Can Artificial Intelligence Improve Nondestructive Evaluation of Concrete Strength?

by Seyed Alireza Alavi, Martin Noël, Hamed Layssi, and Farid Moradi

Compressive strength is commonly adopted as a representative indicator of many hardened properties of concrete. For existing structures, knowledge of in-place concrete properties is vital to any evaluation and rehabilitation project. Nevertheless, there exist several challenges associated with conventional methods for evaluating concrete strength once a structure has been built.[1-4] Core sampling is not always a viable option for many concrete structures (for example, concrete tanks, sewer trunks, and tunnel linings), and the representativeness of samples in large structures is difficult to obtain.

In-place nondestructive test (NDT) methods can be correlated to concrete compressive strength to reduce the number of required cores.[5] The SonReb method[6] estimates concrete compressive strength based on combined ultrasonic pulse velocity (UPV) and rebound number (RN) measurements. Like all NDT methods, project-specific calibration curves are required due to the heterogeneous nature and diversity of concrete mixtures[7-9]; hence, it is not currently possible to accurately estimate the concrete strength of existing structures without extraction of cores.

Artificial intelligence (AI) is a tool used to interpret complex information and increase productivity. The adoption of AI for civil engineering applications has been relatively slow but is beginning to garner increasing attention through demonstration of practical use cases. This article explores the extent to which AI can be integrated with the SonReb method for nondestructive evaluation of concrete compressive strength in reinforced concrete structures.

NDT Methods

ACI 228.2R-13[5] provides a comprehensive overview of NDT methods for concrete strength evaluation, including the rebound hammer test (ASTM C805/C805M-08[10]) and UPV measurements (ASTM C597-16[11]). The rebound hammer test is an easy and cost-effective means of evaluating the in-place uniformity of concrete (primarily near the surface), while UPV measurements are generally used to evaluate the internal quality and integrity of concrete materials by measuring the velocity of compressive stress waves passing through a member.[12,13] Theoretical formulations support the existence of a direct relationship between Young's modulus and wave velocity, while empirical relationships have long been established to link Young's modulus with compressive strength.[14-16] Because of the challenges in predicting concrete strength by means of NDT resulting from inherent variabilities in concrete material properties, NDT methods, and physical/scientific connections and relevance between any NDT method and concrete strength, ACI Committee 228, Nondestructive Testing of Concrete, recommends the development of site/material specific calibration curves and a statistical approach to analyze the data. For existing structures, ACI 228.1R-19[17] recommends that six to nine different locations should be selected for coring, and a minimum of two cores should be obtained to establish the in-plane compressive strength (that is, a minimum of 12 cores is needed to establish a strength relationship). EN13791:2019[18] outlines a procedure that allows the use of RN measurements without any core tests under certain conditions, though this approach provides only conservative estimates of the strength class of concrete rather than accurate predictions of compressive strength.

NDT methods can be combined to improve their general reliability and reduce sensitivity to factors such as moisture content, aggregate size, cement type, and reinforcement ratio.[14,19,20] The SonReb method has been proposed as a simple approach that nevertheless presents a notable improvement over single-input test methods. Some authors have suggested that UPV and RN are distinctly affected by potential influencing factors,[6,15,21] though, the extent to which this may be the case is still up for debate.

Artificial Intelligence

AI excels at predicting outcomes based on implicit relationships identified through various algorithms used to interpret large amounts of data. Machine learning (ML) is a subset of AI focusing on algorithms that enable computers to learn and make predictions or decisions without being programmed.[22-24] Figure 1 presents a flowchart for a typical supervised ML model. Two data sets are used in the modeling procedure: the training and the testing data set. Applying a learning algorithm to the training data, the computer "learns" potential relationships between input and output data. The testing data set is then used to evaluate the performance of the model, and the procedure is repeated until the ML model satisfies the evaluation criteria.

AI has recently been proposed as a tool to estimate the compressive strength of concrete based on the SonReb method.[25-33] Although the results of previous studies are promising, there is still no practical model for use in the industry.[20] In a separate paper, the development of an ML model based on the SonReb method is described and compared to existing approaches.[22] To emphasize simplicity and compatibility with current practice and considering the lack of concrete mixture information available for many existing structures, the ML model was developed with only two inputs: 1) pulse velocity from the direct UPV test; and 2) RN from the horizontal rebound hammer test as shown in Fig. 2. For the development of the ML model, a database was created using results from published literature as well as an experimental testing program with concrete cylinders and cubes between 7 to 365 days in age and representing a wide range of mixture designs and compressive strengths. (Additional details on the training and testing databases are presented elsewhere.[22])

The experimental procedure for each specimen tested in the laboratory included direct UPV tests, followed by the horizontal rebound hammer test, and finally, the compressive strength test on the same specimens, as shown in Fig. 3.

The model was developed using the adaptive neuro-fuzzy inference system (ANFIS) algorithm in MATLAB. To ensure a robust model performance and avoid a biased outcome, the training (462 data points) and testing data sets (20 data points) were obtained from distinct sources. The model performance was compared against linear and nonlinear regression analyses, as well as existing equations in the literature, and was found to provide the most reliable predictions of

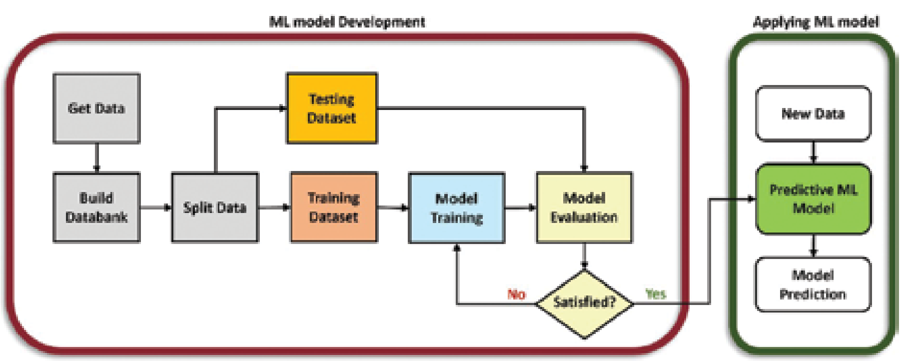

Fig. 1: Flowchart for supervised ML model

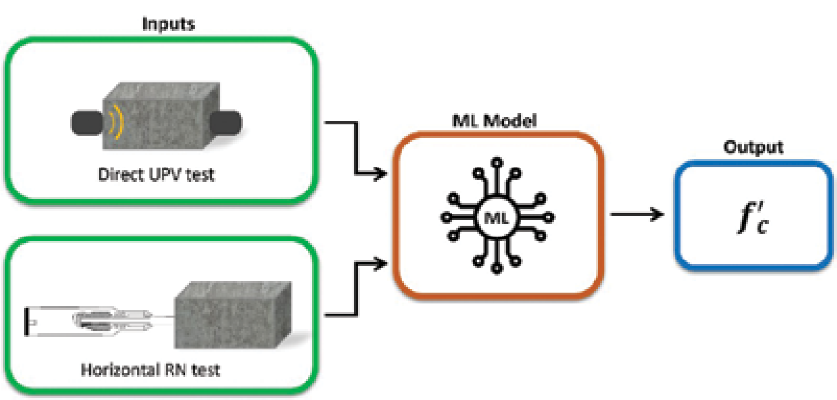

Fig. 2: ML model parameters

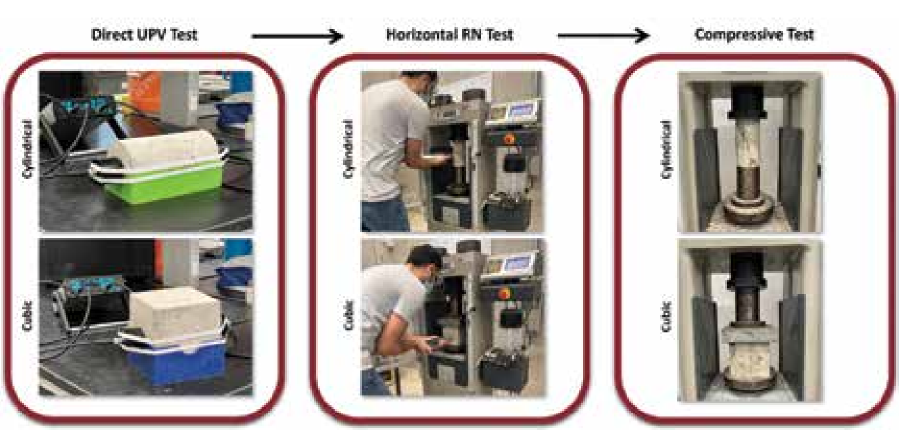

Fig. 3: Experimental test procedure

concrete strength among the considered models, with a mean absolute error of less than 10%.[22] After developing the ML model, a graphical user interface (GUI) app was produced and used for three case studies that are presented in the following section. Each case study provided unique data that had not been seen by the model during its training phase. This approach was adopted to thoroughly evaluate the real-world performance of the ML model.

Case Studies

The accuracy of the model for real-world applications was evaluated using three case studies. In each case study, a systematic methodology was followed, including: 1) performing NDT (UPV and RN) on the concrete structures at select test areas; 2) extracting concrete core samples from the same test areas for compressive strength tests; 3) estimating compressive strength using the proposed ML model and traditional mathematical models, commonly known as the Breysse equation and the Gasparik equation; and 4) comparing the test results from each method.

Case Study 1: RC slab

A partially reinforced concrete slab was fabricated in the laboratory for an independent research project[32] with overall dimensions of 2 x 2 m (6.5 x 6.5 ft) and 300 mm (12 in.) thick. The concrete for the slab was supplied from a local ready mixed concrete company. Twelve testing points (as shown in Fig. 4) were selected for this case study.

Figure 5 presents the test results. The best prediction was obtained from the proposed ML model with a mean absolute percent error (MAPE) of 9.69% and coefficient of variation (COV) of 6.1%. Breysse and Gasparik's equations produced average errors of 28.96% (COV 8.4%) and 36.35% (COV 6.2%), respectively, and both consistently overpredicted the compressive strength of the core samples.

Case Study 2: Existing concrete building

A two-story building on a university campus in Canada required in-place assessment of concrete members as part of its rehabilitation program. The predicted strength results are presented in Fig. 6. The MAPE of the ML model was 12.85% (COV 11.4%), while the errors of the Breysse and Gasparik equations were 19.79% (COV 18.9%) and 33.73% (COV 16.4%), respectively. The MAPE for the ML model reduces to 10.2% if the two column measurements (Col G4Z and Col G4) are excluded. The results suggest that the model performed generally better for flat slab and wall sections than for columns, although the reason for this discrepancy is still under investigation.

Case Study 3: Elevated foundation

A construction error in the elevated foundation of a storage silo in a mining facility resulted in poor consolidation of concrete and moderate to severe honeycombing on or around the lower layer of steel reinforcement, as well as the area close to the embedded plates near the opening. A detailed test plan was designed to evaluate the damaged area (Fig. 7).

The results of the ML model and the Breysse and Gasparik equations are compared in Fig. 8. All of the predictive models tended to underpredict the concrete strength; Gasparik's equation had the lowest MAPE of 21.75% and COV of 17.02%, while both the ML model and Breysse's equation

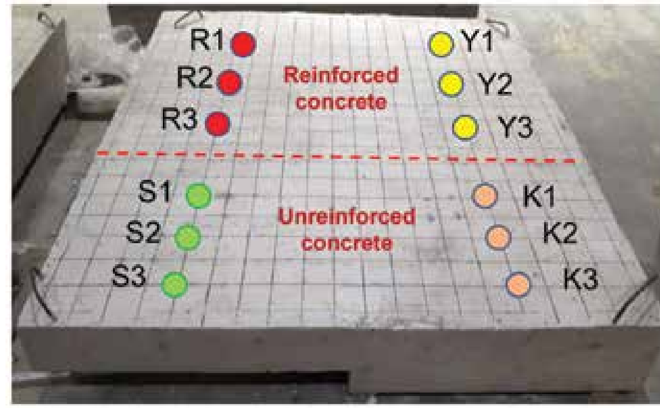

Fig. 4: RC slab with marked testing points (Note: 1 mm = 0.04 in.)

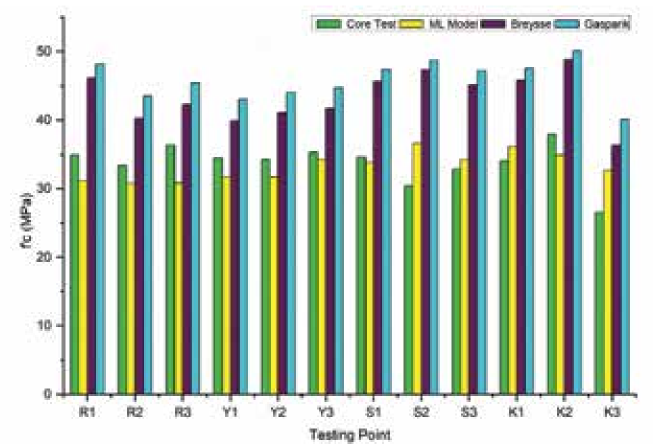

Fig. 5: Strength predictions for Case Study 1 (Note: 1 MPa = 145 psi)

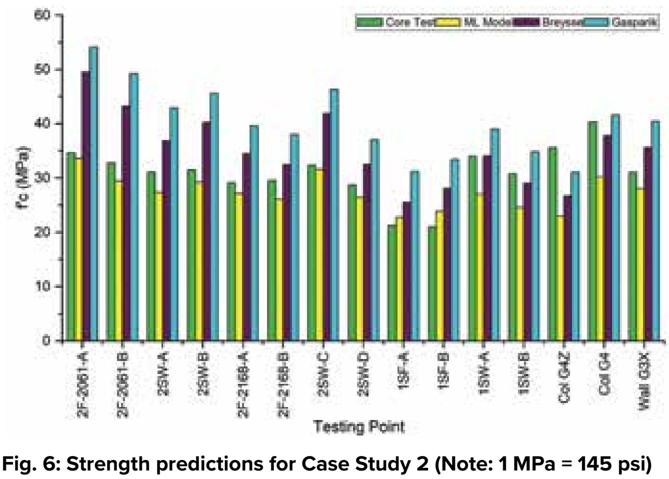

Fig. 6: Strength predictions for Case Study 2 (Note: 1 MPa = 145 psi)

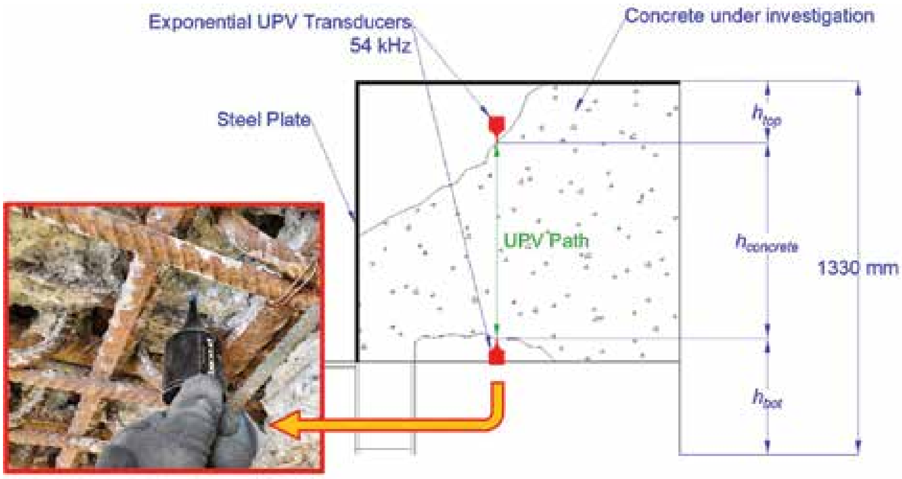

Fig. 7: UPV tests for Case Study 3 (Note: 1 mm = 0.04 in.)

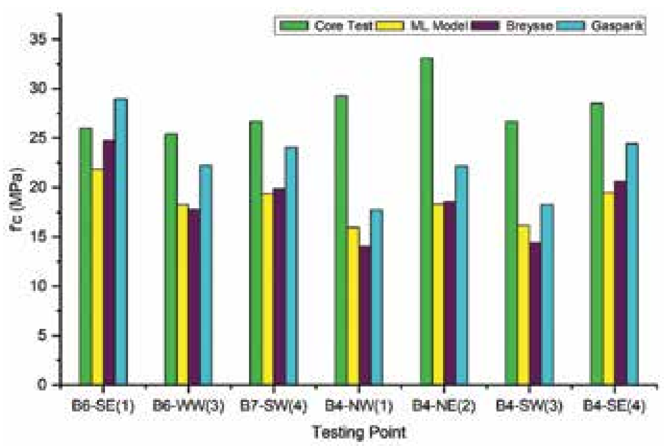

Fig. 8: Strength predictions for Case Study 3 (Note: 1 MPa = 145 psi)

gave similar performance (with average errors of 33.33% and 32.9%, and COV values of 11% and 20%, respectively).

Discussion

Concrete is a heterogeneous and diverse material. Compressive strength values obtained by crushing cylinders from a single batch of concrete can easily vary by 10% or more.[33,34] In this context, achieving 100% accuracy from any model is unrealistic; ensuring consistency and reliability of predictions, as well as identifying potential model limitations, is a more important and achievable goal. This study has presented evidence that AI is a tool that can contribute toward this effort. And in the same way that all tools are used, engineering judgment is required to interpret the outcomes.

The AI model presented in this article maintains the simplicity of the SonReb method by keeping only two input parameters (UPV and RN).[22] The benefits of this approach include more available data for model training, as well as wide applicability because no information on concrete mixture design, curing conditions, or age are required. As demonstrated through the presented case studies, reasonably good predictions were obtained for sound reinforced concrete and flat surfaces with low to moderate amounts of reinforcement. Notable exceptions were obtained for columns in Case Study 2 (possibly attributed to higher reinforcement ratios or geometric effects) and for defective/damaged concrete in Case Study 3. In both cases, the model underpredicted the actual concrete strength by approximately 30% on average (that is, estimates were conservative). As further investigation on the effects of reinforcement congestion and member geometry on NDT measurements and associated model outputs are warranted, it is unsurprising that the poor-quality concrete with visible honeycombing corresponded to a higher average error in the compressive strength predictions because all the training data was obtained from sound concrete specimens. This serves to highlight the engineer's role in interpreting results from tools such as AI. As AI models become more robust and larger training databases are available, their capabilities will also increase; while AI can increase our productivity, engineers will continue to play a vital role in the condition assessment of structures for the foreseeable future.

Ongoing work is currently being conducted to investigate whether model accuracy can be further improved by considering additional input parameters, such as geometry (which was initially ignored despite its known effect on concrete strength and NDT measurements), age, and basic mixture design parameters. The obvious challenge is that in order to consider more parameters, the size of the database must be correspondingly increased. Compiling sufficient good-quality data and filtering outliers/poor-quality results is a complex task; however, as seen in the proliferation of AI in other disciplines, the result can be quite powerful. Overall, the results obtained to date are encouraging and suggest that AI can be adapted to solve key challenges in the construction industry when sufficient data is available.

Finally, the importance of statistical/confidence level concepts to interpret ML predictions, as ACI 228.1R-19[17] recommends for all cases, should not be overlooked. This is the subject of ongoing work by the authors and is an essential step for evaluating and applying model outcomes.

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Selected for reader interest by the editors after independent expert evaluation and recommendation.

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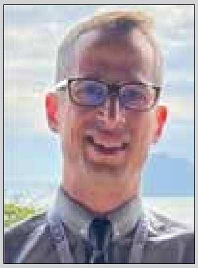

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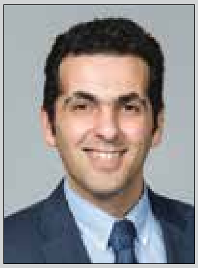

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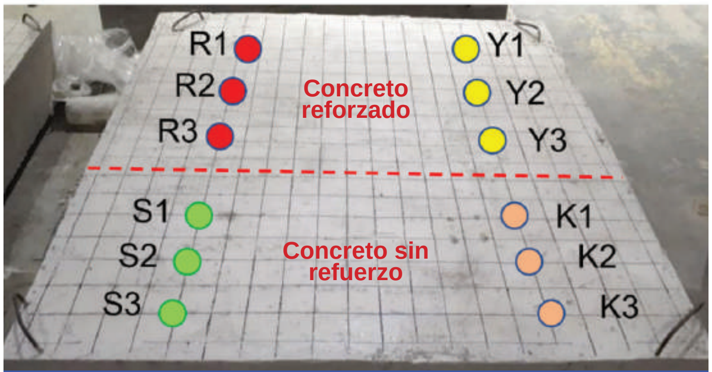

Figura 4: Losa de concreto reforzado con los puntos de prueba marcados (Nota: 1mm = 0.04 in).

El procedimiento de prueba para cada espécimen probado en el laboratorio incluye una prueba de velocidad de pulso ultrasónico en posición de medida directa, seguido por una prueba de martillo de rebote horizontal, y finalmente, la prueba de resistencia a compresión de ambos especímenes, como se muestra en la Figura 3.

El modelo fue desarrollado utilizando el algoritmo del sistema adaptativo de interferencia neurodifusa (ANFIS) en MatLab. Para garantizar un rendimiento sólido del modelo y evitar obtener resultados sesgados, el conjunto de datos de entrenamiento (462 puntos de datos) y el conjunto de datos de prueba (20 puntos de datos) fueron obtenidos de fuentes distintas. El rendimiento del modelo fue comparado con un análisis de regresión lineal y no lineal, así como con ecuaciones existentes en la literatura, y se encontró que proporciona las predicciones más confiables de la resistencia del concreto entre los modelos considerados, con un error absoluto medio inferior al 10%[22]. Después de desarrollar el modelo de aprendizaje automático, se produjo una aplicación de interfaz gráfica de usuario (GUI), la cual fue utilizada en tres casos de estudio presentados en la siguiente sección. Cada caso de estudio proporcionó datos únicos que no habían sido vistos por el modelo en la fase de entrenamiento. Este enfoque se utilizó para evaluar exhaustivamente el rendimiento del modelo de aprendizaje automático en el mundo real.

Casos de estudio

La exactitud del modelo para aplicaciones en el mundo real se evaluó utilizando tres casos de estudio. En cada caso se siguió una metodología esquemática, incluyendo: 1) ejecución de pruebas de campo no destructivas (velocidad de pulso ultrasónico y número de rebotes); 2) extracción muestras de núcleos de concreto de las mismas áreas seleccionadas para la prueba de resistencia a la compresión; 3) estimación de la resistencia a la compresión utilizando el modelo de aprendizaje automático y los métodos matemáticos tradicionales, comúnmente conocidos como ecuación de Breysse y ecuación de Gasparik; y 4) comparación de los resultados obtenidos en cada método.

Caso de estudio 1. Losa de concreto reforzado

Una losa de concreto parcialmente reforzada fue fabricada en el laboratorio para un proyecto de investigación independiente[32] con dimensiones de 2 x 2 metros (6.5 x 6.5 ft) y 300 mm (12 Plg) de espesor. El concreto para la losa fue suministrado por una empresa local de concreto premezclado. Doce puntos de prueba (mostrados en la Figura 4) fueron seleccionados para este caso de estudio.

La figura 5 presenta los resultados de la prueba. La mejor predicción se obtuvo con el modelo de aprendizaje automático, con un porcentaje de error absoluto promedio (MAPE) de 9.69%, y un coeficiente de variación (COV) de 6.1%. Las ecuaciones de Breysse y Gasparik generaron errores promedios de 28.96% (COV 8.4%) y 36.35% (COV 6.2%), respectivamente, y ambos sobreestimaron consistentemente la resistencia a la compresión de los núcleos de concreto.

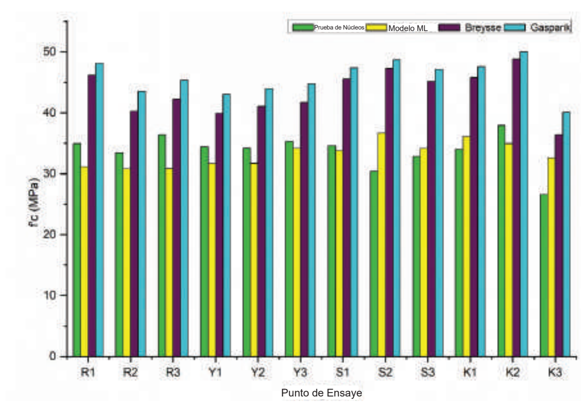

Figura 5: Predicciones de resistencia para el Caso de estudio 1. (Nota: 1MPa = 145 psi)

Caso de estudio 2. Construcción existente de concreto

Un edificio de dos pisos en el campus de una universidad en Canadá requiere evaluar la resistencia a la compresión del concreto como parte de un programa de rehabilitación. Los resultados de la predicción se presentan en la Figura 6. El MAPE del modelo de aprendizaje automático fue de 12.85% (coeficiente de variación igual a 11.4%), mientras que los errores obtenidos con las ecuaciones de Breysse y Gasparik fueron de 19.79% (COV de 18.9%) y 33.73% (COV de 16.4%) respectivamente. El MAPE para el modelo de aprendizaje automático se reduce a 10.2% si son excluidas dos mediciones en columnas (columna G4Z y columna G4). Los resultados sugieren que el modelo funcionó mejor para losas planas y secciones de muro que para columnas, aunque la razón de esta diferencia aún se encuentra bajo investigación.

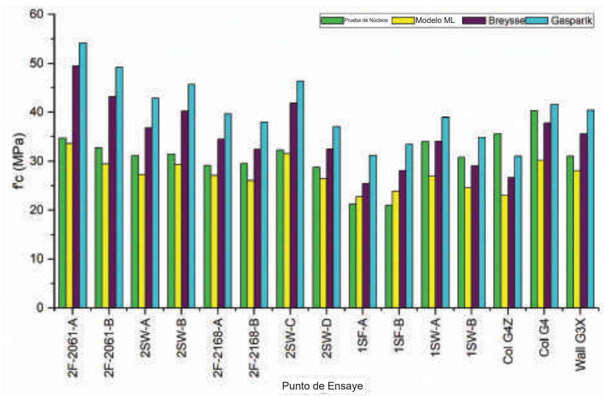

Figura 6: Predicciones de resistencia para el caso de estudio 2. (Nota: 1MPa = 145 psi)

Caso de estudio 3. Cimentación elevada

Un error de construcción en la cimentación elevada de un silo de almacenamiento en una instalación minera dio como resultado una consolidación deficiente del concreto y una formación de paneles moderados a severos alrededor de la capa inferior del acero de refuerzo, y la zona dio un rendimiento similar (con errores promedio de 33.33% y 32.9%, con coeficientes de variación de 11% a 20%, respectivamente).

Discusión

El concreto es un material heterogéneo y diverso. Los valores de resistencia a la compresión obtenidos ensayando cilindros de una misma mezcla de concreto fácilmente pueden variar en un 10% o más[33,34]. En este contexto, obtener un porcentaje de exactitud del 100% para cualquier modelo no es realista; garantizar la coherencia y confiabilidad de las predicciones, así como identificar posibles limitaciones del modelo, es un objetivo más importante y alcanzable. Este estudio presenta evidencia de que la inteligencia artificial es una herramienta que puede contribuir a este esfuerzo. Y de la misma manera que todas las herramientas son utilizadas, se requiere criterios de ingeniería para interpretar los resultados.

El modelo de inteligencia artificial presentado en este artículo conserva la simplicidad del método SonReb manteniendo solo dos parámetros de entrada (velocidad de pulso ultrasónico y número de rebote)[22]. Los resultados de este enfoque incluyen mayor disponibilidad de información para el entrenamiento del modelo, así como una amplia aplicabilidad debido a que no se requiere información sobre el diseño de la mezcla del concreto, condiciones de curado, o edad del concreto. Como se demuestra en los casos de estudio presentados, se obtuvieron predicciones razonablemente buenas para concreto sano y superficies planas con cantidades de refuerzo bajas y moderadas. Se obtuvieron excepciones notables para las columnas del caso 2 (posiblemente debidas al alto grado de refuerzo o efectos geométricos) y para concreto dañado o defectuoso en el caso de estudio 3. En ambos casos, el modelo subestima la resistencia actual del concreto en un promedio de

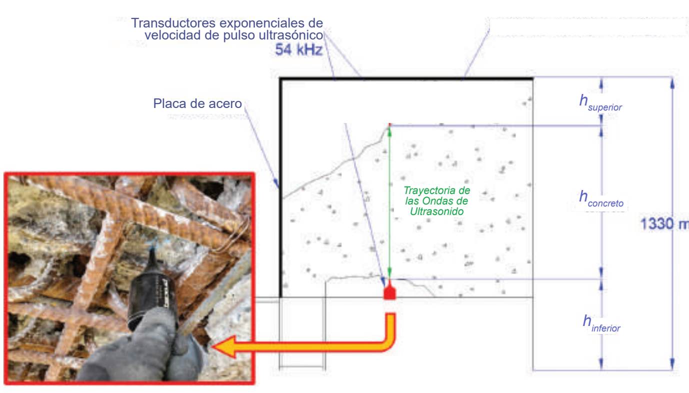

Figura 7: Pruebas de velocidad de pulso ultrasónico para el caso de estudio 3. (Nota: 1 mm = 0.04 in.)

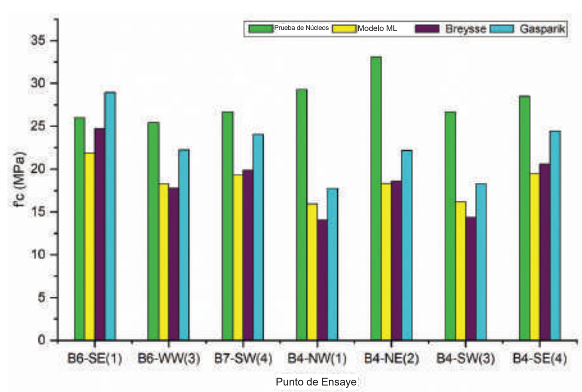

Figura 8: Predicciones de resistencia para el caso de estudio 3. (Nota: 1MPa = 145 psi)

30% aproximadamente (esto es, las estimaciones fueron conservadoras). Como se justifica una mayor investigación sobre los efectos de la congestión en el refuerzo y la geometría de los miembros en las mediciones de las pruebas no destructivas y los resultados del modelo asociado, no es sorprendente que el concreto de mala calidad con panal visible correspondiera con el error promedio más grande en la predicción de la resistencia a la compresión, ya que los datos de entrenamiento fueron obtenidos para especímenes de concreto sanos. Esto sirve para destacar el rol de los ingenieros en la interpretación de los resultados obtenidos de herramientas como la inteligencia artificial. A medida que los modelos de inteligencia artificial se vuelven más sólidos y se dispone de bases de datos de capacitación más grandes, sus capacidades también aumentarán; si bien la inteligencia artificial puede aumentar nuestra productividad, los ingenieros seguirán desempeñando un papel vital en la evaluación del estado de las estructuras en el futuro previsible.

Actualmente se está llevando a cabo un trabajo en curso para investigar si la precisión del modelo se puede mejorar aún más considerando parámetros de entrada adicionales, como la geometría (que inicialmente se ignoró a pesar de su efecto conocido sobre la resistencia del concreto y las mediciones de los métodos de prueba no destructivos), la edad y los parámetros básicos de diseño de la mezcla. El desafío obvio es que, para considerar más parámetros, el tamaño de la base de datos en consecuencia debe aumentar. Recopilar datos suficientes de buena calidad y filtrar valores atípicos o resultados de mala calidad es una tarea compleja; sin embargo, como se ve en la proliferación de la inteligencia artificial en otras disciplinas, el resultado puede ser bastante poderoso. En general, los resultados obtenidos hasta la fecha son alentadores y sugieren que la inteligencia artificial se puede adaptar para resolver desafíos clave en la industria de la construcción cuando se dispone de datos suficientes.

Finalmente, no se debe pasar por alto la importancia de los conceptos estadísticos de nivel de confianza para interpretar las predicciones del modelo de aprendizaje automático, como recomienda ACI 228.1R-19[17] para todos los casos. Este es el tema del trabajo continuo de los autores y es un paso esencial para evaluar y aplicar los resultados del modelo.

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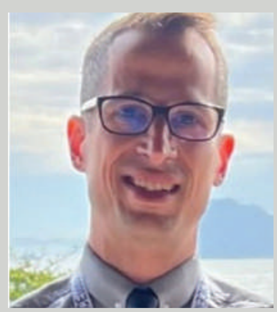

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