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Predictive Modeling of Resistivity Curves for use as Quality Assurance Testing of Ready-Mix Concrete

Kennedy, Evan.[1], Cai, Yilin.[1], Aryal, Ashrant.[1], and Hartell, Julie.[1]
[1] Department of Construction Science, Texas A&M University, 574 Ross St., College Station, Texas

ABSTRACT:

This study explores the potential of surface resistivity testing as a quality control and quality assurance (QC/QA) tool for ready-mix concrete. Unlike compressive strength, resistivity measurements capture both physical and chemical changes over time, making them a more sensitive indicator of mixture design variations. The research introduces a machine learning (ML) model to predict surface resistivity, following AASHTO T358 standards, as concrete matures.

A dataset of 59 concrete mixtures (708 samples) was randomly divided into training (60%), validation (20%), and testing (20%) sets. The model incorporates key mixture parameters such as cement type, water-to-cement ratio, aggregate types, fly ash, silica fume, admixtures, and supplier sources. Resistivity values at 1, 3, 7, 14, 21, 28, and 56 days were used to train and test various ML models, including Random Forest (RF), Decision Tree, Linear Regression, Artificial Neural Networks (ANN), and Recurrent Neural Networks (RNN).

Random Forest was selected due to its superior performance on smaller datasets and its reduced risk of overfitting. Despite challenges such as limited sample size, large time gaps in data collection, and a high ratio of variables to outputs, the RF model achieved an accuracy of 85-91% (MAPE: 9-15%). Accuracy was validated using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

This ML-driven approach offers a valuable tool for improving QA/QC processes, ensuring that delivered concrete complies with design specifications through resistivity-based assessments.

1. INTRODUCTION

Surface resistivity and form factor are widely recognized as key indicators of concrete durability, particularly in relation to chloride ion penetration. These properties correlate with the long-term performance of reinforced concrete structures. Current standards rely on single-point resistivity measurements at 28, 56, or 90 days to assess concrete performance. However, this approach has been found inadequate in fully capturing durability parameters such as freeze-thaw resistance and salt scaling (Hartell et al., 2023). Concrete, as a composite material, undergoes deterioration primarily due to environmental exposure. The timeline for visible durability degradation depends largely on mixture design quality.

Mixture design parameters, including water-to-cementitious material ratio (w/cm), supplementary cementitious materials (SCMs), and chemical admixtures, significantly influence overall material performance (ACI 211). A comprehensive series of tests is required to demonstrate a mixture's adequacy for specific construction applications. Current practice involves mixture design approval based on pre-construction submittals and routine quality assurance (QA) testing, including air content, slump, and compressive strength. However, these tests provide no direct insight into the actual mixture design of the placed concrete. Moreover, maintaining batch-to-batch consistency still remains a challenge for producers. Yet, no robust framework currently exists to evaluate actual mixture design compliance during construction.

While past research has primarily focused on surface resistivity as an indicator of concrete durability and permeability, its potential as a powerful quality assurance tool remains largely underutilized in the industry. QC/QA practices continue to rely heavily on compressive strength as the primary acceptance criterion, overlooking the added value of resistivity measurements. Recent studies have demonstrated that tracking resistivity changes over time provides a more comprehensive assessment of concrete properties, identifying key mixture components such as w/cm and binder composition. (Hartell 2020; Gulrez, 2018)

Additionally, existing studies have not explored the use of machine learning (ML) models to predict surface resistivity curves for ready-mix concrete based on mixture design parameters. This approach could enhance the QC/QA process during the construction phase, addressing limitations of current practice that often fail to reflect long-term durability. These tools applied during the QC/QA process could enhance quality assurance leading to more resilient structures, reducing premature repair or replacement needs.

This gap raises key questions: How can resistivity be effectively integrated into QA/QC practices to provide a more comprehensive means for concrete mixture design acceptance? What role can ML play in bridging this gap by predicting resistivity curves that benchmark compliance during construction? To address these challenges, this research proposes a predictive ML framework that generates resistivity curves at key curing intervals using mixture designs as inputs.

This study advances the field by introducing an ML model capable of predicting resistivity curves for ready-mix concrete based on mixture design parameters. By comparing predicted curves with real-time resistivity measurements of field samples, this approach provides a practical tool for identifying discrepancies between delivered and specified concrete mixtures. Integrating durability performance characteristics along with key mixture design identification into QC/QA protocols moves beyond the traditional reliance on compressive strength alone. Furthermore, this framework ensures that concrete placement aligns with both design specifications and performance standards, laying the foundation for broader adoption of resistivity-based metrics in industry practices.

2. LITERATURE REVIEW

The prediction of concrete resistivity is essential for optimizing the durability and lifespan of concrete structures (K.D, 1997). Due to the complex nature of concrete chemistry, accurately forecasting resistivity changes over time remains a challenge. However, Machine Learning (ML) has emerged as a powerful tool for addressing this issue. For instance, Uddin et al. (2023) demonstrated the effectiveness of ML-based predictive models in estimating the properties of fiber-reinforced 3D-printed concrete (3DP-FRC). These models leverage complex datasets, including mixture compositions, curing conditions, and other relevant variables, to provide accurate predictions of concrete behavior.

The application of machine learning (ML) techniques to predict concrete properties—such as compressive strength, flexural strength, and resistivity—has been widely explored in recent studies. Common ML models, including Random Forest (RF) (Breiman, 2001), Support Vector Machines (SVM), and Gradient Boosting Machines (GBM), have demonstrated effectiveness in predicting concrete’s compressive strength (CS). These models process complex mixture data and accurately forecast mechanical properties (Uddin et al., 2023).

Among these methods, RF has been particularly recognized for its robustness in handling both small and large datasets with complex relationships. Its accuracy is largely attributed to ensemble learning, where multiple decision trees are constructed from random data subsets to predict final outcomes. This makes RF well-suited for analyzing the effects of concrete chemistry (Raju et al., 2023). A notable study applying RF to resistivity prediction is *Estimating Electrical Resistivity from Logging Data for Oil Wells Using Machine Learning* (Al-Fakih et al., 2023). This research successfully employed RF to estimate resistivity using logging data, highlighting its ability to handle high-dimensional datasets with multiple features. Similarly, RF models have been applied to predict concrete resistivity based on factors such as water-cement ratio, mix design, and curing time, yielding highly accurate results (Al-Fakih et al., 2023).

To evaluate model performance, Al-Fakih et al. (2023) used Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE), with lower values indicating greater predictive accuracy. Beyond resistivity, RF models have also proven highly effective in predicting compressive strength by leveraging extensive datasets that incorporate various mixture components and curing conditions (Izadgoshasb et al., 2021; Al-Fakih et al., 2023).

The importance of effective feature selection has been emphasized in numerous studies as a key factor in enhancing the performance of predictive models. Incorporating temporal data—such as resistivity measurements over time, or at different curing stages—has been shown to improve identification of key components of a concrete mixture design (i.e. water to cement ratio and binder composition). This approach provides a valuable tool for QC/QA of concrete mixtures placed during the construction phase. These improvements stem from tracking changes in resistivity over time as concrete matures, offering a more comprehensive assessment of its properties. Current standards, which rely on a single-point resistivity measurement, have been found to provide insufficient evidence for performance evaluation and quality assurance (Hartell et al. 2023, Gulrez, 2018).

Techniques like Shapley Additive Explanations (SHAP) have been utilized to interpret feature importance, providing insights into how individual variables, such as the water-to-binder ratio or cement content, affect the resistivity and mechanical properties of concrete (Uddin et. al., 2023).

Despite the success of machine learning models, challenges remain in predicting concrete resistivity with the same level of reliability seen in other construction material predictions. One significant challenge is the lack of large, high-quality datasets, which are often required to train accurate models. Many existing studies rely on small sample sizes, limiting the ability of the models to generalize across various real-world scenarios (Izadgoshasb et. al., 2021). Machine learning models, particularly Random Forest, have shown to be accurate across similarly sized data sets in predicting concrete properties such as resistivity over time. The use of accurate metrics like MAPE and RMSE ensures the robustness and reliability of these models, as demonstrated in studies like (Al-Fakih et. al., 2023).

3. METHODOLOGY

3.1 Experimental Testing

The concrete mixtures analyzed in this study were prepared using materials sourced from various locations, with all components tested and handled according to established standards to ensure their quality. Key features of the ready-mix concrete designs that influenced resistivity readings included Portland cement types (I, I/II, III), supplementary cementitious material replacement (fly ash, silica fume, slag cement) aggregate type and gradation, water-to-cementitious material (w/cm), and chemical admixtures (air-entrainer and water-reducer).

Type-I, Type-I/II, and Type III Portland cements were sourced from two different suppliers over a five-year period. Class-C fly ash (FA) was sourced from four different producers providing chemical variability for comparative purposes. Coarse aggregates from three different quarries and of varying gradation (#56, #57, & #67) were used. A single source of fine aggregate (natural sand) was used. All materials were stored in laboratory conditions prior to batching. Materials met ASTM specifications, and properties such as aggregate specific gravity and absorption were tested for mixture design requirements. Potable water, tempered to lab conditions, ensured consistency during mixing, while air-entraining and water-reducing admixtures were selectively incorporated to modify fresh mixture performance and percent air content (6% ± 1%).

A total of 59 unique mixture designs varying in w/cm (0.4, 045, 0.5, 0.55, 0.6), fly ash content (5% to 25%), silica fume content (2% to 8%), slag cement content (5% to 40%), paste content (20% to 30%), aggregate type, cement type, and with or without admixtures were prepared. From each concrete batch, six 4"x8" cylinder replicates were designated for resistivity testing. Resistivity testing was performed at 1-, 3-, 7-, 14, 21-, 28- and 56-day time intervals in a temperature-controlled laboratory environment following *AASHTO T 358-17: Surface Resistivity Indication of Concrete's Ability to Resist Chloride Ion Penetration.* The range of each variable is listed in Table 1.

Table 1: Range of variables in the dataset

Variables	Cement type	W/C Ratio	Fly Ash	Silica Fume	Air-entrainer	Cement supplier
Range	Type1/Type2	0.4~0.5	0~20%	0~8%	0~6%	I/II/III

Curing methods adhered to ASTM C511, ensuring uniform hydration and strength development. For this study, immersion curing in limewater was selected as it is the most widely used form of curing in industry. Not all facilities have access to curing chambers. It was determined that under standard conditions (ASTM C511), there is no significant difference between both curing methods (Gulrez and Hartell, 2017; Hartell 2020).

3.2 Model Development

The methodology for developing a machine learning model to predict concrete resistivity is structured into five key stages. First, *data collection and feature selection* were conducted, involving the acquisition of resistivity data from 59 unique mixture designs. As previously stated, each mixture design hosts six cylinder replicates with four measurements per replicate captured per day per replicate, for a total of 9,912 data points.

Second, the *data preprocessing* involves handling missing values and preparing the dataset for machine learning. Specifically, there were 4 missing values. These values were addressed using polynomial feature transformation and regression-based imputation. Polynomial features of degree two were generated from the training dataset to capture nonlinear relationships between variables. Additionally, during data analysis, errors introduced by manual data entry, such as misplaced decimal points, were identified and corrected in this step.

Next, the *model development phase* employs multiple machine learning models suitable for multi-output regression problems to predict concrete resistivity. It involves a systematic process of dataset splitting and feature transformation. The dataset is divided based on the unique mixture designs to prevent data from the same mixture design, including its replicas, from appearing simultaneously in the training, validation, or testing sets. This ensures that the validation and testing sets contain entirely new mixture designs, avoiding data leakage and providing an unbiased evaluation of the model's performance. For the multi-output prediction task, Linear regression, Random Forest, Decision tree, artificial neural networks, and recurrent neural networks are utilized in this paper. The RNN model is tailored to capture temporal dependencies in resistivity data, requiring interpolation to produce continuous resistivity curves across the 56-day period.

The *model evaluation and validation process* involve assessing the predictive performance of the trained models using a combination of statistical metrics and systematic validation techniques. Key metrics employed include RMSE, MAPE, and standard deviation, which provide insights into the model's accuracy, precision, and reliability. Grid search techniques are applied to the model with best performance to optimize hyperparameters systematically and reduce computation burden. The selected hyperparameters are summarized in Table 2. The correlation matrix of input parameters is shown in Figure 1.

Table 2: Optimized hyperparameters for the Random Forest model

Hyperparameter	Selected value
n_estimators	50
Max_depth	None
Min_samples_split	10
Min_samples_leaf	4
Max_features	Sqrt
Bootstrap	True

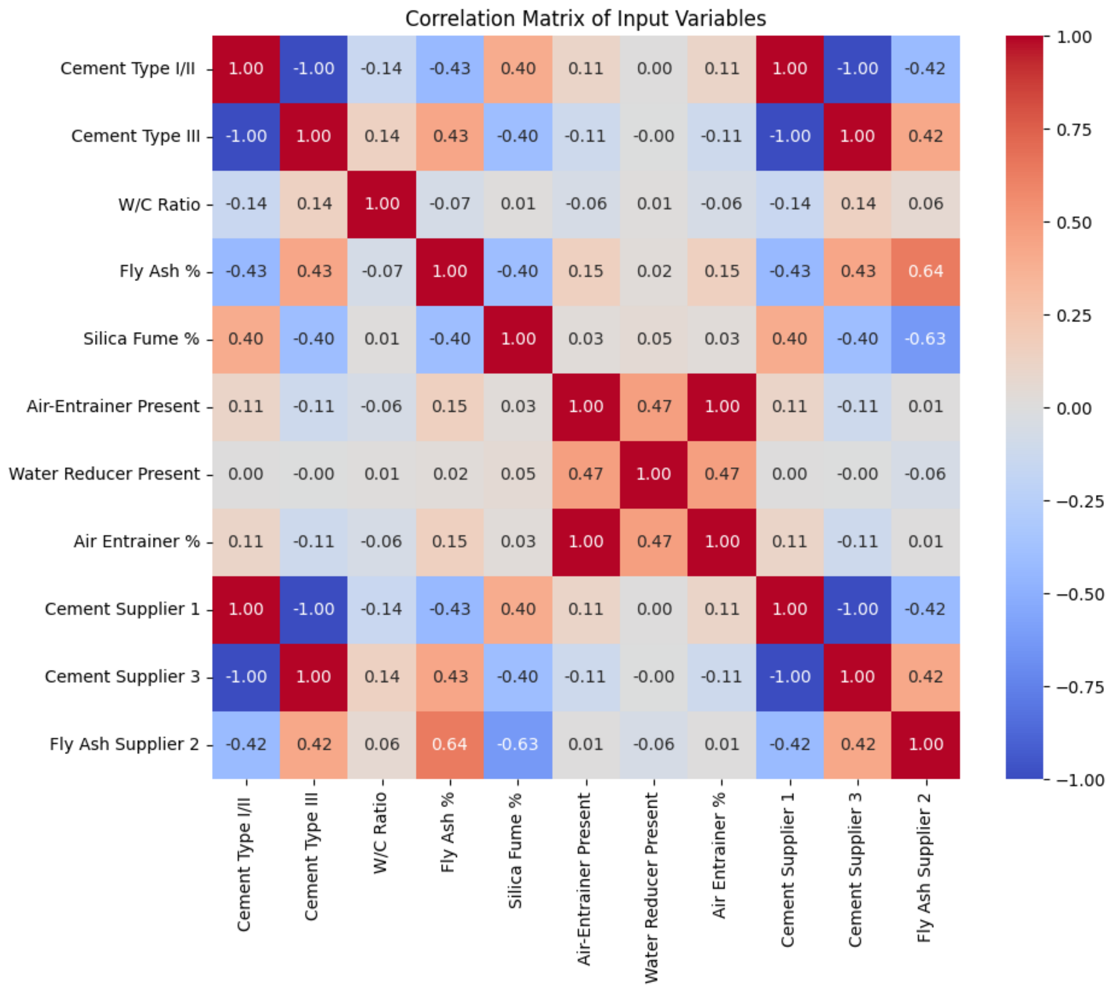

Figure 1: Correlation matrix of input parameters

Lastly, the *testing phase* focuses on evaluating the model's generalization performance on an independent testing dataset comprising entirely new mixture designs not encountered during training or validation. The trained model's predictions are compared against the ground truth resistivity values to compute evaluation metrics such as RMSE, MAPE, and standard deviation. These metrics are used to quantify the accuracy and reliability of the predictions. Although unconventional in machine learning, MAPE was understood as the primary accuracy metric for this temporal data as was also seen in (Al-Fakih et. al., 2023). This restructured testing and accuracy recognition approach yielded reliable insights into model performance, ensuring a fair and realistic comparison among the ML models.

4. RESULTS & DISCUSSION

The entirety of the resistivity testing dataset is not included herein; only the results of the model development and its efficacy in predicting key parameters are demonstrated. Results can be viewed in Appendix A, Figures 2 to 12.

MAPE was included as a form of error representation as it was observed that RMSE values failed to capture a relative sense of error across the temporal data intervals studied. This was attributed to larger standard deviations in seen as the concrete matured Table 2.

Table 1: Random Forest (RF) Model Accuracy Metrics

Accuracy Measurements	Day 1	Day 3	Day 7	Day 14	Day 21	Day 28	Day 56
RMSE	0.659	0.884	1.126	1.731	2.107	2.524	3.433
STD	0.6599	0.8868	1.0930	1.6726	1.9951	2.3584	3.191
MAPE	13.13%	9.82%	11.30%	12.74%	12.19%	12.95%	14.94%

Greater model accuracy was observed for most mixture designs in earlier stages of maturing, such as days one, three, and seven as seen both in Table 2 and Figures 2-4. These intervals exhibited consistent trends, allowing the model to predict resistivity values with minimal deviation. However, as the intervals between data points increased, such as Days fourteen (14), twenty-one (21), and twenty-eight (28) seen in Figures 5-7, accuracy decreased respectively. Larger intervals of captured data in later days presented challenges for the model to maintain similar levels of precision leading to overestimates in resistivity reading projected at Day fifty-six (56) noticed in Figure 8.

Aligning with known effects of silica fume (SF) on resistivity (Sadrmomtazi et. al., 2017), models predicting those curves showed to fit well within actual recorded ranges Figures 9-10. The ML model’s ability to learn the overall relationship of resistivity gain was evident, as deviations were distinctly noticeable against the established trends. Such deviations were characterized by sudden jumps or dips in resistivity, diverging from the common trend of gradual resistivity gain as seen in Figures 11-12 from day fourteen (14) to day twenty-eight (28).

Splitting of data by mixture design sample sets rather than individual readings was found to be critical in mitigating data leakage. Resistivity trends across mixture designs were effectively distinguished, with variations introduced by material properties, including water-to-cement ratios, cement types, aggregate types, admixtures, and supplementary cementitious materials as was expected given previous comparative model and SHapley Additive exPlanations (SHAP) studies similar to the studies demonstrated in *Al-Fakih et. al., 2023; Alyami et. al., 2023; and Uddin et. al., 2023* namely.

An importance factor is also conducted to identify the most important factors for predicting the resistivity. Among all input variables, silica fume exhibits the highest importance by a significant margin with an importance of 0.57, suggesting it plays a dominant role in influencing resistivity development. This result aligns with the known effects of silica fume in a concrete mixture will lead to a small reduction of its pore solution alkalinity and alkali ion concentration while also refining the pore structure of the cementitious matrix. This limits ionic mobility and solution conductivity; therefore, significantly increases electrical resistivity. Fly ash also demonstrates relatively high importance of 0.16, likely acting as a proxy for the presence of fly ash in the mixture. Other influential variables include w/cm with the importance factor of 0.11, and cement types with an importance of 0.04, which align with established factors that influence pore solution chemistry, thereby affecting the electrical resistivity of a concrete mixture.

The potential of ML applications in concrete quality assurance programs was confirmed. Predictive resistivity models were shown to intertwine as a viable tool to enhance verification of non-destructive testing in acceptance of ready-mix concrete. This tool will reduce reliance on destructive testing and improve compliance with design specifications. Further development of non-destructive testing methods is recommended to integrate ML tools more effectively into construction practices, improving both efficiency and accuracy in quality assurance practices.

5. CONCLUSION

The model's primary objective is to enhance quality control and assurance programs ensuring that the delivered concrete mixture aligns with the specified design standards and the mixture design approved at the qualification stage. This approach will refine quality assurance processes through simple model validation strategies, offering a more reliable and cost-effective solution for verifying mixture design compliance during a construction project.

Key aspects of this study include promising preliminary findings obtained from the proof-of-concept RF model presented. The RNN model overfitted the data, memorizing training samples, recalling similar sample data during validation and testing. This issue was addressed by switching to a Random Forest model, which was more robust with the smaller dataset utilized in this predictive model.

Several limitations were identified. The relatively small dataset, coupled with uneven time intervals for resistivity data collection, restricted the model's ability to increase consistency in predictability. The initial RNN model overfitted the data, memorizing training samples, recalling similar sample data during validation and testing. In future work, this model will be retested with the inclusion of the total population. RNN models have been shown to have higher accuracy reporting on temporal data or multi-output predictions compared to other models (Sumbatilinda, 2024). The time intervals selected were based on current industry standards for reporting resistivity measurements. Included in these intervals are days key to current quality acceptance measurements paired with data found to be useful for determining fly ash content and detecting silica fume additions to concrete mixtures (Gulrez, 2018). Additionally, a high ratio of input variables to output data points presented challenges in achieving full generalizability. Increasing the sample size to include further captured data from the total population will likely improve model accuracy. These findings indicate a need for dataset expansion to the full population of concrete mixture designs available to process in future work.

Generating resistivity data requires long-term measurements—typically up to 56 days—which are both time-consuming and costly. Moreover, the resistivity data itself is subject to considerable uncertainty. Even with identical mixture designs, significant variations in resistivity values can be observed over time. This suggests the presence of latent factors or uncontrolled variables influencing the outcomes. These findings indicate a need for dataset expansion to the full population of concrete mixture designs available to process in future work. Such insights are crucial not only for improving resistivity prediction but also for enabling inverse design approaches, where mixture composition is inferred from observed resistivity behavior. As a result, the model does not yet account for all factors affecting resistivity variations, requiring further data expansion. Additionally, Zhang et. al., 2024 has provided robust data further elucidating that model selection has greater impact on accuracy than other methods employed in ML.

Future work will focus on advancing the non-destructive method to improve concrete mixture design verification and durability assessments, namely, a more holistic ML model like the model presented in this study. Continued research will aim to replace current verification standards with a machine learning-based predictive model, which can determine the full mixture composition of a concrete sample using only a laboratory-tested surface resistivity curve. Observed resistivity curves from unknown samples will be compared against predicted curves generated by the model, achieving a specified level of certainty regarding mixture composition.

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APPENDIX A

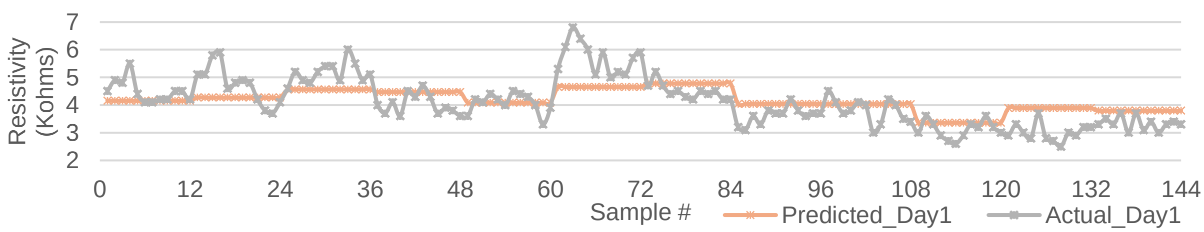

Figure 2: Predicted vs. Actual Day 1 Resistivity Measurements

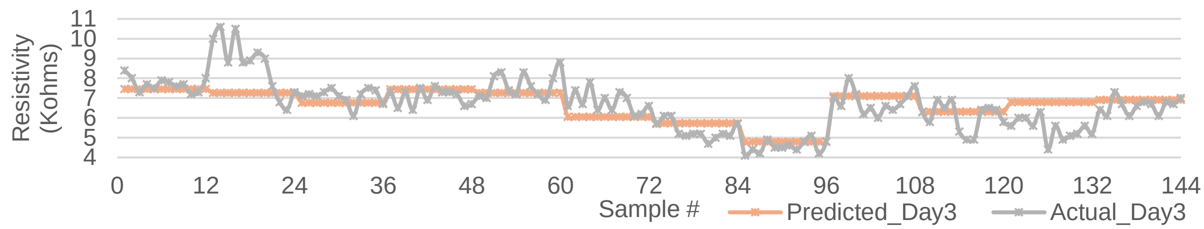

Figure 3: Predicted vs. Actual Day 3 Resistivity Measurements

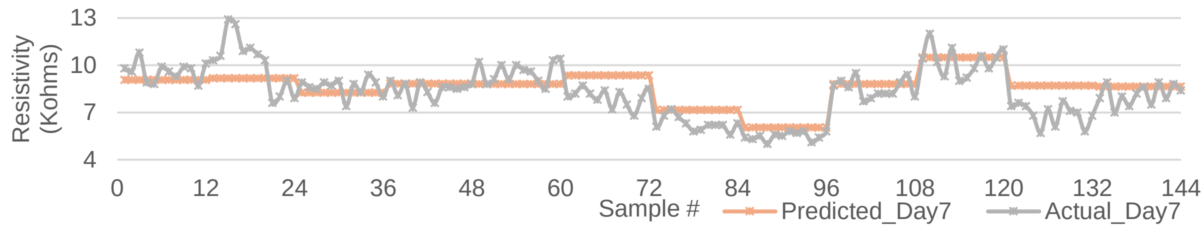

Figure 4: Predicted vs. Actual Day 7 Resistivity Measurements

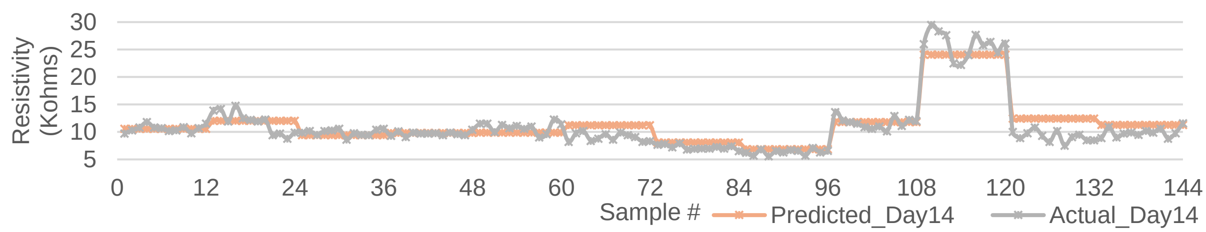

Figure 5: Predicted vs. Actual Day 14 Resistivity Measurements

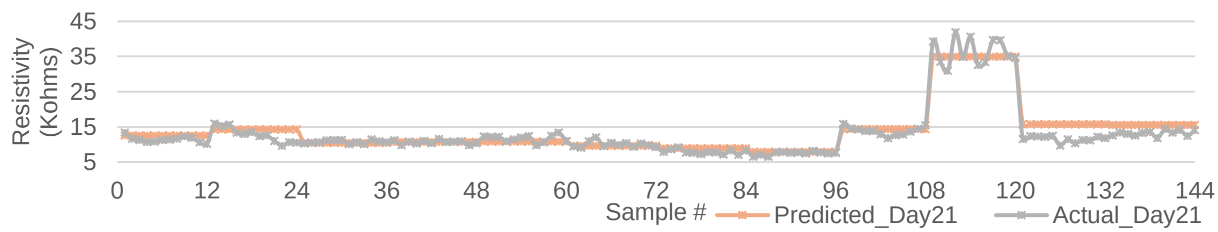

Figure 6: Predicted vs. Actual Day 21 Resistivity Measurements

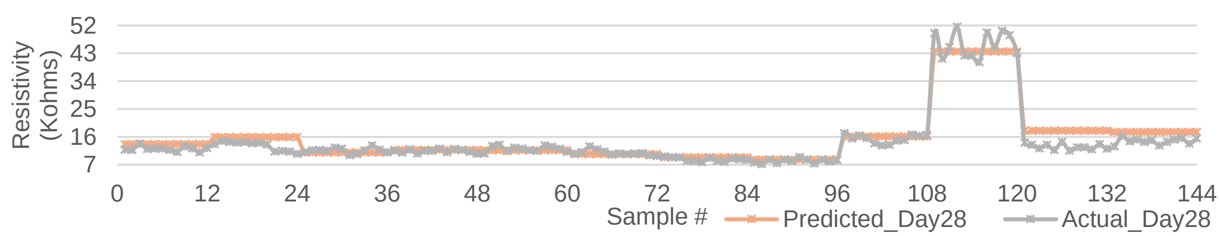

Figure 7: Predicted vs. Actual Day 28 Resistivity Measurements

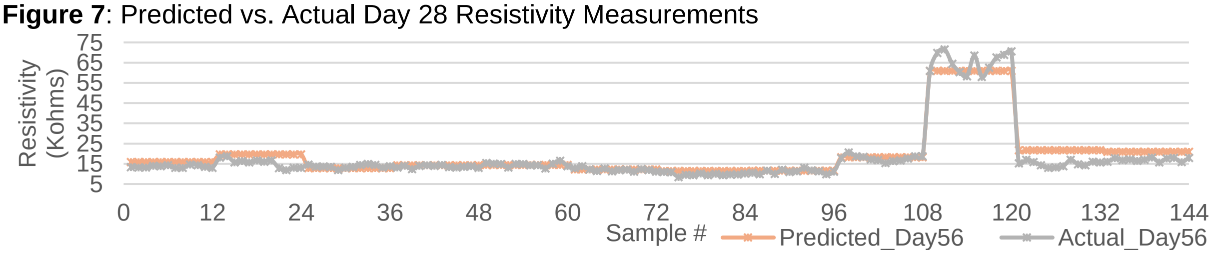

Figure 8: Predicted vs. Actual Day 56 Resistivity Measurements

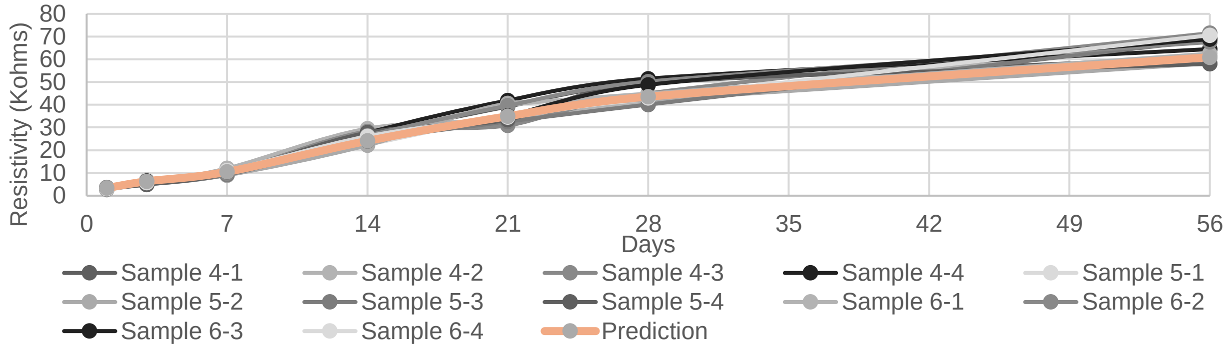

Figure 9: Sample 3-Resistivity Gain Over Time (0.45 w/c ratio / 0.08% Silica Fume (SF) Present)

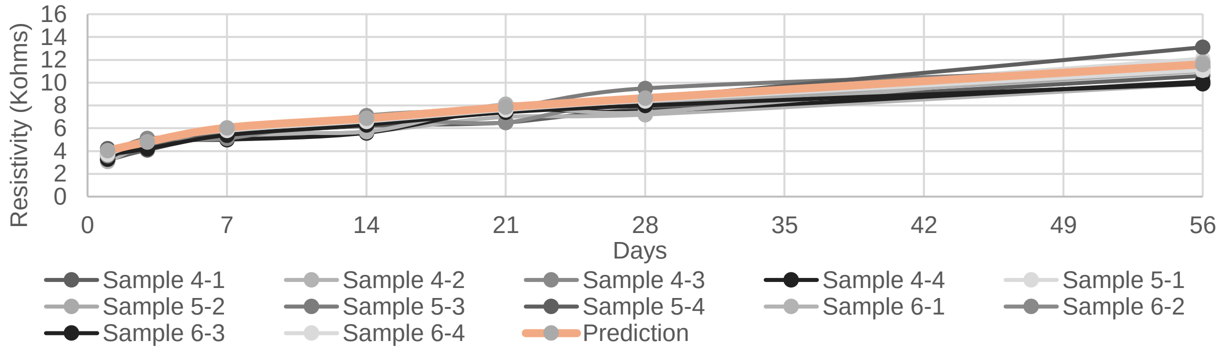

Figure 10: Sample 4-Resistivity Gain Over Time (0.5 w/c ratio / 0.2% Fly Ash (FA) Present / Air- entrainer Present)

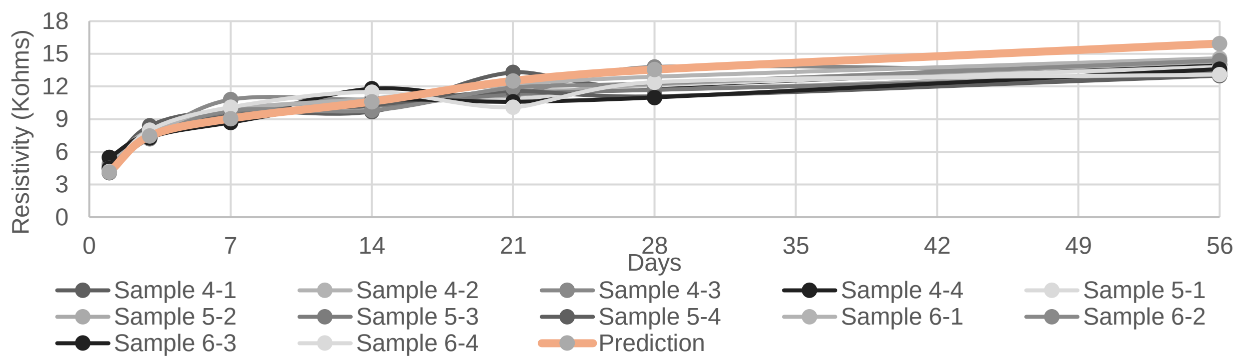

Figure 11: Sample 1-Resistivity Gain Over Time (0.4 w/c ratio / Air-entrainer present)

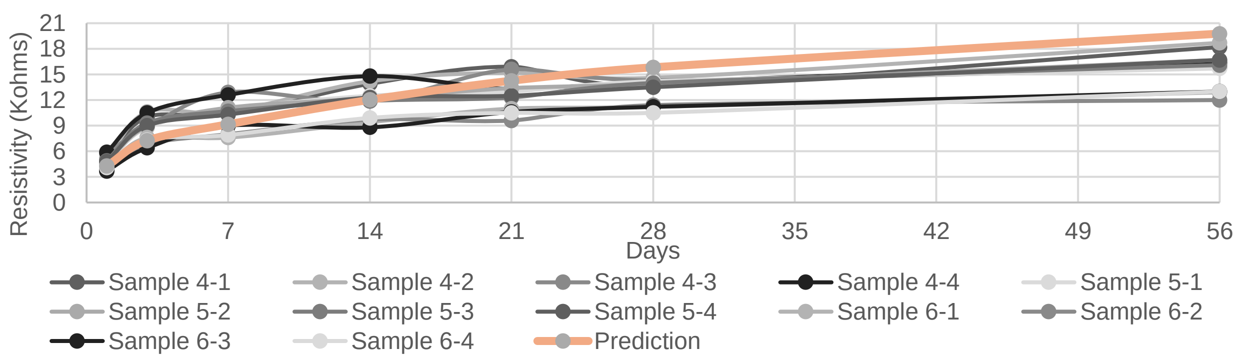

Figure 12: Sample 2-Resistivity Gain Over Time (0.45 w/c ratio / Air-entrainer & Water-reducer Present)