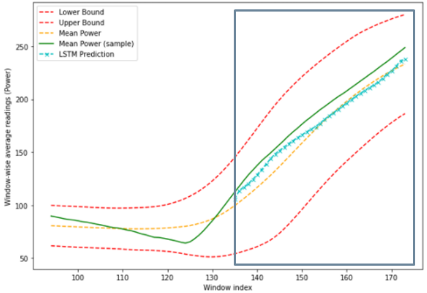
Production Process Signal Prediction

Input Predict

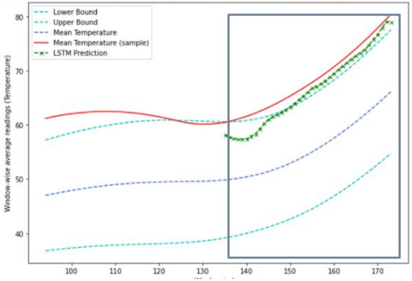


Current time: 130
Input: Window 91~130
Predict: window 131~170

Power Prediction

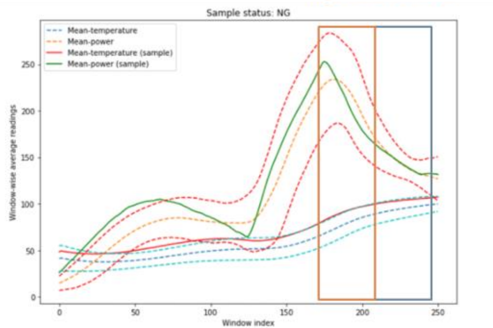


Temperature Prediction

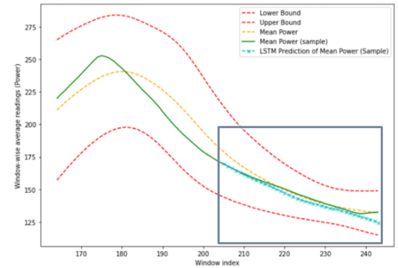


Production Process Signal Prediction

Input Predict

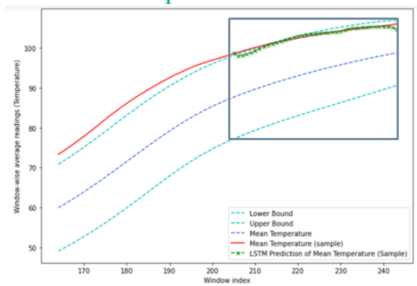


Power Prediction



Current time: 205
Input: Window 165~205
Predict: window 206~245

Temperature Prediction



Conclusions

Effects:

Monitoring & prediction the production process in real time.

Advantages:

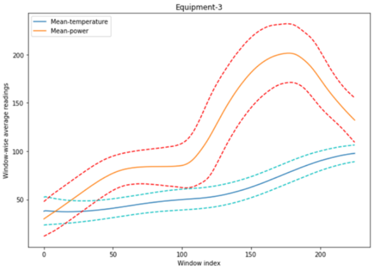
Easy to use and apply.

Result can be explained mathematically.

Limitations:

Few variables considered.

The interaction of different variables is not considered.



Future application in DRB:

A stable signal may improve the reliability of production process.

DRB can perform monitoring and prediction the signals of the production process in real time.

In the monitoring process, DRB can try to control the signal process by adjusting the fomula.

공정 시뮬레이션

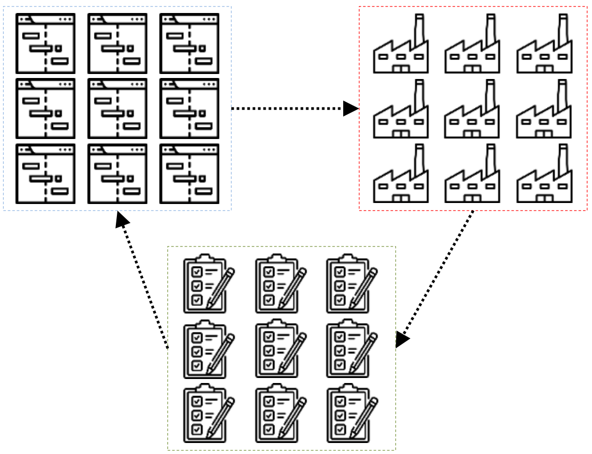
1. Monitoring
2. Detection
4. Diagnosis
3. Prediction
5. Auto control

Contents

Topics

Prediction simulation tools for process recipe

Process for making optimal recipes



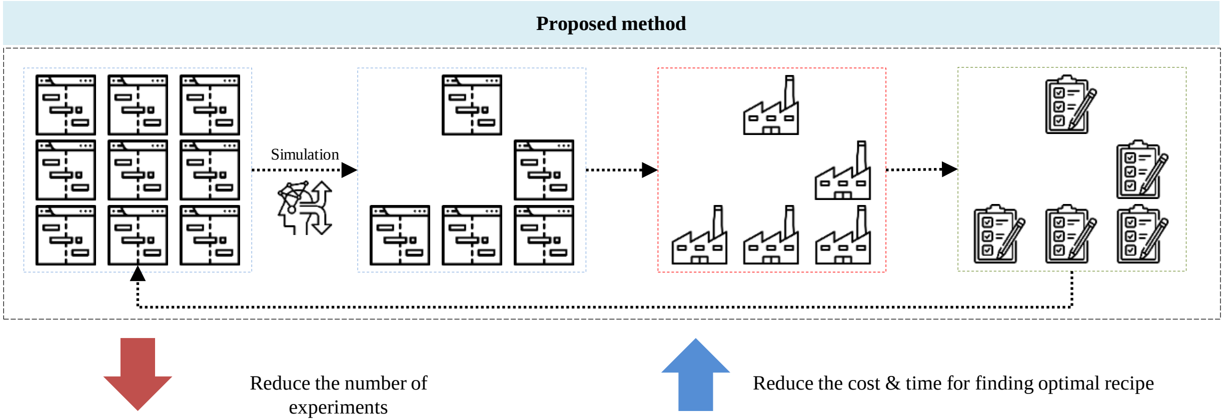
Problems in current recipes making process

- According to experts, 3~5 months are needed to make an optimal recipe.
- To make an optimal recipe, many recipe candidates are suggested. To prove the performance of candidates, many experiments must be conducted in factory.

- If the performance of recipe candidates can be predicted, we can dramatically reduce the number of experiments needed.

Topics

Prediction simulation tools for process recipe

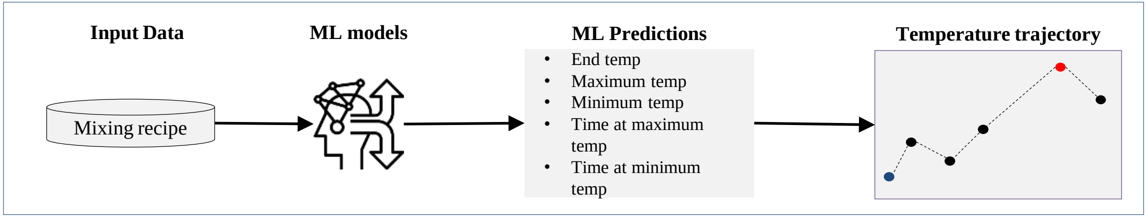


- Our proposed method's target is to predict the performance of recipe candidates before conducting experiments in factory.
- It can be able to exclude recipe candidates which is predicted poor performance.

Methodology

Target 1: Generate the temperature trajectory using prediction walk model

- Temperature prediction is very important because **vulcanization** occurs when the temperature of the channel exceeds the threshold
- To generate the temperature trajectory, 5 prediction models(End temperature, Maximum temperature, Minimum temperature, Time at maximum temperature and Time at minimum temperature) are trained.
- By predicting the extreme value of the temperature and its time point, we simulate the situation inside the channel according to the recipe
- Using Machine Learning(ML) models, generate the trajectory of temperature

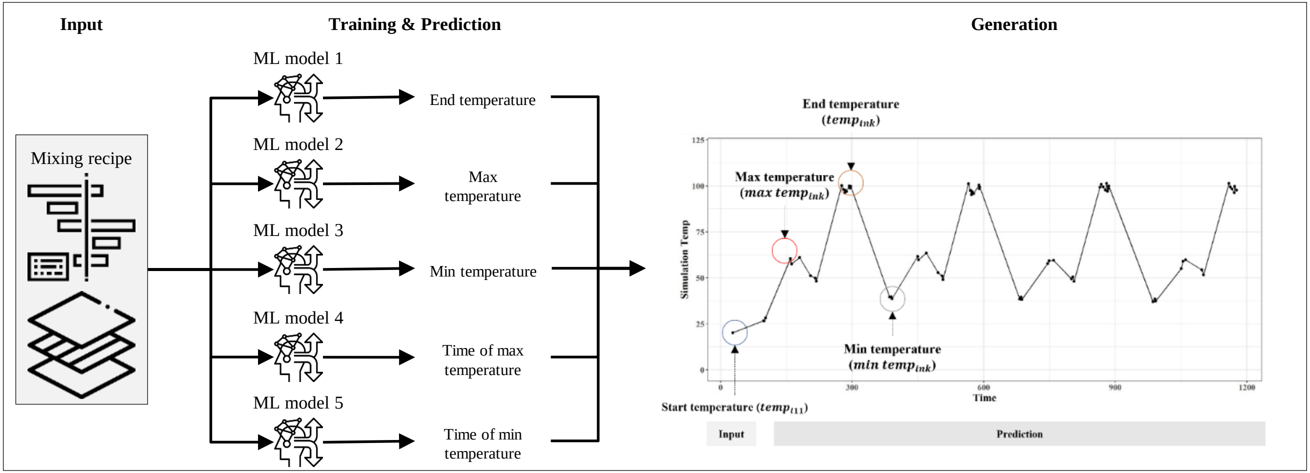


Process of predicting temperature and trajectory

Methodology

Target 1: Generate the temperature trajectory using prediction walk model

- Prediction walk model consists of five ML predictive models, using prediction results, Prediction walk model generates the temperature trajectory

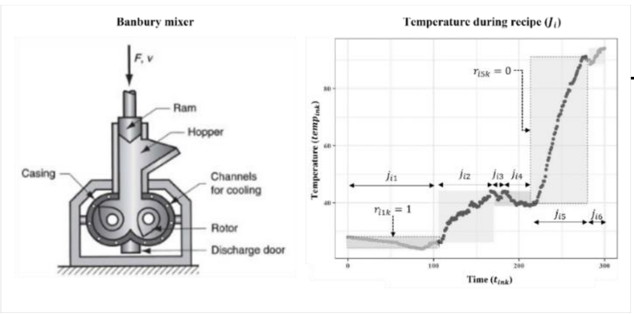


Methodology

Target 2: Predict the results of mixing

- The temperature change of mixing process has a great influence on the quality of rubber
- Using temperature information from 'Target 1', ML models can predict the results of mixing
- The mixing result appears as a measurement result of the viscosity of rubber(tan delta, high/low torque)

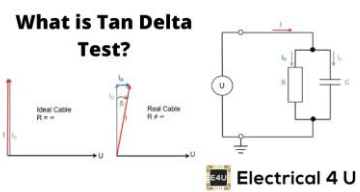
Temperature trajectory

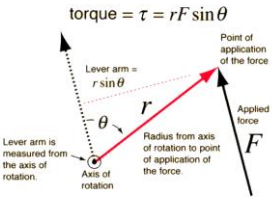


Feature extraction

Mixing result

- Viscoelastic of rubber (tangent delta)
- Low/High torque





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Methodology

Predictions Process 1st : Predicting temperatures and times (Target 1)

Machine learning models

Input Recipe information

Batch NO	Job Seq	Time	Voltage
1	1	T_{11}	V_{11}
1	2	T_{12}	V_{12}
1	3	T_{13}	V_{13}
2	1	T_{21}	V_{21}
2	2	T_{22}	V_{22}
2	3	T_{23}	V_{23}

- Ram On/Off
- Mixing Time
- Total voltage

Prediction result

Batch NO	Job Seq	Time	Temp
1	1	t_{11}	$Temp_{11}$
1	1	t_{12}	$Temp_{12}$
1	1	t_{13}	$Temp_{13}$
1	2	t_{21}	$Temp_{21}$
1	2	t_{22}	$Temp_{22}$
1	2	t_{23}	$Temp_{23}$
1	3	t_{31}	$Temp_{31}$
1	3	t_{32}	$Temp_{32}$
1	3	t_{33}	$Temp_{33}$

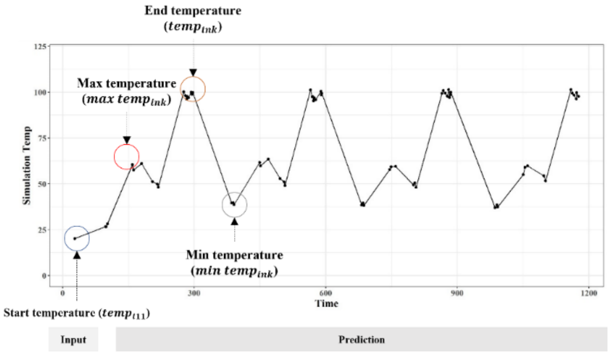
- Prediction of temperature and time

- Our proposed method's (Prediction walk model) target is to predict the performance of recipe candidates before conducting experiments in factory.
- Prediction walk model generates the temperature trajectory incorporating machine learning prediction results

Methodology

Predictions Process 1st : Predicting temperatures and times (Target 1)

Generated trajectory example



Parameter setting

- Define the job schedule (Job sequence, Time, Voltage)
- Setting the start temperature ($Temp_1$)

Trajectory generating

- Predict the temperatures and time points.
- Predicted temperature is set to start temperature for next job sequence.
- Repeat predicting until the total job sequences are ended.

- Combining the prediction results by prediction walk model, the temperature trajectory is generated

Methodology

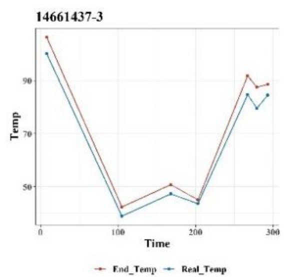
Prediction Process 2nd : Generating temperature trajectory (Target 1)

Prediction result

Batch NO	Job Seq	Time	Temp
1	1	t_{11}	$Temp_{11}$
1	1	t_{12}	$Temp_{12}$
1	1	t_{13}	$Temp_{13}$
1	2	t_{21}	$Temp_{21}$
1	2	t_{22}	$Temp_{22}$
1	2	t_{23}	$Temp_{23}$
1	3	t_{31}	$Temp_{31}$
1	3	t_{32}	$Temp_{32}$
1	3	t_{33}	$Temp_{33}$

- End temp
- Maximum temp
- Minimum temp
- Time at maximum temp
- Time at minimum temp

Generated temperature trajectory



- Example of temperature trajectory vector

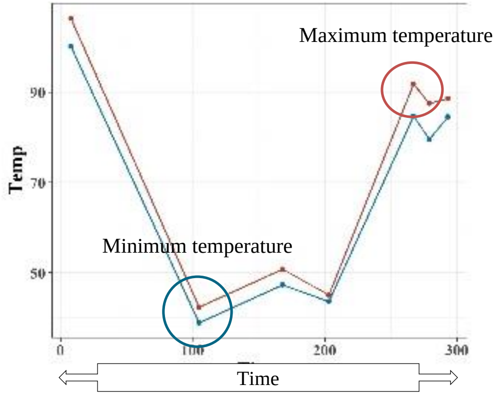
Seq	1	2	3	4	5
Time(s)	1	30	150	180	290
Temp	19	50	70	100	80

- The temperature trajectory consists of time and temperature vectors
- The blue line is real temperature trajectory and the red line is generated trajectory by prediction walk model

Methodology

Prediction Process 3rd : Extracting trajectory features (Target 2)

Temperature trajectory basic information



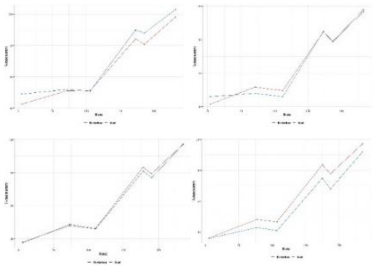
- First, the maximum and minimum temperature values are extracted from temperature trajectory
- Second, the total mixing time values are extracted.

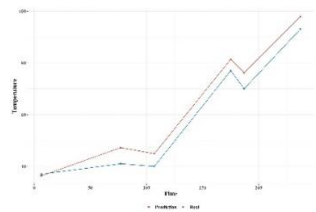
Methodology

Prediction Process 3rd : Extracting trajectory features (Target 2)

Trajectory characteristic information

Target Trajectory	Reference Trajectory





- For predicting the quality of mixing results, the trajectory characteristic are extracted
- Hausdorff distance, Frechet inception distance and Dynamic time wrapping are calculated
- The trajectory distances are calculated between reference trajectory, the reference trajectory is chosen as universal temperature trajectory

Methodology

Prediction Process 4th : Predicting mixing result (Target 2)

Features

Index	Features	Description
1	Max temp	The maximum temperature during the total mixing
2	Min temp	The minimum temperature during the total mixing
3	Time	Mixing time
4	Haus	Hausdorff distance
5	DTW	Dynamic time wrapping
6	FRE	Frechet inception distance

Response variables

Index	Response variables	Description
1	δ_i	Tangent delta value
2	lt_i	Low torque value
3	ht_i	High torque value

Prediction process

$$\delta_i^1 = f(Max\ temp, Min\ temp, Time, Haus, DTW, FRE)$$
$$lt_i^1 = f(Max\ temp, Min\ temp, Time, Haus, DTW, FRE)$$
$$ht_i^1 = f(Max\ temp, Min\ temp, Time, Haus, DTW, FRE)$$

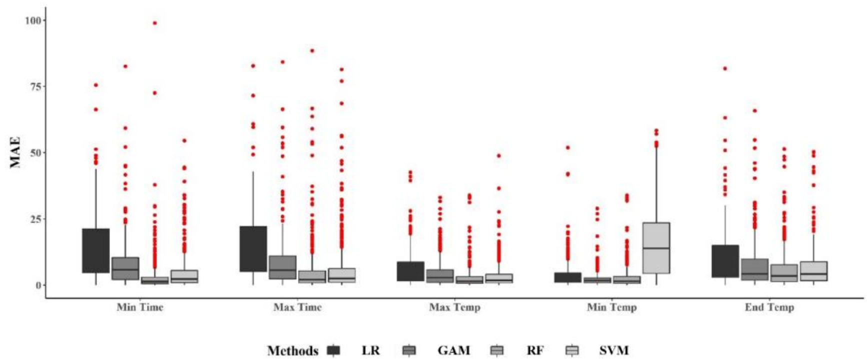
$$\delta_i^t = f(f(\delta_i^{t-1}), f(lt_i^{t-1}), f(ht_i^{t-1}))$$
$$lt_i^t = f(f(\delta_i^{t-1}), f(lt_i^{t-1}), f(ht_i^{t-1}))$$
$$ht_i^t = f(f(\delta_i^{t-1}), f(lt_i^{t-1}), f(ht_i^{t-1}))$$

- For predicting the mixing results, first predict the response variables using features. Second, using recursive prediction methods, estimate the target values
- Recursive prediction methods shows the better performance than original prediction

Model Performance

Temperature prediction result

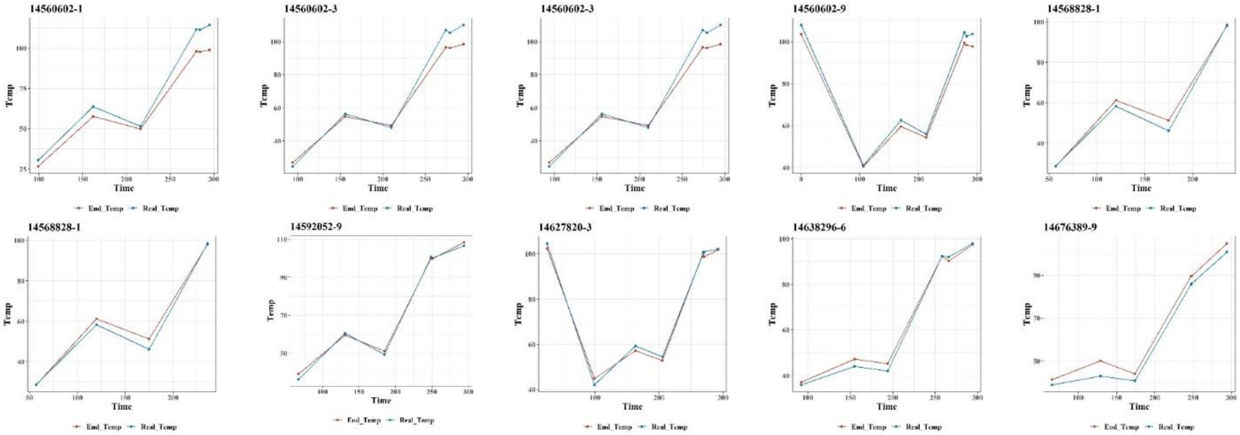
- For training the prediction walk model, 4 ML algorithms are applied for predicting the response variables
- Linear Regression(LR), General Additive model(GAM), RF(Random Forest), SVM(Support Vector Machine)
- Because Random Forest shows the best performance in prediction, we select the algorithms for prediction walk model

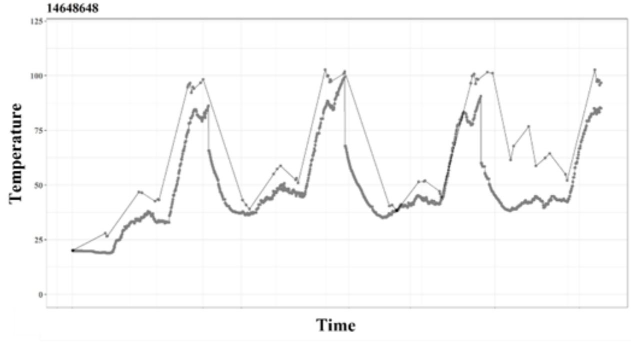


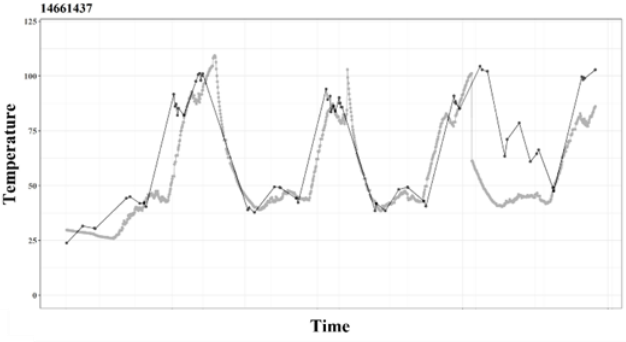
Model Performance

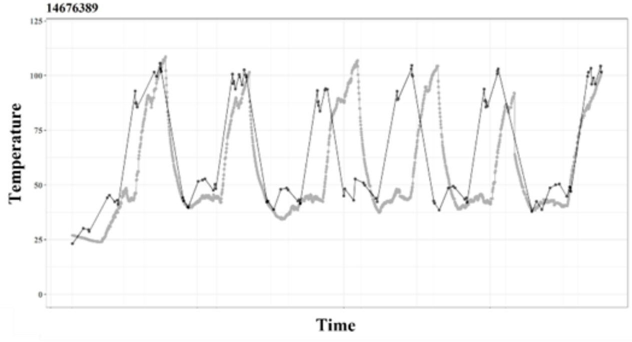
The results of trajectory generating

- The blue line is real temperature trajectory during job sequences and the red line is generated trajectory.
- The predicted trajectories are similar with real trajectories.




14648648
Temperature
Time


14661437
Temperature
Time

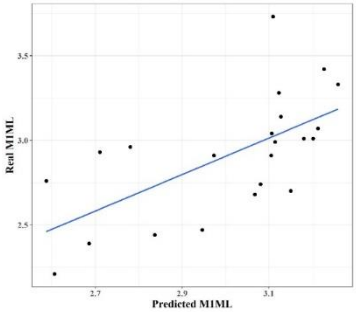

14676389
Temperature
Time

Model Performance

The results of prediction mixing results

1st Step original prediction result

Index	Target variable	Features	MAE
1	D2MN	Max Temp, Min Temp, Time, Haus, DTW, FRE, Integrated Temp	7.40
2		Max Temp, Min Temp, Time, Haus, DTW, FRE	7.21
3		Max Temp, Min Temp, Time, Integrated Temp	7.66
4		Max Temp, Min Temp, Time	7.44



2nd Step recursive prediction result

Index	Target variable	Features	MAE
1	D2MN (Tan delta)	Before Updating	7.18
2		After Updating	6.86
3	M1ML (Low Torque)	Before Updating	0.28
4		After Updating	0.29
5	M1MH (High Torque)	Before Updating	1.22
6		After Updating	1.10

- Prediction model shows the best performance when using trajectory information
- Updated values have less error than before updating

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Conclusion

Contribution

- The proposed simulation tool for predicting the results is necessary for making recipes.
- It can reduce the required experiment trials.
- Simulation tool is very practical considering specs of the current mixing equipment

Limitations

- Some errors are shown in prediction results, we have to improve the model performance
- For improving the model performance, the more detail information during jobs are needed.
- We expect to improve the model through the more detailed information, analysis of the time and relationship between the materials which is put in.

Conclusion

Further research issues

Future features

Present features

Temperature **Time** **Voltage**

\+

Detail job information

Recipe schedule **Materials** **Control System**

- In this project, we used only temperature, time and voltage informations.
- If more detail informations are supported such as recipe schedule, materials and control systems, we can improve the performance of the proposed simulation tool
- Our future target is developing the AI scheduler for optimizing the recipe schedule using such as Deep Reinforcement Learning technique

DRB smart factory

원재료 → **생산** (혼련 → 압출 → 재단 → 조인트) → **제품** (검사)

원재료	생산			제품
투입량, 투입순서	작업계획	작업실적 /현황	작업환경	양/불량

작업현황	**1. Monitoring**
작업이상상황	**2. Detection**
불량의 원인	**4. Diagnosis**
작업완료시간	**3. Prediction**
작업의사결정 및 **생산최적화**	**5. Auto control**