Development Of the Novel Engineered Cementitious Composite (ECC) Mix Design Method Using AI Techniques

Session: B.E Civil Engineering 2020

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Certification

This is to certify that Ali Mohammad, 345073 and Abdur Rafay, 353726 and Azaan Ali Jamali, 332832 have successfully completed the final project Development of the Novel Engineered Cementitious Composite (ECC) Mix Design Method Using AI Techniques**,** at the NUST Balochistan Campus (NBC), to fulfill the partial requirement of the degree Civil Engineering.

External Examiner

[Name of Examiner]

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Development of the Novel ECC Mix Design Method Using AI Techniques

Sustainable Development Goals

(Please tick the relevant SDG(s) linked with FYDP)

SDG No	**Description of SDG**	**SDG No**	**Description of SDG**
SDG 8	Decent Work and Economic Growth	SDG 9	Industry, Innovation, and Infrastructure
SDG 12	Responsible Consumption and Production	SDG 10	Reduced Inequalities

Range of Complex Problem Solving			
	Attribute	**Complex Problem**	
2	Depth of analysis required	Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models.	
3	Depth of knowledge required	Requires research-based knowledge much of which is at, or informed by, the forefront of the professional discipline and which allows a fundamentals-based, first principles analytical approach.	
Range of Complex Problem Activities			
	Attribute	**Complex Activities**	
1	Range of resources	Involve the use of diverse resources (and for this purpose, resources include people, money, equipment, materials, information and technologies).	
2	Level of interaction	Require resolution of significant problems arising from interactions between wide ranging and conflicting technical, engineering or other issues.	
3	Innovation	Involve creative use of engineering principles and research-based knowledge in novel ways.	
4	Consequences to society and the environment	Have significant consequences in a range of contexts, characterized by difficulty of prediction and mitigation.	
5	Familiarity	Can extend beyond previous experiences by applying principles-based approaches.	

Abstract

The enhanced mechanical and durability properties of Engineered Cementitious composite (ECC) are making it famous throughout the world. However, due to unavailability of material design guides its mix design is still based on extensive experimentation which is a highly uneconomical and time-consuming process. This study aims to develop a machine learning based model capable of predicting the suitable mix design for ECC using supervised machine learning algorithms. A Suitable mix design using different algorithms would be proposed after the validation through the lab experimentation.

Keywords Mix design, Engineered Cementitious composite (ECC), machine learning, algorithms.

Undertaking

I certify that the project **[ECC Mix Design Using AI Techniques]** is our own work. The work has not, in whole or in part, been presented elsewhere for assessment. Where material has been used from other sources it has been properly acknowledged/ referred.

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Chapter 1

1.1. Introduction:

Conventional concrete is a common construction material because of its properties like durability and workability but the Ordinary Portland cement mixes are almost unbendable, with a strain capacity of only 0.1%, this leads to a highly brittle concrete. The absence of flexibility is the utmost cause of under strain failure[1a].To overcome the flaws in the conventional concrete many new concrete developments were made in 1990s like high strength concrete , self-consolidation concrete , green concrete but due to the limitations in concrete technology that cannot fully address the structure resilience , durability and sustainability have led to the invention of Engineered Cementitious Composite (ECC)with unique and distinctive properties[2a].

On average, approximately two tons of concrete is used annually by every person on the earth [1]. Despite its many advantages, Concrete is recognized for its brittle behaviour, which means it fractures abruptly under tension and absorbs less energy [2]. To improve its tensile properties and energy absorption capacity, ductile elements can be coupled with concrete. One of the most common is reinforced cement concrete (RCC) in which steel rebars are provided for enhanced tensile strength and ductility [2]. However, due to the large diameters of rebars, the generated cracks bridged at a macro level [3]. According to the fracture mechanics of the composite, the crack width is directly proportional to the diameter of the reinforcement [4,5]. The design philosophy of RCC is based on cracked composite, and these macro cracks can reduce the structural integrity. These macro-cracks can cause serious problems related to durability. They can also aid in the corrosion of the steel reinforcements as they provide a path for moisture and other hazardous chemicals to deteriorate the micro-structure [6]. To resolve this concern, short discrete Fibers were used as reinforcing agents within the cementitious mix termed as Fiber reinforced concrete (FRC). The use of FRC is increasing rapidly due to its enhanced mechanical and fracture properties [3].

Engineered Cementitious Composite (ECC) belongs to the broad class of Fiber reinforced concrete (FRC) [6], as it contains Fiber in a cementitious matrix. A newer class of Ultra-High-Performance Concrete (UHPC), with optimized gradation of granular constituents, emphasizes high compressive strength (over 150 MPa) and can sustain post-cracking tensile strength of 5 MPa [7,10]. In general, UHPC has tensile strain capacity of 0.2% or less. ECC 2 represents a family of materials with the common feature of being ductile, with tensile strain capacity typically beyond 2% [11,13]. The material microstructure of ECC is systematically tuned for synergistic interactions between the microstructural components, based on a body of knowledge known as ECC micromechanics. In other words, the Fiber, matrix, and Fiber/matrix interface features are deliberately engineered to interact with one another in a certain prescribed manner, when the composite is loaded. The emphasis of this design basis is the reason behind its name Engineered Cementitious Composites.

The tensile ductility, the strain capacity at peak strength, of ECC is typically two orders of magnitude higher than that of normal concrete, while its compressive strength ranges from a low of a few MPa (e.g., a fire-resistive highly insulative ECC for steel protection [14] to over 200 MPa (ultra-high strength ECC designed for impact and blast resistance [15]. The elastic limit for both normal concrete and FRC is reached at about 0.01%. The emphasis of ECC on tensile ductility is evident and aims at supporting infrastructure resilience, durability, and sustainability by suppressing fracture failure.

In the modern era of artificial intelligence (AI), machine learning (ML) has demonstrated promising results in predicting the material properties of composites [16,18]. It can accommodate complex datasets and predict the results within seconds with high accuracy [19,20]. Various ML based algorithms have been developed over the years to predict various parameters of a material or concrete in civil engineering, including Gene Expression Programming (GEP), Decision Tree (DT), Random Forest (RF), Artificial Neural Networks (ANN), and Support Vector Machine (SVM) [21,24]. Initially, ML was applied for the prediction of mechanical and durability properties of conventional concrete [25,26]. Later, it was also applied for special-purpose concretes like self-compacting concrete and high-strength concrete [19,20].

1.2. PROBLEM STATEMENT

ECC is material on which research is conducted from 1990s till date due to its high tensile strength. Different Fibers with different properties have shown different strength but a proper mix design is not yet proposed in ACI code due to which a classification of ECC based on its strength and mix proportions for required strength are difficult to predict without experimentation.

1.3. Literature Review:

TYPE OF CONCRETE	MACHINE LEARNING TECHNIQUE	DATA SETS	INPUTS PARAMETERS	OUTPUT PARAMETERS	REFERENCE
Fiber-reinforced concrete containing waste rubber and	Linear regression, ridge regression, lasso regression, support	905	water/cementratio (W/C), percentage of rubber, replacement level of recycled	compressivestrength	Pal, A., Ahmed, K. S., Hossain, F. Z., & Alam, M. S. (2023). Machine learning models for predicting compressive strength of Fiber-reinforced concrete
recycled aggregate	vector machine, k- nearest neighbors, artificial neural network, decision tree, random forest, AdaBoost, Voting Regressor, Gradient Boost, CatBoost, and XGBoost.		concrete aggregate (RCA), percentage ofFiber.		containing waste rubberand recycled aggregate. Journal ofCleaner Production, 138673.

Fiber reinforced concrete	artificialneural network(ANN)	15176	Portland cement content,Class-F fly ash content, Class-C fly ash content, Ground granulated blastfurnace slag content, Cementitious material content, Silica sand 0.2 mm, Water content, Water to binderratio, Fiber characteristics (PVA), Volume fraction.	compressive strength, flexural strength, anddirect tensilestress-strain curve	Morsy, A. M., Abd Elmoaty, M., & Harraz, A. B. (2022). Predicting mechanical properties of Engineering Cementitious Compositereinforced with PVA using artificial neural network. Case Studies in Construction Materials, 16, e00998.
Normal and High strength concrete	Adaptive Neuro-FuzzyInference System (ANFIS) and optimal	145	Compressive strength of concrete	Elastic modulus	Ahmadi-Nedushan B. Prediction of elastic modulus of normal andhigh strength concrete using ANFIS and optimal nonlinear
	nonlinear regression				regression models.Constr Build Mater.2012; 36:665–73.
RP (Fiber reinforced polymer) Confined Concrete	RP (Fiber reinforced polymer) Confined Concrete	238	The thickness of the FRP jacket, Diameter and Height to diameter ratio of a cylinder, ultimate tensile strength of FRPin hoop direction,	Uniaxial compressive strength	Mozumder RA, Roy B, Laskar AI. Support vector regression approach to predict the strength of FRP confined concrete. Arab J Sci Eng. 2017; 42:1129–46.

CarbonFiber Reinforced Lightweight Concrete	Artificial Neural Network (ANN) andSupport Vector Machine (SVM)	144	cement content in a mix, amount of silica fumes present, amountof aggregate, amount of carbon Fiber and temperature	compressiveand flexuralstrength	Tanyildizi H. Prediction of the strength propertiesof carbon Fiber- reinforced lightweight concrete exposed to the high temperature using artificial neural network and support vector machine. Advances in civil engineering. 2018; 2018:1–10.
3D-Printed Concrete	DTR, XG Boost, SVM, GPR	77 for flexural & 49 for tensile	Water, cement, silica fume, fly ash, coarse aggregate, fine aggregate, viscosity modifying agent, Fibers, Fiber properties,print speed, andnozzle area	Tensile andflexural strength	Ali A, Riaz RD, MalikUJ, Abbas SB, UsmanM, Shah MU, et al. Machine Learning-Based Predictive Model for Tensile and Flexural Strength of 3D-Printed Concrete. Materials. 2023;16(11):4149.

high-performance Fiber-reinforced cementitious composites (HPFRCC)	artificialneural network(ANN), support vector regression (SVR), classification and regression tree (CART),and extreme gradient boosting tree (XGBoost)	387	Fly ash-to- binder ratio, Slag-to-binder ratio, Rice husk-to-binder ratio, Limestone-to- binder ratio, Metakaolin-to-binder ratio, Silica fume-to-binder ratio, Sand-to-binderratio, Water-to-binder ratio, Superplasticizer content, Fiber volume, Fiber length, Fiber diameter	compressive strength (fc), the tensile strength (ft), and the tensile strain capacity (εcu)	Guo, P., Meng, W., Xu, M., Li, V. C., & Bao, Y. (2021). Predicting mechanical properties ofhigh-performance Fiber- reinforced cementitious composites by integrating micromechanics and machine learning. Materials, 14(1 2), 3143.
steel Fiber reinforced concrete	neuro-fuzzy inference systems (ANFIS), artificial neural networks (ANN), and gene expression programming (GEP)	307	cement content (C), water (W), water-to- cement ratio (W/C), coarse aggregate (CA), fine aggregate (FA),length (L), diameter (D), volume fraction (Vf), temperature(T), and heating rate (HR).	compressive strength	Alabduljabbar, H., Khan,K., Awan, H. H., Alyousef, R., Mohamed, A. M., & Eldin, S. M. (2023). Modeling the capacity of engineered cementitious composites for self-healing using AI-based ensemble techniques. Case Studiesin Construction Materials, 18, e01805.

Fiber reinforced concrete	linear regression (LR), back-propagation neural network (BPNN), classification	617	general- purpose cement(GPC), fly ash (FA), silica fume (SF), hydrated lime powder (LP), fine sand,	self-healingcracks	Chen, G., Tang, W., Chen, S., Wang, S., & Cui, H. (2022). Prediction of self- healing of engineered cementitious compositeusing machine learning
	and regression tree (CART),and support vector regression (SVR)		polyvinyl alcohol (PVA)Fibers, water, and high-rangewater-reducingadmixture (HRWR)		approaches. Applied Sciences, 12(7), 3605.
Steel Fiber-Reinforced Concrete	support vector regression(SVR)	166	Cement, water, sand, coarse aggregate, superplasticizer , silica fume,fly ash, steelFiber, Fiber length, Fiber dia,	compressive strength	Li, Y., Zhang, Q., Kamiński, P., Deifalla, A. F., Sufian, M., Dyczko, A., ... & Atig, M. (2022). Compressive strength of steel Fiber-reinforced concrete employing supervised machine learning techniques. Materials,15(12), 4209.

1.4. Aims and Objectives:

- To conduct comprehensive and tensile literature review on ECC Mix Design.
- To propose the novel ECC mix design method using AI Techniques (ANN and GP)
- To validate the proposed Mix design results with experimental results

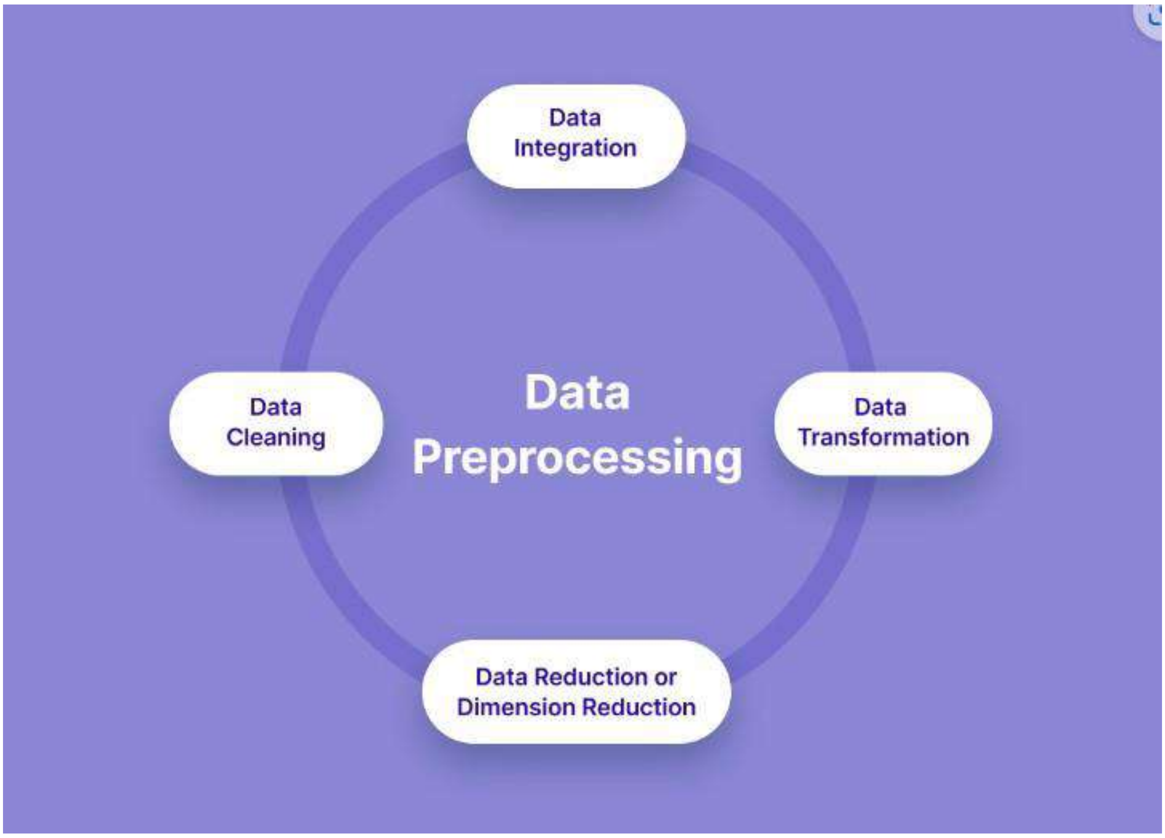
1.5. Methodology:

1. DATA COLLECTION AND ORGANIZATION:

The initial step for developing a predictive model is data collection and organization. This is usually a time-consuming task, as the data must be comprehensive, and representative of the system being modeled. For this study, the dataset was collected from published literaturebased on the material studies of ECC.

2. DATA PREPROCESSING:

Data preprocessing is a crucial step for developing an efficient and accurate ML model. It includes four main processes: data cleaning, data transformation, data reduction, and data integration. Machine learning algorithms cannot be trained on data that is not properly processed because that wouldintroduce bias to the models.



3. Data Cleaning:

Data cleaning is the process of identifying and correcting errors and outliers in the dataset. Anomalous data can significantly lower the accuracy of the model. Therefore, data cleaning was performed to remove four data points which were having extremely high tensile strength (over 10 MPa).Furthermore, data reduction and integration were also performed to keep the input and output parameters at a minimum.

4. Data integration and reduction:

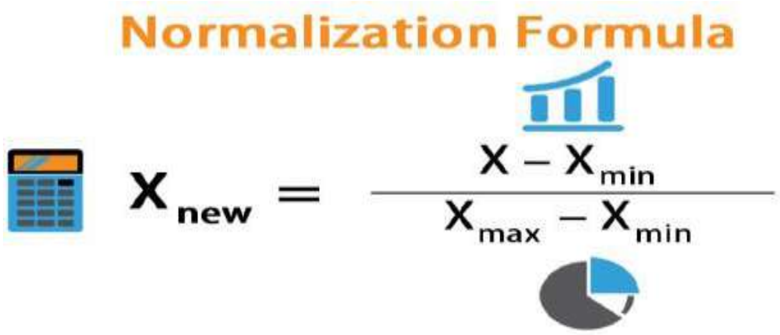
Data reduction and integration were performed to keep the input and output parameters at a minimum.

5. Data transformation:

Data transformation was performed by presenting the complete stress-strain in the form of four ordinates. ML based algorithms can process numerical data only. Therefore, to enable the model to predict the stress-strain curve a bilinear idealized curve was assumed. The bilinear stress-strain curve isa graphical representation of the relationship between stress and strain in ECC. This curve requires justtwo coordinate points to develop the complete constitutive model. In this way the output the output parameters were the four ordinates of this curves which were predicted by the ML model.

6. DATA NORMALIZATION:

The dataset normalization was also performed to transform all the values of the datasetbetween 0 and 1. The objective of normalization is to convert data so that it is dimensionless and/or has similar distributions. The model’s accuracy is improved significantly by normalization.



7. TRAINING PROCESS:

8. Performance Evaluation:

To assess the model's performance accuracy four fundamental error quantifiers from basic statistics are used. These indicators enabled in establishing a mathematical connection between predicted (Ypre) and actual (Yactual) results. Their indicators root means square error(RMSE), absolute error (MAE), Pearson correlation coefficient (R) and coefficient of determination (R^2).

9. Hyperparameter Tunning:

Hyperparameters are parameters that define and control the learning process itself, andas such, they are said to be external to the predictive model being learned. The values of hyperparameters can determine the final values of model parameters after training is complete.These values need to be optimized iteratively to obtain a highly accurate model. Nevertheless,hyperparameters play a critical role in predictive modeling by influencing the learning processand the predictive power of the trained model.

The predictive model will be trained separately for each output parameter to enhance the prediction accuracy of the model. This should be done because each output has a separate relationship with the input parameters. Furthermore, the dataset should randomly be split into two datasets in which one was used for training and the other for testing.

Chapter 4

1.6. 4.1 Proposed Solution/Results & Discussion

In material studies, particularly in Engineered Cementitious Composites (ECC), the challenge lies in developing accurate predictive models due to the complexities inherent in material behavior. To address this, a comprehensive approach integrating data collection, preprocessing, and model training is proposed. By sourcing datasets from published literature and employing meticulous data preprocessing techniques including cleaning, reduction, integration, transformation, and normalization, the proposed solution ensures dataset integrity and uniformity essential for model accuracy. Through rigorous training, performance evaluation, and hyperparameter tuning, the predictive model adapts to the intricacies of ECC material characteristics, yielding robust predictions. Additionally, training separate models for distinct output parameters and employing randomized data splitting techniques enhance prediction accuracy and model generalization, laying the foundation for advancements in ECC material science and engineering.

Results:

The total 176 data size is collected from different past research papers.

The input features for ML model are:

Cement (kg/m3)

- Fly ash(kg/m3)
- Water(kg/m3)
- SAND (kg/m3)
- Super Plasticizer (HRWRA)
- Fibers(kg/m3)
- Length of Fibers(mm)
- Diameter (micro m)
- Nominal strength (MPa)
- Young’s modulus (GPa)
- Elongation (%)

The output features for ML model are.

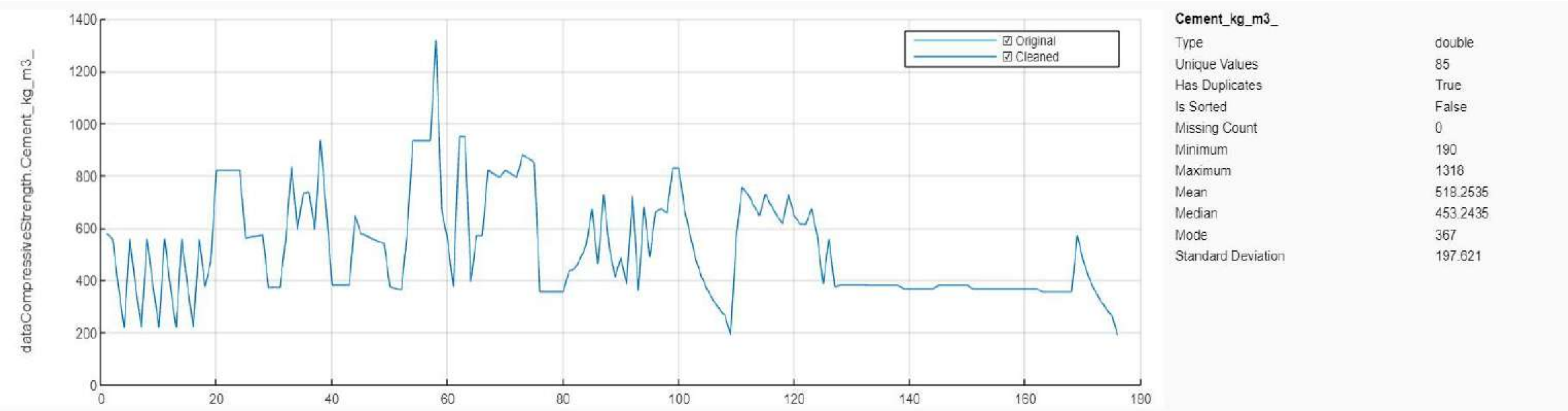
- Compressive strength (MPa)
- Tensile strength (MPa)
- Strain capacity (%)
- Flexural strength (MPa)
- Yield stress -strain and ultimate stress- strain

The MATLAB R2023b is used for data preprocessing that includes data cleaning, data smoothing, and data outlier cleaning.

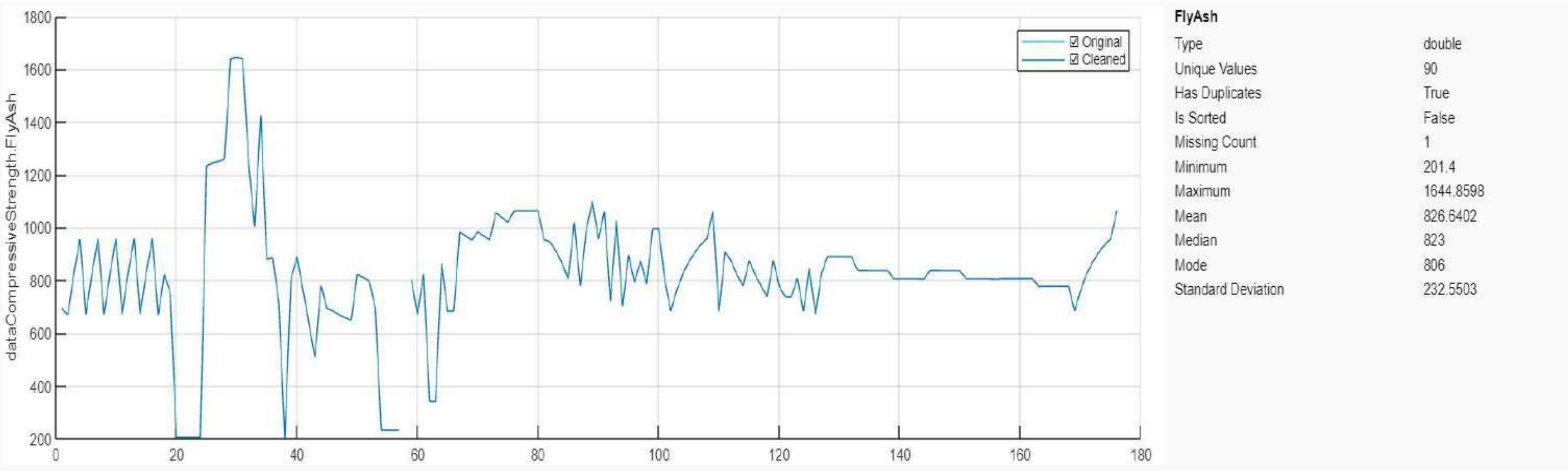
NOTE: THE DATA IS ANALYZED FOR THE FEATURE COMPRESSIVE STRENGTH ONLY IN THIS REPORT.

2. ORIGINAL DATA:

Cement (kg/m3)

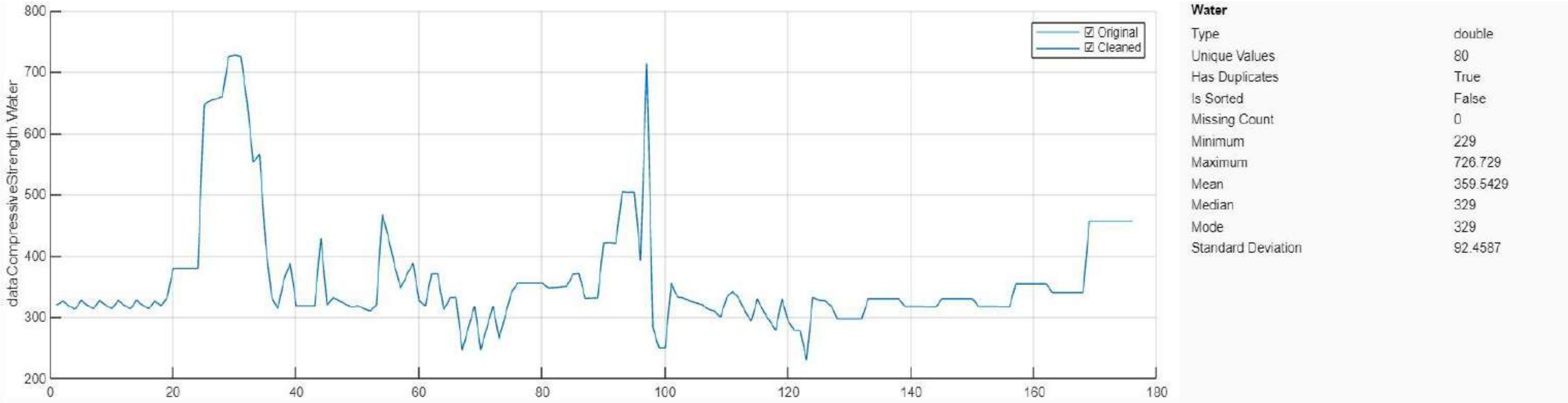


Fly ash(kg/m3)

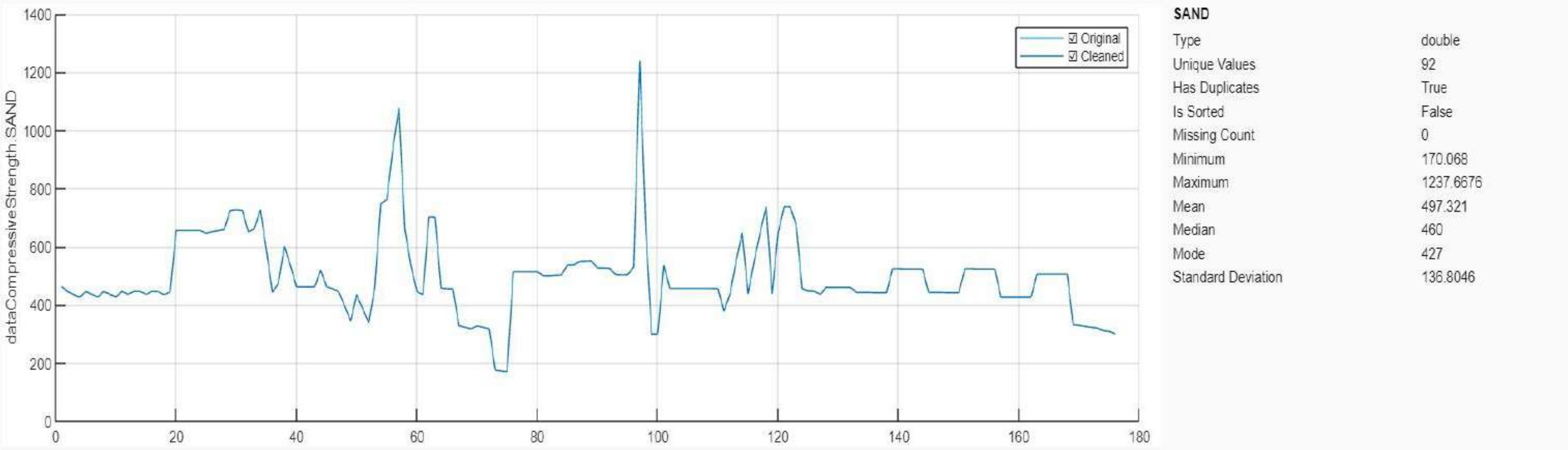


Original
Cleaned
dataCompressiveStrength.FlyAsh
1800
1600
1400
1200
1000
800
600
400
200
0
20
40
60
80
100
120
140
160
180
FlyAsh
Type double
Unique Values 90
Has Duplicates True
Is Sorted False
Missing Count 1
Minimum 201.4
Maximum 1644.8598
Mean 826.6402
Median 823
Mode 806
Standard Deviation 232.5503

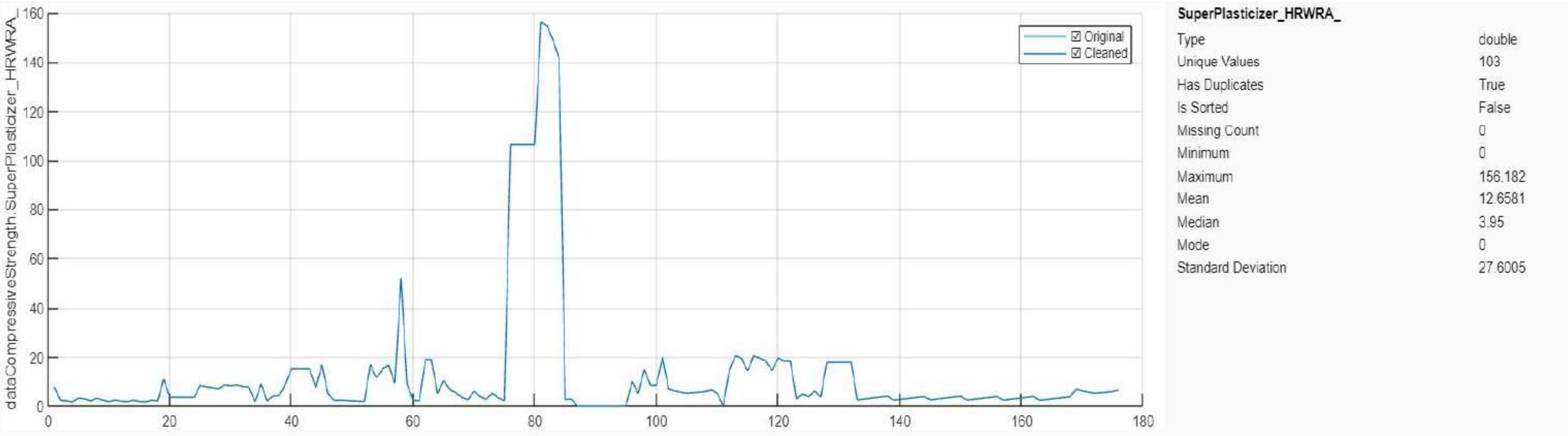
Water(kg/m3)



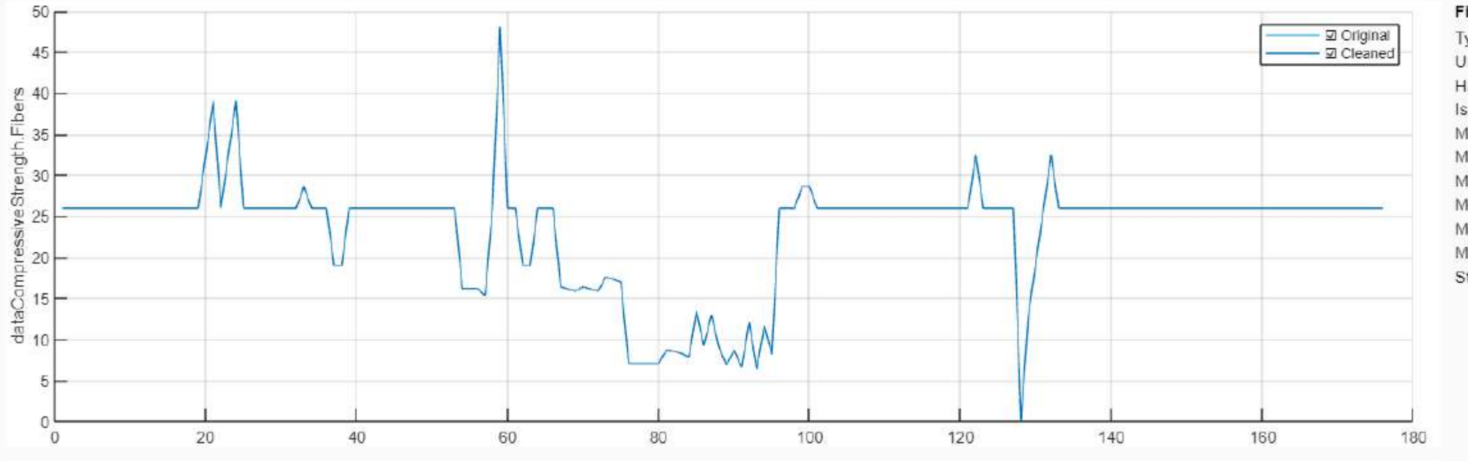
SAND (kg/m3)


dataCompressiveStrength.SAND
☑ Original
☑ Cleaned
SAND
Type double
Unique Values 92
Has Duplicates True
Is Sorted False
Missing Count 0
Minimum 170.068
Maximum 1237.6676
Mean 497.321
Median 460
Mode 427
Standard Deviation 136.8046

Super Plasticizer (HRWRA)



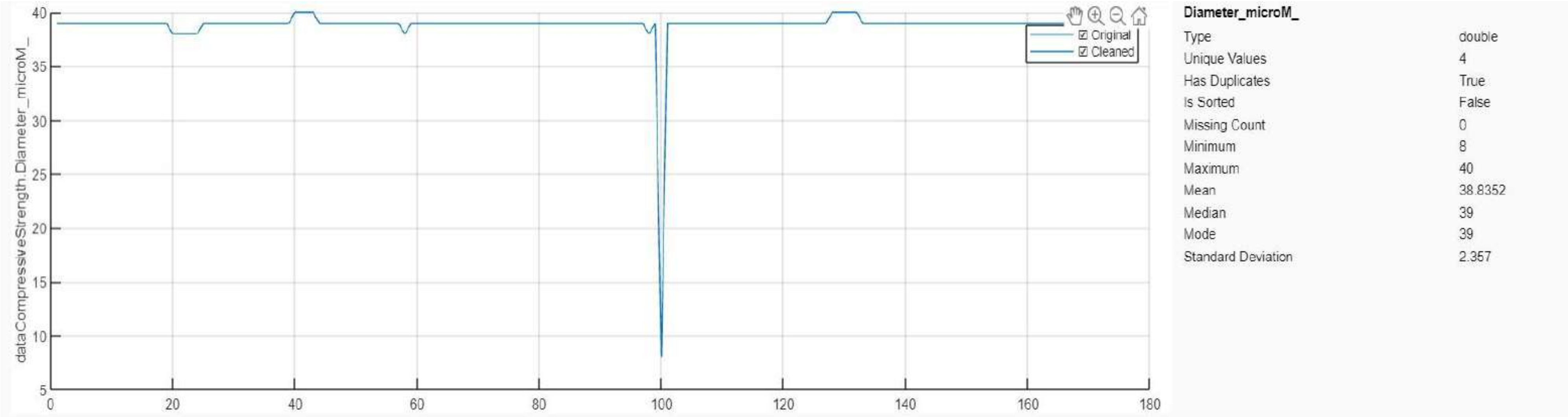
Fibers(kg/m3)



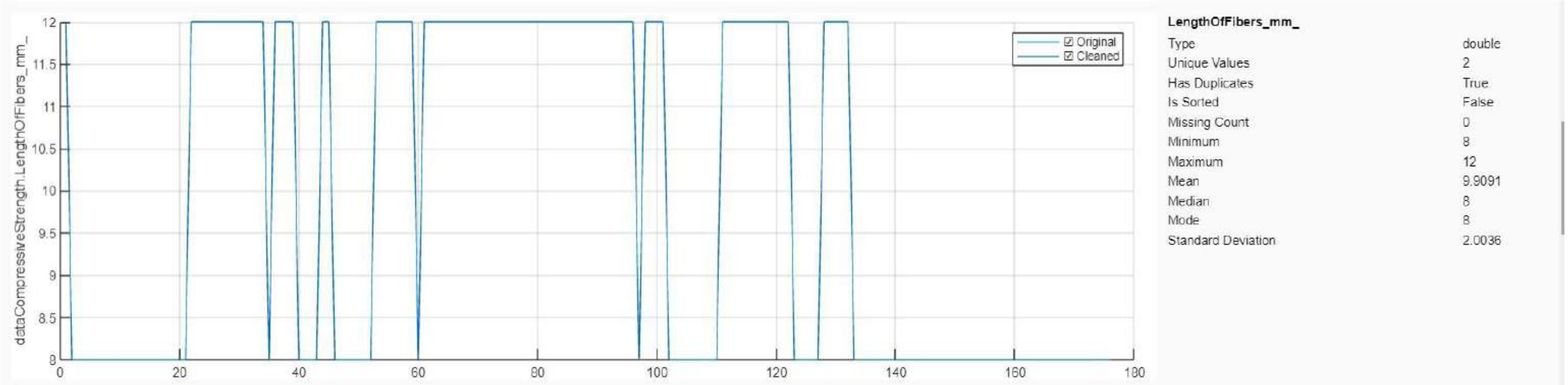
Fibers

Type	double
Unique Values	38
Has Duplicates	True
Is Sorted	False
Missing Count	0
Minimum	0
Maximum	48
Mean	23.3692
Median	26
Mode	26
Standard Deviation	6.8295

Diameter (micro m)

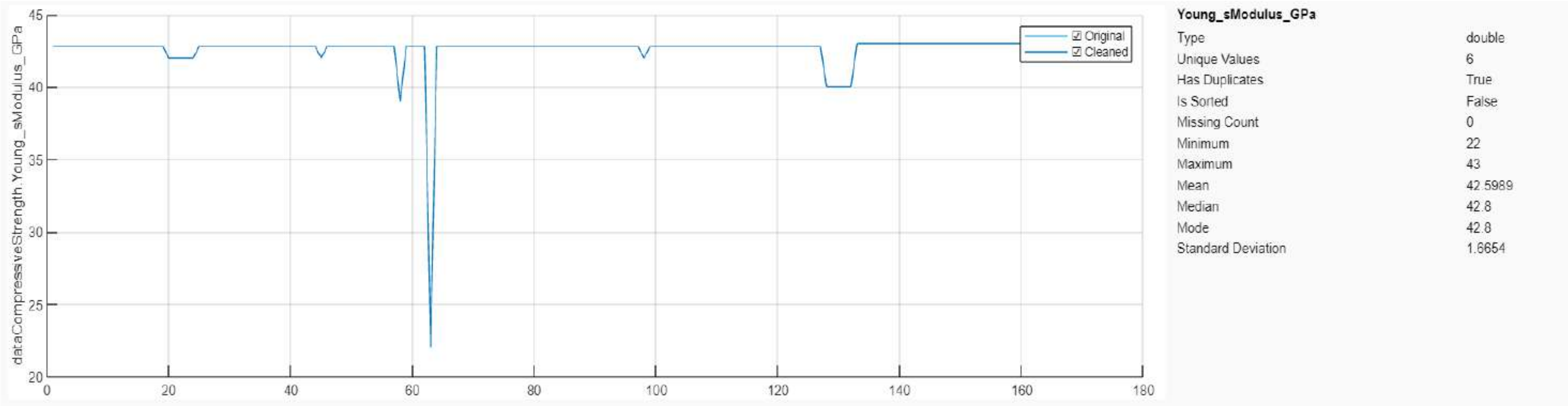


Length of Fibers(mm)

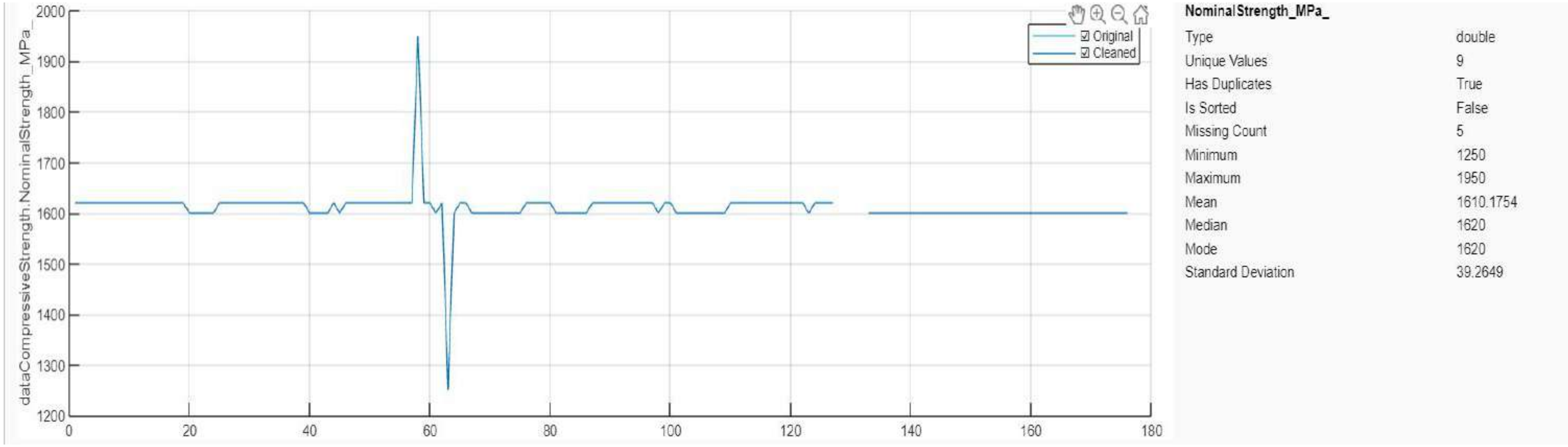


dataCompressiveStrength.LengthOfFibers_mm_
Original
Cleaned
LengthOfFibers_mm_
Type double
Unique Values 2
Has Duplicates True
Is Sorted False
Missing Count 0
Minimum 8
Maximum 12
Mean 9.9091
Median 8
Mode 8
Standard Deviation 2.0036

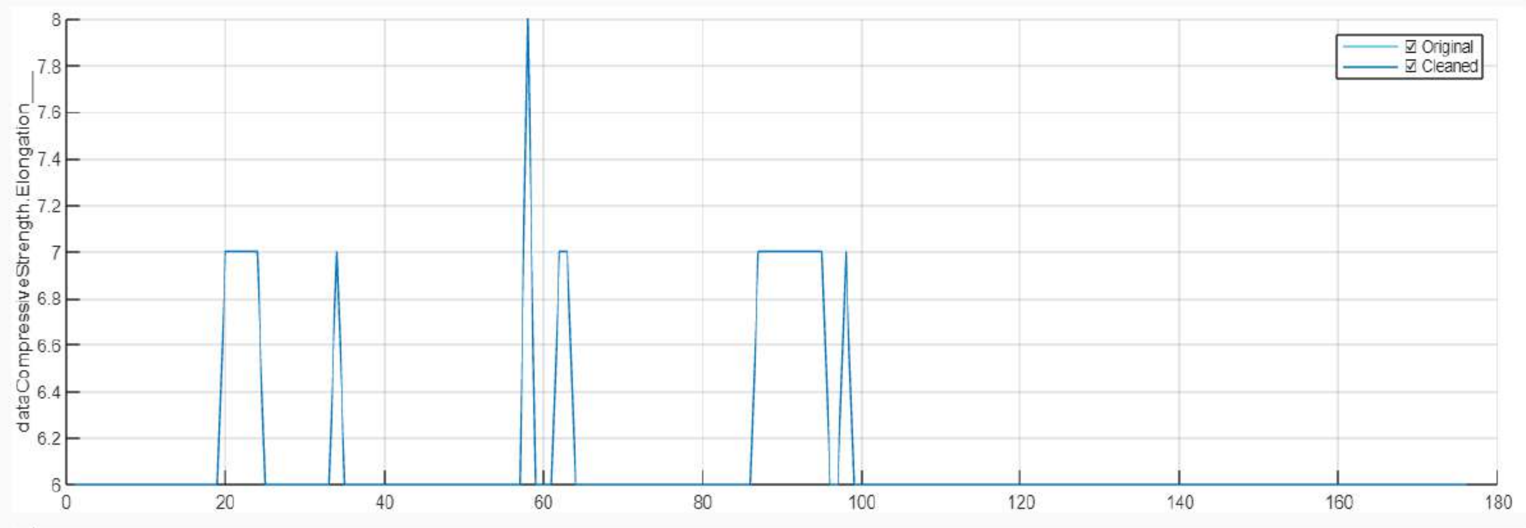
Young's modulus (GPa)



Nominal strength (MPa)

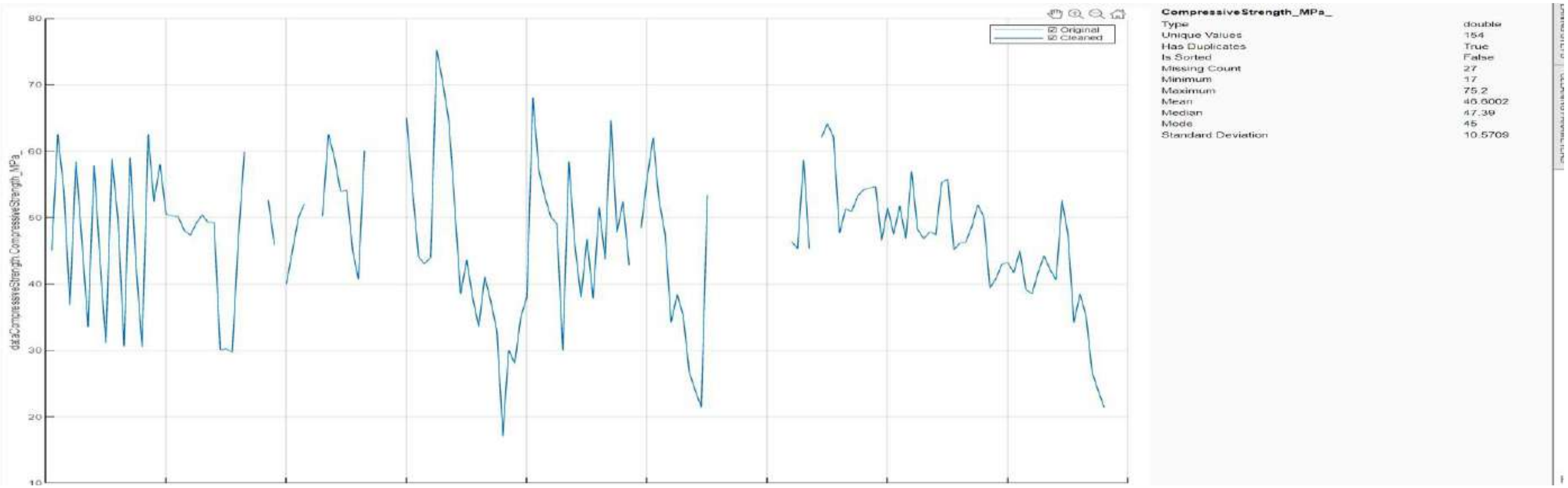

dataCompressiveStrength.NominalStrength_MPa_
2000
1900
1800
1700
1600
1500
1400
1300
1200
0
20
40
60
80
100
120
140
160
180
☑ Original
☑ Cleaned
NominalStrength_MPa_
Type double
Unique Values 9
Has Duplicates True
Is Sorted False
Missing Count 5
Minimum 1250
Maximum 1950
Mean 1610.1754
Median 1620
Mode 1620
Standard Deviation 39.2649

Elongation (%)



Elongation___	
Type	double
Unique Values	3
Has Duplicates	True
Is Sorted	False
Missing Count	0
Minimum	6
Maximum	8
Mean	6.1136
Median	6
Mode	6
Standard Deviation	0.33575

COMPRESSIVE STRENGTH(MPa)



DATA SUMMARY

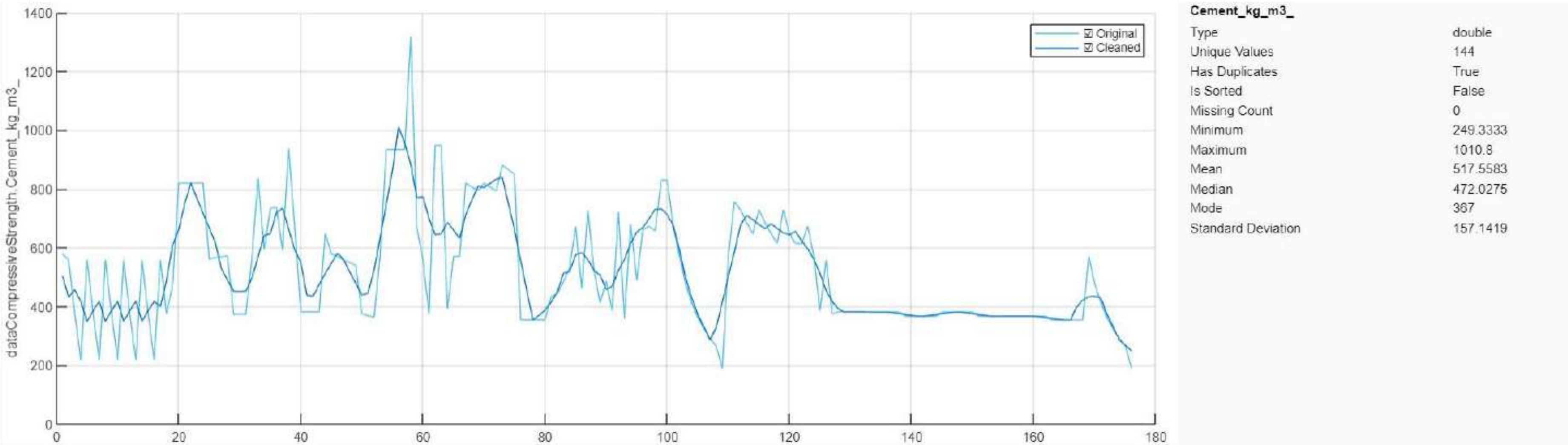
Data Summary

DataType	table
NumVariables	13
NumObservations	176
NumVarsWithMissing	3
NumVarsWithDuplicates	13

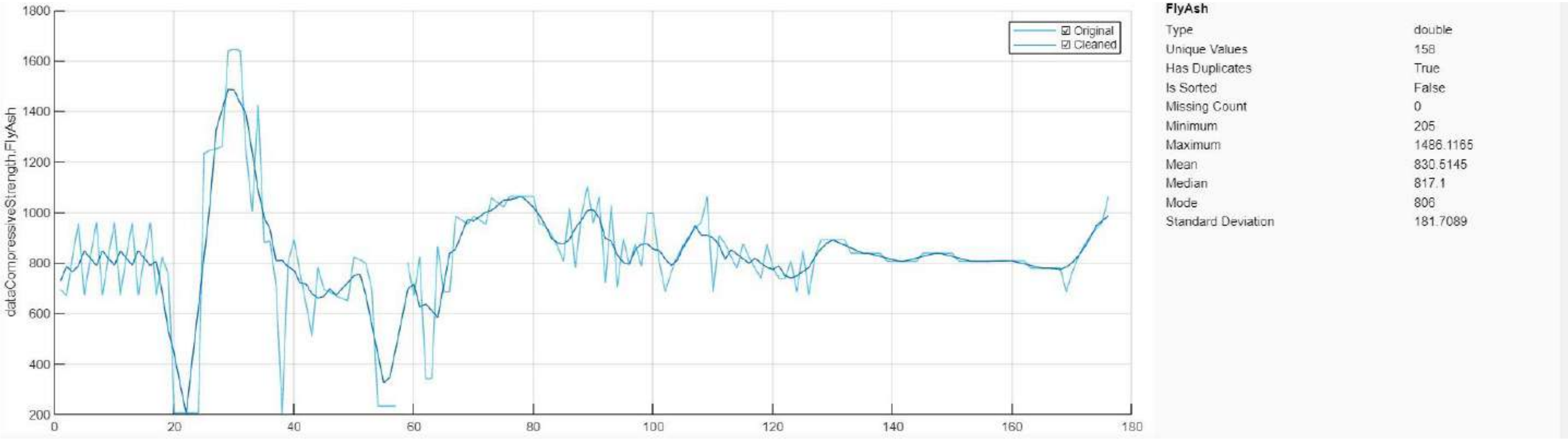
		1 Type	2 Unique Values	3 Has Duplicates	4 Is Sorted	5 Missing Count	6 Minimum	7 Maxim...	8 Mean	9 Median	10 Mode	11 Standard Deviation
1	Cement_kg_m3_	double	85	True	False	0	"190"	"1318"	"518.2535"	"453.2435"	"367"	"197.621"
2	FlyAsh	double	90	True	False	1	"201.4"	"1644.8598"	"826.6402"	"823"	"806"	"232.5503"
3	Water	double	80	True	False	0	"229"	"726.729"	"359.5429"	"329"	"329"	"92.4587"
4	SAND	double	92	True	False	0	"170.068"	"1237.6676"	"497.321"	"460"	"427"	"136.8046"
5	SuperPlasticizer_HRWRA_	double	103	True	False	0	"0"	"156.182"	"12.6581"	"3.95"	"0"	"27.6005"
6	Fibers	double	38	True	False	0	"0"	"48"	"23.3692"	"26"	"26"	"6.8295"
7	NameOfFiber	categorical	2	True	False	0	""	""	""	""	""	""
8	LengthOfFibers_mm_	double	2	True	False	0	"8"	"12"	"9.9091"	"8"	"8"	"2.0036"
9	Diameter_microM_	double	4	True	False	0	"8"	"40"	"38.8352"	"39"	"39"	"2.357"
10	NominalStrength_MPa_	double	9	True	False	5	"1250"	"1950"	"1610.1754"	"1620"	"1620"	"39.2649"
11	Young_sModulus_GPa	double	6	True	False	0	"22"	"43"	"42.5989"	"42.8"	"42.8"	"1.6654"
12	Elongation__	double	3	True	False	0	"6"	"8"	"6.1136"	"6"	"6"	"0.33575"
13	CompressiveStrength_MPa_	double	154	True	False	27	"17"	"75.2"	"46.6002"	"47.39"	"45"	"10.5709"

3. PREPROCESSED DATA:

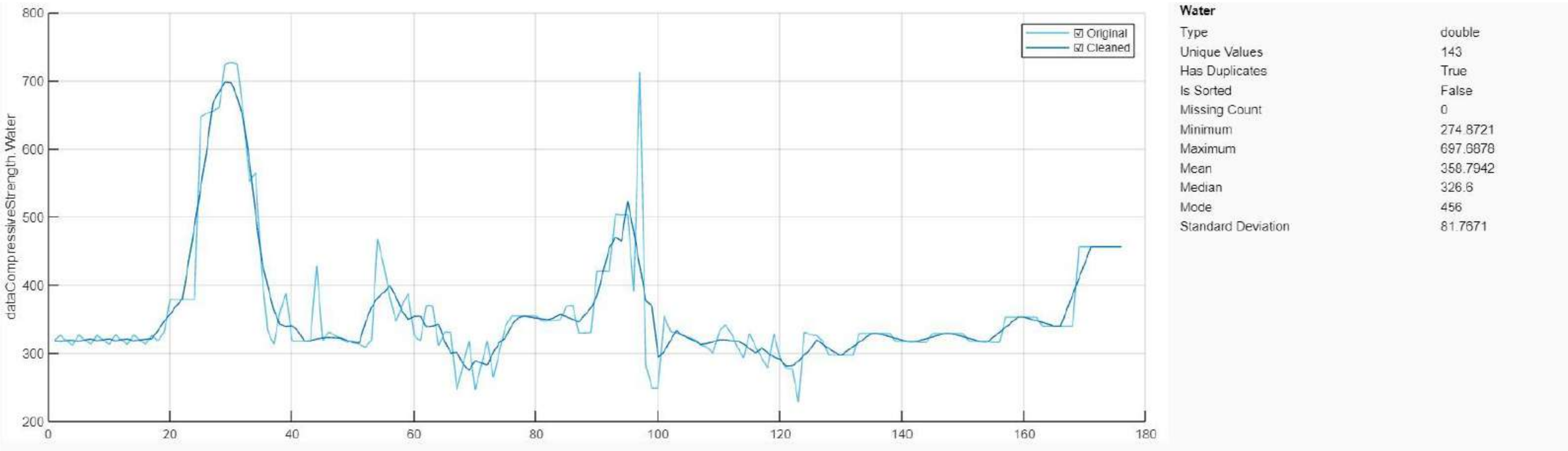
Cement (kg/m3)



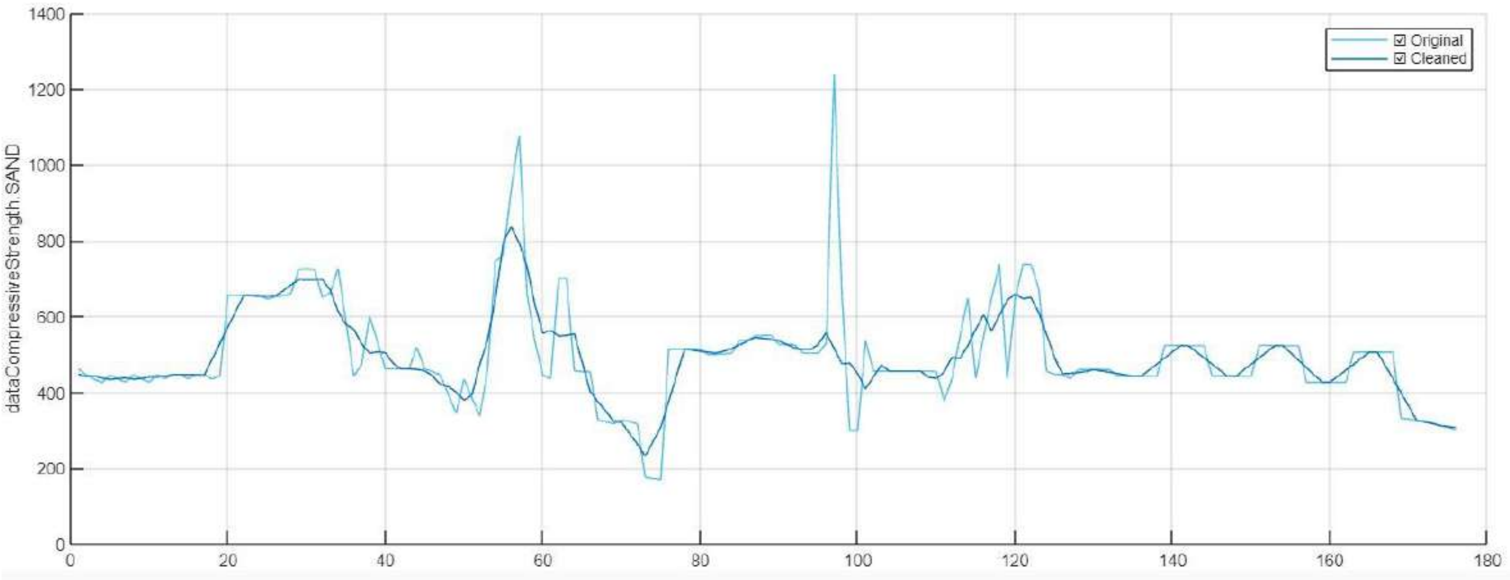
Fly ash(kg/m3)


Original
Cleaned
dataCompressiveStrength.FlyAsh
1800
1600
1400
1200
1000
800
600
400
200
0
20
40
60
80
100
120
140
160
180
FlyAsh
Type double
Unique Values 158
Has Duplicates True
Is Sorted False
Missing Count 0
Minimum 205
Maximum 1486.1165
Mean 830.5145
Median 817.1
Mode 806
Standard Deviation 181.7089

Water(kg/m3)

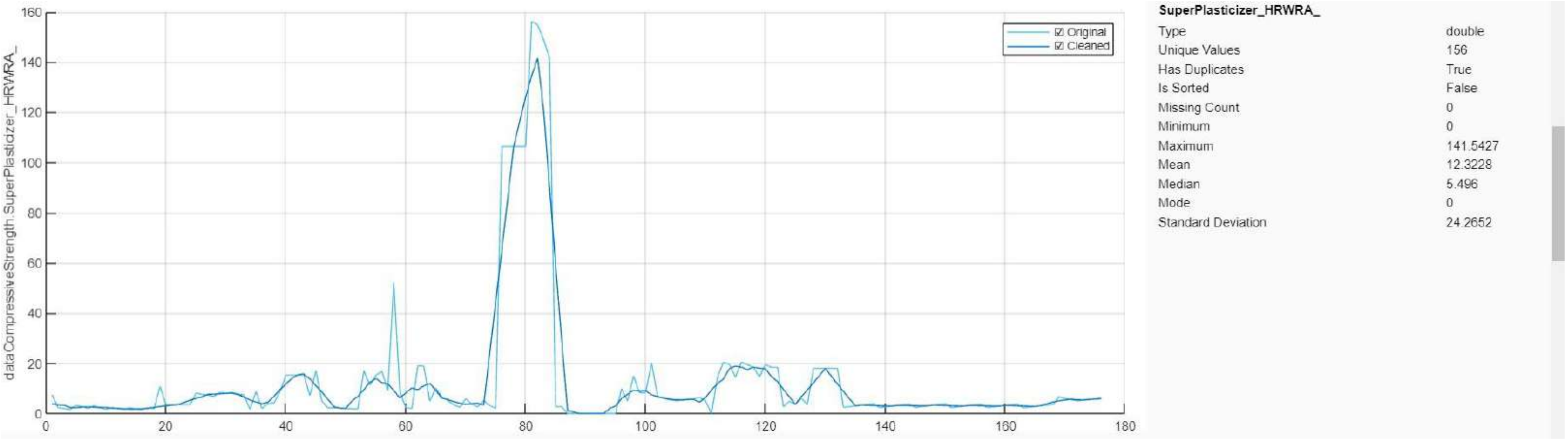


SAND (kg/m3)

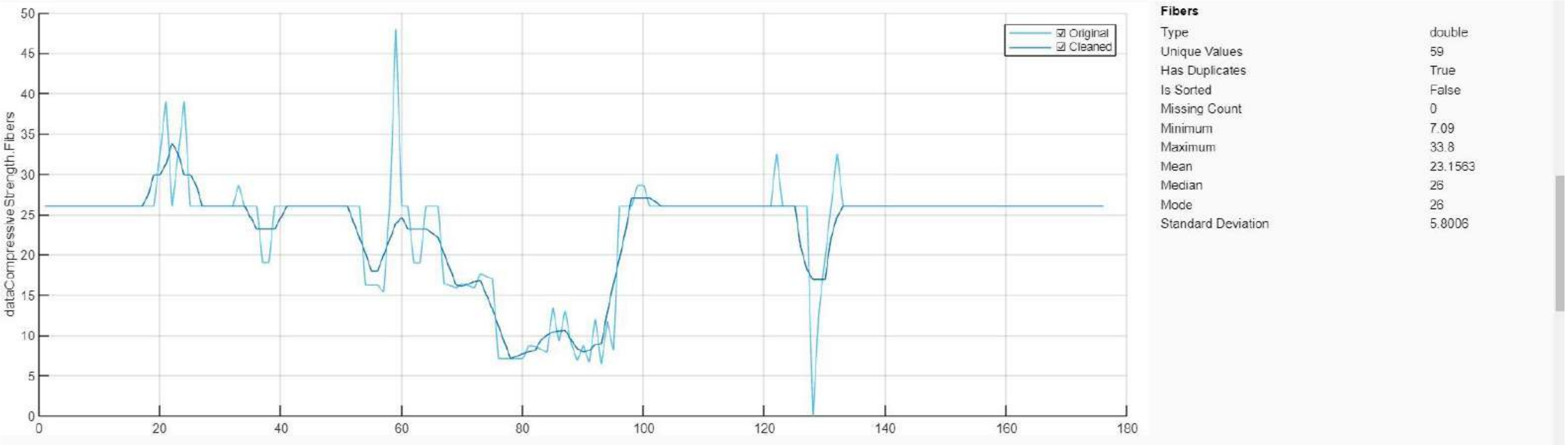


SAND	
Type	double
Unique Values	156
Has Duplicates	True
Is Sorted	False
Missing Count	0
Minimum	231.8932
Maximum	836.5
Mean	493.4869
Median	475.35
Mode	456
Standard Deviation	101.1608

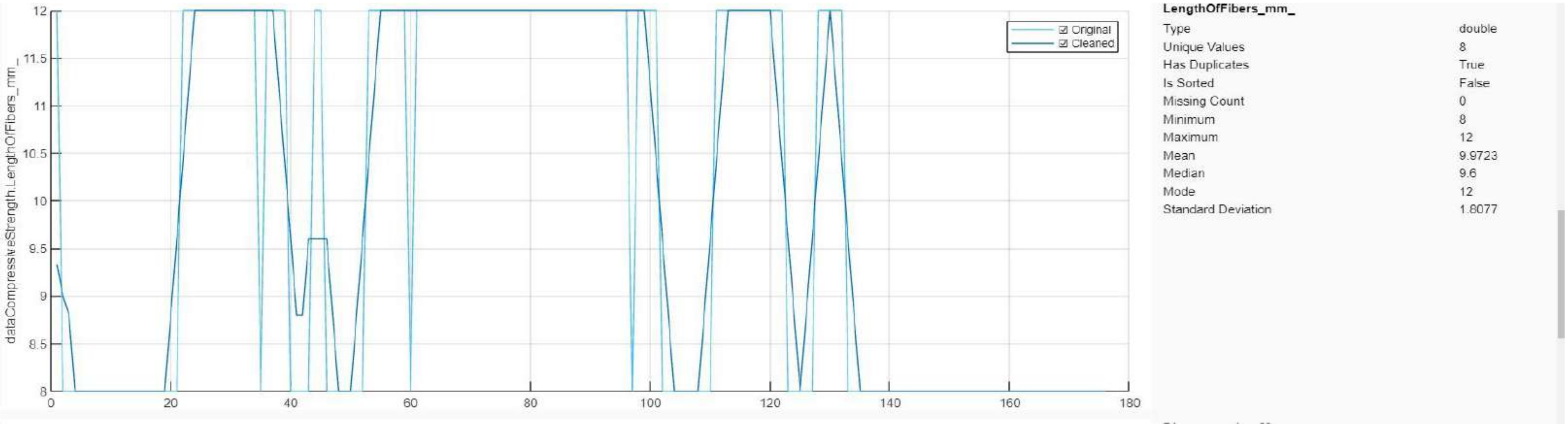
Super Plasticizer (HRWRA)



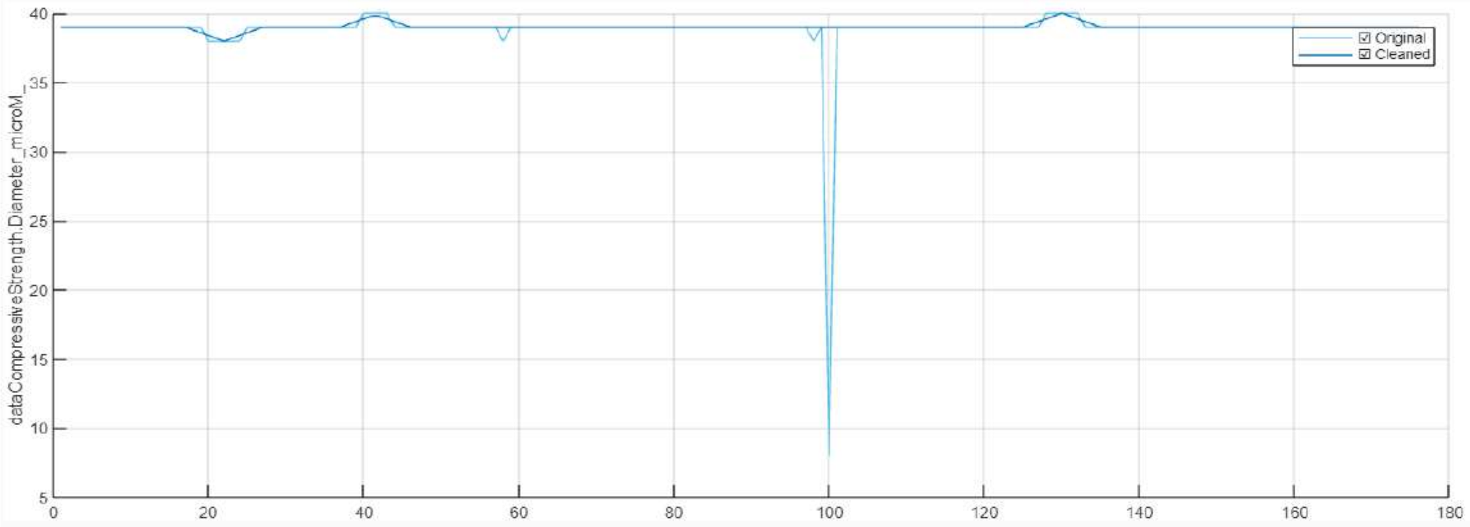
Fibers(kg/m3)


dataCompressiveStrength.Fibers
☑ Original
☑ Cleaned
Fibers
Type double
Unique Values 59
Has Duplicates True
Is Sorted False
Missing Count 0
Minimum 7.09
Maximum 33.8
Mean 23.1563
Median 26
Mode 26
Standard Deviation 5.8006

Length of Fibers(mm)



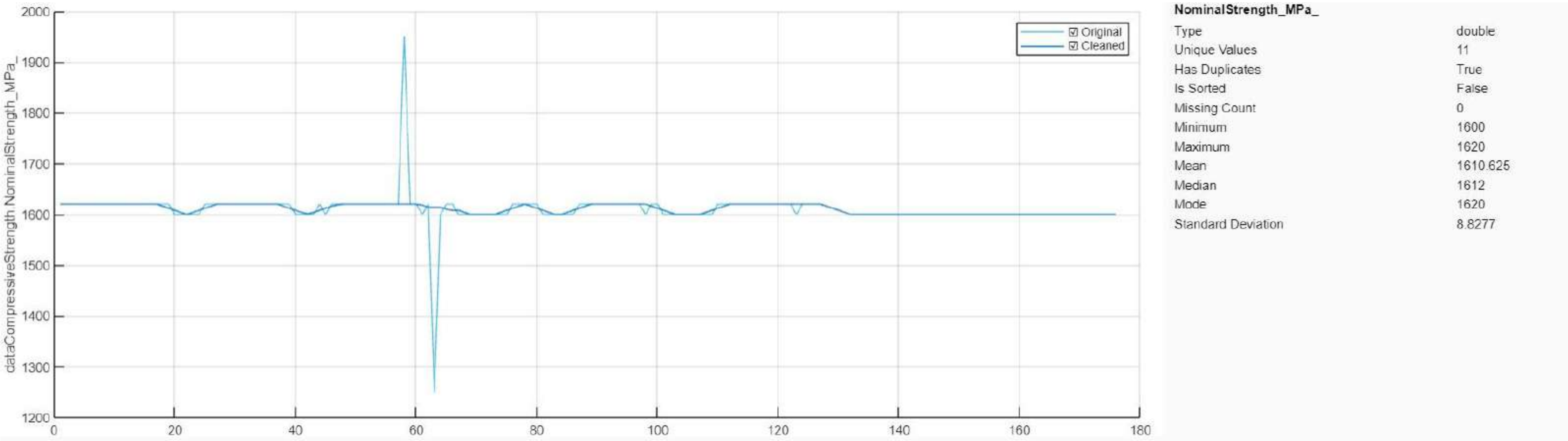
Diameter (micro m)



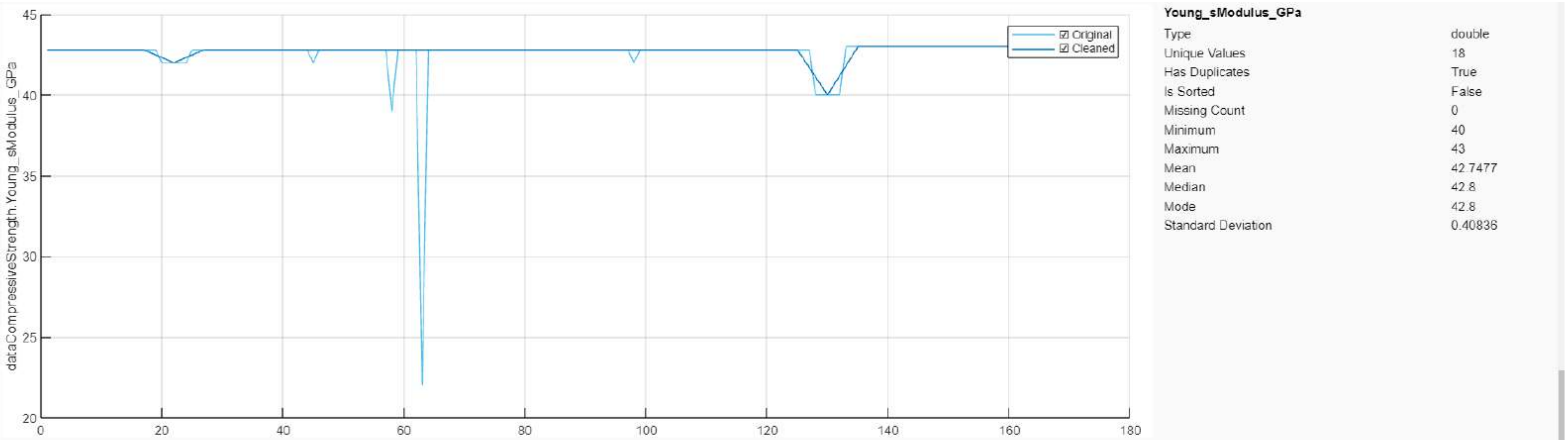
Diameter_microM_

Type	double
Unique Values	11
Has Duplicates	True
Is Sorted	False
Missing Count	0
Minimum	38
Maximum	40
Mean	39.0227
Median	39
Mode	39
Standard Deviation	0.22815

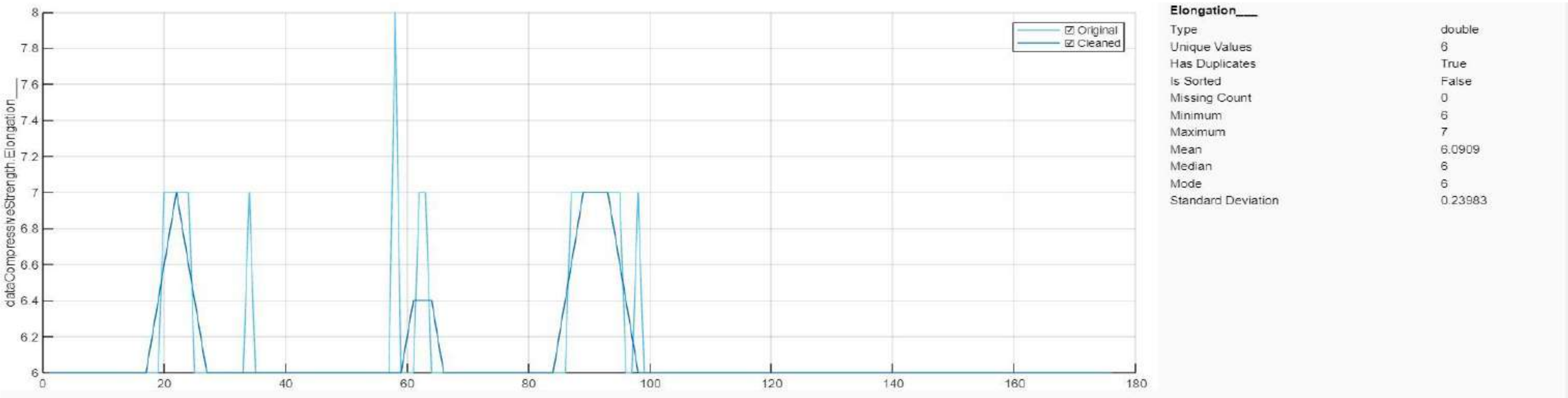
Nominal strength (MPa)



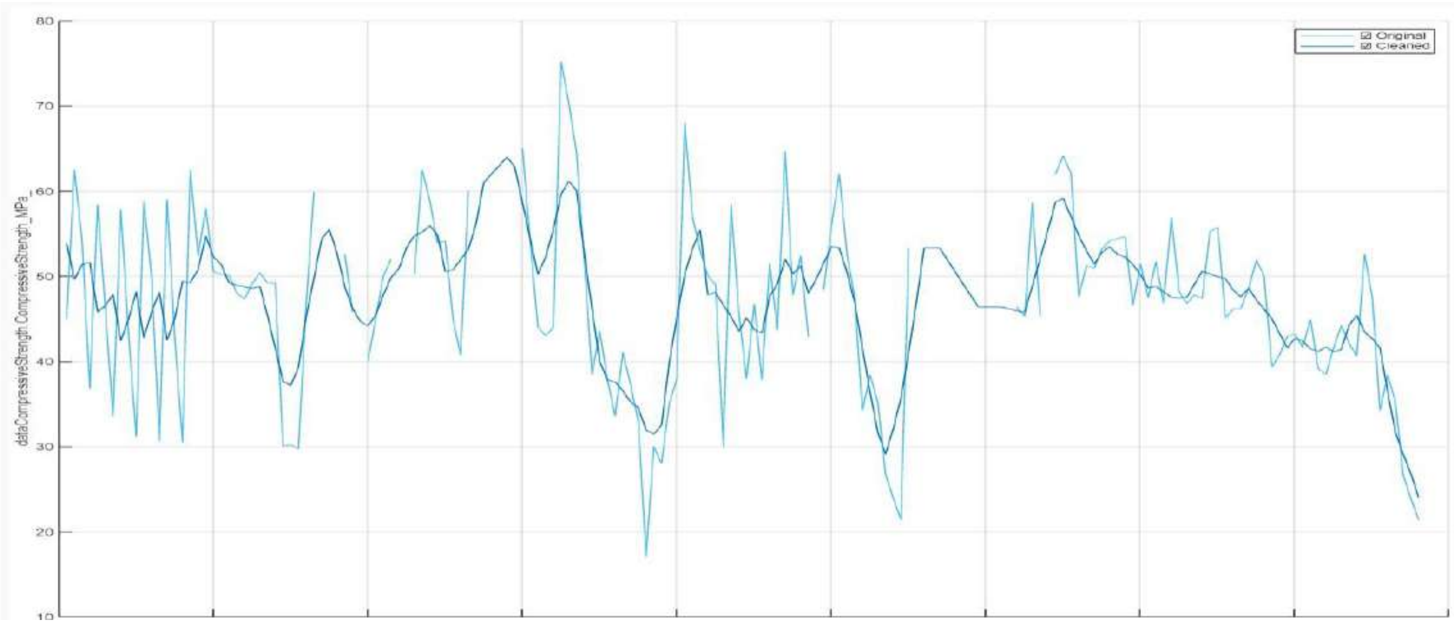
Young’s modulus (GPa)


dataCompressiveStrength.Young_sModulus_GPa
Original
Cleaned
45
40
35
30
25
20
0
20
40
60
80
100
120
140
160
180
Young_sModulus_GPa
Type double
Unique Values 18
Has Duplicates True
Is Sorted False
Missing Count 0
Minimum 40
Maximum 43
Mean 42.7477
Median 42.8
Mode 42.8
Standard Deviation 0.40836

Elongation (%)



COMPRESSIVE STRENGTH(MPa)



CompressiveStrength_MPa_

Type	double
Unique Values	168
Has Duplicates	True
Is Sorted	False
Missing Count	0
Minimum	24
Maximum	64
Mean	47.5286
Median	48.254
Mode	53.3
Standard Deviation	7.1734

DATA SUMMARY

ta Summary

taType	table
umVariables	13
umObservations	176
umVarsWithMissing	0
umVarsWithDuplicates	13

		1	2	3	4	5	6	7	8	9	10	11
		Type	Unique Values	Has Duplicates	Is Sorted	Missing Count	Minimum	Maxim...	Mean	Median	Mode	Standard Deviation
1	Cement_kg_m3_	double	144	True	False	0	"249.3333"	"1010.8"	"517.5583"	"472.0275"	"367"	"157.1419"
2	FlyAsh	double	158	True	False	0	"205"	"1486.1165"	"830.5145"	"817.1"	"806"	"181.7089"
3	Water	double	143	True	False	0	"274.8721"	"697.6878"	"358.7942"	"326.6"	"456"	"81.7671"
4	SAND	double	156	True	False	0	"231.8932"	"836.5"	"493.4869"	"475.35"	"456"	"101.1608"
5	SuperPlasticizer_HRWRA_	double	156	True	False	0	"0"	"141.5427"	"12.3228"	"5.496"	"0"	"24.2652"
6	Fibers	double	59	True	False	0	"7.09"	"33.8"	"23.1563"	"26"	"26"	"5.8006"
7	NameOfFiber	categorical	2	True	False	0	""	""	""	""	""	""
8	LengthOfFibers_mm_	double	8	True	False	0	"8"	"12"	"9.9723"	"9.6"	"12"	"1.8077"
9	Diameter_microM_	double	11	True	False	0	"38"	"40"	"39.0227"	"39"	"39"	"0.22815"
10	NominalStrength_MPa_	double	11	True	False	0	"1600"	"1620"	"1610.625"	"1612"	"1620"	"8.8277"
11	Young_sModulus_GPa	double	18	True	False	0	"40"	"43"	"42.7477"	"42.8"	"42.8"	"0.40836"
12	Elongation__	double	6	True	False	0	"6"	"7"	"6.0909"	"6"	"6"	"0.23983"
13	CompressiveStrength_MPa_	double	168	True	False	0	"24"	"64"	"47.5286"	"48.254"	"53.3"	"7.1734"

Chapter 5

1.7. 6.1 Summary and Future work

The proposed solution outlines a systematic methodology for developing accurate predictive models in Engineered Cementitious Composites (ECC), addressing the challenges inherent in material behavior prediction. Through comprehensive data collection, preprocessing, and model training, the approach ensures dataset integrity and model robustness. By leveraging machine learning techniques, including data cleaning, transformation, and normalization, coupled with performance evaluation and hyperparameter tuning, the predictive models demonstrate adaptability and accuracy. Future work could delve deeper into exploring advanced machine learning algorithms and incorporating additional parameters to enhance prediction capabilities further. Moreover, extending the research to incorporate real-world experimentation for validating the proposed mix design methods would strengthen its applicability and reliability in ECC material studies, paving the way for innovative developments in material science and engineering.

Chapter 6

7.1 Conclusion & Recommendation

In conclusion, the project "Development of the Novel Engineered Cementitious Composite (ECC) Mix Design Method Using AI Techniques" presents a groundbreaking approach to revolutionize ECC mix design. By leveraging supervised machine learning algorithms, the project aims to predict optimal mix designs, addressing the traditional challenges of time-consuming and costly experimentation.

Through meticulous data organization, preprocessing, and model training, the project ensures the integrity and robustness of the predictive model. By considering various ML algorithms and optimizing hyperparameters, the proposed solution strives to achieve accurate predictions of ECC mix designs.

The project represents a significant contribution to advancing ECC technology, aligning with the principles of responsible consumption and production. Future research could focus on refining the model and validating it in real-world construction projects, fostering innovation and sustainability in the construction industry.

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