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Artificial Intelligence Neural Network: Compressive Strength Prediction of Recycled Aggregate Concrete Samples

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ARTIFICIAL INTELLIGENCE NEURAL NETWORK: COMPRESSIVE STRENGTH PREDICTION OF RECYCLED AGGREGATE CONCRETE SAMPLES

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DEDICATION

This thesis is dedicated to my family and friends whose support and love have changed my dreams to achieved goals.

Sanaa Kawash and Eyad Nijem, for your advice, your patience, and your faith. Because you always understood

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ABSTRACT

Old and demolished structures profusely exist in landfills because they are not being recycled frequently nor being employed correctly. This leads to an increase of construction and demolished wastes (C&D). These demolished structures and blocks can be broken down into smaller components to serve as aggregates (which are called recycled aggregates). Recycled aggregates are not being used regularly because they sometimes have detrimental influence on the compressive strength of concrete.

Recycled concrete aggregate (RCA) reduces compressive strength of the concrete samples due to absorption issues related to the type, and age of the old concrete. Increase in water absorption levels leads to reduction in the compressive strength. If this issue is resolved, consumption of natural resources would decrease, and the use of recycled aggregate would increase which has beneficial reflection on the economy and the environment. The objective of this research was to develop a model to predict the compressive strength of concrete containing different percentages of RCA. This research studied the physical properties that reduce compressive strength, and even included the parameters that are aligned to the concrete mixture and treated them as input parameters in a prediction model. The model was created using artificial intelligence neural network. The built model included a specific prediction algorithm which was Bayesian Regularization Backpropagation which can deal with many types of data, even those of the random type. Although, the data was considered as non-linear, the Bayesian probability algorithm was able to determine the pattern between the data and reduce the error by using the error function which was Mean Squared Error. The experimental data was collected from previous published research works in literature. The collection of the data and the evaluation of the model were both built upon specific criteria. The training results showed the success of the model. The model can be used as a tool by engineers to calculate compressive strength when recycled aggregates are added by entering the physical properties of the mixture. The work done here can be extended in the future to cover optimization of mechanical properties of concrete containing RCA.

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CHAPTER I

INTRODUCTION

Construction technology is rapidly evolving in correspondence to the high demand and increase in the number of projects needed annually worldwide. It is important to address sustainability in the process of infrastructural development; not only that, but also, sustainability must be aligned to projects in construction phase and demolition as well. Sometimes, renovation of built projects may lead to the demolition of parts of the existing structure and replacing those parts with new parts. This might require entirely new materials and mixtures to be used. As required by the *United States Environmental Protection Agency*, the demolished material resulting from new or old projects are to be sent to landfills. Based on the statistics presented by the *United States Environmental Protection Agency*, there were 600 million tons of demolished debris in 2018 recorded only in the United States, and this number fluctuates every year. Scientists and civil engineers have been constantly updating new methods of recycling the archaic aggregates so they could be used as components in new concrete mixtures. This is called Recycled Concrete Aggregate (RCA) which can be defined as crushing old concrete blocks to extract the old aggregate and reusing it in the production of new concrete mixtures.

Concrete recycling is a simple process and might differ slightly depending on the needs of the related project. Usually, it starts by the use of jaws to crush large concrete blocks. Next comes screening process in which the crushed concrete blocks are to be cleaned off dirt and separated based on the particles size into fine or coarse aggregate. In addition, the use of magnet separators might be needed to remove attached metals or reinforcements from the concrete.

Recycled concrete aggregate (RCA) has multiple implementations including highways and geotechnical applications. The use of recycled concrete aggregate has been considered in the United States for at least seventy years (but with some restrictions). Dating back to the reconstruction and maintenance of the US 66 Route in Illinois, pavement aggregates were recycled to produce new material that was used in the project. The nascent methodology of using recycled concrete took place, emphasizing the importance of recycling in the sustainability of the environment and economy (Cackler et al. 3). In the 1940s, during the reconstruction of the US 66 Route, existing old concrete from two lanes was crushed and recycled to meet the project's criteria. The crushed concrete was reused in the other two lanes as a concrete pavement to maximize the use of recycled concrete aggregate RCA (Cackler et al. 3). According to the *US Department of Transportation*, Texas is one of the states that highly adopts recycling concrete yet focuses on its use in transportation projects; in state projects consume higher proportion of the recycled concrete aggregate than those being imported (Gonzalez et al. 10).

Recycling concrete technology is evolving to increase the sufficiency of the concrete recycling methodology. This development in recycling concrete technology has allowed engineers to begin and complete the recycling process, either in plant or on the field, which has reflected in reducing the construction and demolition waste. The first type of recycling technologies is fixed plants which shall include complete processing systems, developed machines, and equipment including feeders, magnets, crushers, and screens (Pacheco-Torgal 213-225). The other type is mobile plants which is considered to be significantly new; mobile plants can be installed at the work site where the concrete recycling process needs to be done. Mobile plants include the equipment required to accomplish the recycling process, similar to the fixed plants, and they range in the recycling capacity per hour (Pacheco-Torgal 212). Mobile plants have sustainable outcomes reflected on both of the environment and economy. It eliminates the need of transferring the construction and demolition waste (C&D) from and to the work site which reduces the trucks trips (Pacheco-Torgal 212). Japan is considered as a leading country when it comes to the production and use of recycled concrete aggregates, and the innovation in creating new methods to recycling sustainability. Since 1999, Japan has adopted the Heating and Rubbing method to recycle concrete components. The Heating and Rubbing is a method in which concrete is being exposed to very high temperatures reaching 300 degrees C. As a result, cement gradually transforms into paste that can be rubbed from the surface of the aggregates without having the physical properties being changed (Shima et al. 53). The country has been developing new methods to reduce the environmental effects and maintain higher sustainability in their projects. In 2003, Fujitsu Japan Limited, an electronics manufacturer, and Shimizu Corporation, a construction company, have created the first on site recycling system. They believe that sustainability should be included in reducing the trips of trucks carrying the aggregates, thus reducing the overall project cost and the truck traffic congestion by eliminating truck 11,000 trips.

According to *Japan for Sustainability*, the system was first applied in the demolition and reconstruction of two structural buildings. The components of the buildings totaling 46,000 tons of debris were recycled to be used as aggregates for the reconstruction of the buildings. The cement powder was then used as a component to improve the foundation.

The processes of recycling concrete aggregate resulting from construction and demolition waste (C&D) and its uses have been discussed, although, recycled aggregates have a few property issues that cannot be avoided. Old aggregates that are used in concrete mixtures have higher water absorption levels and lower density due to the age and type of the parent concrete properties (Pacheco-Torgal 247-248). The variation in recycled aggregate properties can affect mechanical properties of concrete, and it can cause issues of the concrete's workability and durability in the long run (Yehia et al. 1). Many research studies have proven that the high absorption levels of old aggregate, which makes the recycled aggregate behave as a sponge, reduce the compressive strength values of the concrete samples. A research study has been done by researchers at the Jinhua Polytechnic College in China. The researchers have tested two different concrete grades including ten different samples, and they have proven that recycled aggregates have water absorption issues that led to the decrease of compressive strength of concrete. Also, when the replacement level of natural aggregate was increased by recycled aggregate, the compressive strength was affected and decreased (Zhang et al.). The inversely proportional relationship between water absorption and compressive strength of recycled concrete could cause some engineers to outrightly avoid the use of recycled concrete aggregate (RCA) due to the workability issues it could create.

Sharma and Singla have studied the influence of recycled aggregate on concrete samples based on their published research "*Influence of Recycled Concrete Aggregates on Strength Parameters of Concrete*" on SSRG International Journal of Civil Engineering. According to their work, the researchers have prepared five concrete mixtures that have been prepared based on the replacement level of natural aggregate. They started at 0% replacement level, and they gradually increased 25% increments for each mixture to end at 100% replacement level (Sharma and Singla). The results showed a significant decrease in the compressive strength values between the mixture with 0% replacement level (includes natural aggregate only) and the mixture with 100% replacement level (includes recycled aggregate only). They concluded that a 100% replacement level would cause a high reduction in mechanical properties, and almost a 50% reduction in compressive strength. Idagu Francis Ogar is another researcher who has worked on a similar topic and has published a research "*The Effects of Recycled Aggregates on Compressive Strength of Concrete*" on the International Journal of Advanced Engineering Research and Science (IJAERS). The published journal includes an explanation of previous published research works, and a study of an experiment achieved by the researcher. Ogar found that the compressive strength values of the samples with RCA can significantly decrease when tested after 28 days in comparison to their respective test results after 3 days of curing. This effect was attributed to high capacity of absorbing water (Ogar) of the RCA.

Issues regarding recycled concrete aggregate (RCA) can affect its demand to be used in projects, with designers tending to focus on the use of natural aggregates (NA) instead. If some of these issues are to be resolved, it can reflect positively on both the environment and the economy. The procedure of recycling aggregate would reduce the environmental effect of producing natural aggregate and the pollution effects of the demolition waste. According to the *U.S department of the interior* the cost of extracting natural aggregate (NA) is relatively higher than using recycled concrete aggregate (Wilburn and Goonan 7). Referencing the tedious process of extracting natural aggregate (NA), natural aggregate production varies by source and methodology, a high proportion of aggregate is produced from marine sources. A satellite navigation is used to locate the gravel and stones beneath the water surface, then a suction arm is used to pull the targeted gravel to the surface. This methodology is used often due to the properties of the marine aggregate, although, it is economically and timely extravagant. Although, land rocks might seem a more approachable source, the prodigious rock structures cannot be drilled through to produce smaller sizes without the use of explosive materials. Special engineers and explosive materials specialists are required to plan the blasting process to avoid any force reactions or virulent gas leaks in the surrounding environment (Onyelowe et al. 448-450). Figure 1 below briefly explains the process of extracting aggregates from either a marine or a land source.

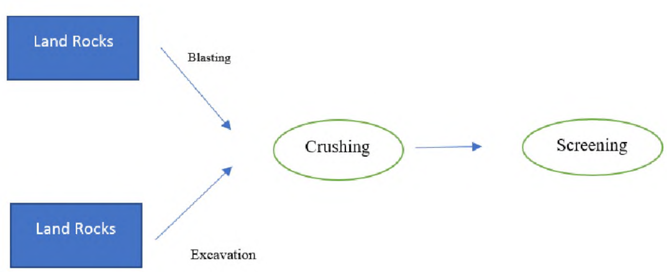

Figure 1: Aggregate Extraction

In addition, recycling aggregate and increasing its use in concrete projects in a higher capacity would decrease the construction and demolition waste (C&D). This can be accomplished by maintaining the mechanical properties of the concrete produced by recycled concrete aggregate (RCA). In the recent few years, sustainability has been interconnected with engineering, primarily to maintain low-cost projects that last for longer periods of time, as well as to reduce the environmental pollution effects. Nonetheless, the United States recorded 569 million tons of Construction and Demolition waste (C&D) in 2017, compared to 170 million tons in 2003 (Material-specific data, epa.gov).

The volume of waste has not decreased in over two decades, on the contrary, it increased. Table 1 summarizes the increase in construction landfill over almost three decades. According to the *United States Environmental Protection Agency*, waste management has become a prime topic. Annual reports are being released every year to show statistics of debris resulting from demolition by state and locations of landfills (Material-specific data, epa.gov). More importantly, different methodologies on how to reduce the waste are continuously outlined with a focus on recycling procedures to reuse the materials.

Table 1: Debris Generated in the United States by Weight (in thousands of tons). *EPA.gov*

Year	**1990**	**2005**	**2015**	**2016**	**2017**
Debris Generated by Weight	135,530	170,000	547,878	560,607	569,436

Recycling concrete can be beneficial in a comprehensive way as summarized in the following:

- Reduction in landfill and waste transfer costs
- Generating new jobs related to the waste management and sustainability field which would enhance the economy
- Decreasing levels of mining natural resources, and using existing ones that are not used
- Using the recycled materials as a component in multiple projects related to infrastructure, roadways and bridges, or even structural premises.

1.1 Problem Statement

Generally, there is no specific standard manual to follow when preparing concrete mixtures. Concrete mixtures vary by the type of cementitious material that is being used, the type of aggregates (that can be either coarse or fine aggregate), the addition of fly ash, or the addition of chemical components such as concrete superplasticizer that controls the increase of water amounts in concrete mixtures. The same applies when preparing concrete mixtures with the addition of recycled aggregate. The fundamental difference between the traditional concrete mixture and the novel RCA concrete mixtures is the replacement of the natural aggregate (NA) by recycled aggregate (RA). Although, it is important to follow a standard specification to test concrete samples for mechanical properties; the specifications are usually regulated by the country. American Society for Testing and Materials (ASTM International) and American Association of State Highway and Transportation Officials (AASHTO) have several specifications for concrete samples testing for each of the mechanical properties. The specifications may differ upon the application of the concrete being prepared. According to "*AASHTO T 22/ASTM C39, Standard Method of Test for Compressive Strength of Cylindrical Concrete Specimens*" the compressive strength test for cylindrical cubes can be summarized in sequencing steps. First, the used machine should be able to provide a sufficient load, then the prepared specimens should have no more than 2% difference diameters, if not identical. The dimensions (including the diameter of each specimen) should be recorded. Each specimen should be placed and aligned with the axes of the center or the thrust after cleaning it up of dirt. The load can then be applied until it reaches the ultimate capacity where the specimen breaks and shows signs of fracture, numbers on the digital screen must be recorded and cannot be adjusted. The standard test can be applied for samples created in the lab with either natural aggregate (NA), recycled aggregate (RA), or both. Concrete samples that include recycled concrete aggregate (RCA) can show unpredictable compressive strength values as discussed previously in this chapter.

This issue can create a dilemma due to the irregular compressive strength values that would result by the use of recycled concrete aggregate (RCA) besides the other properties that can cause reduction in the compressive strength. Creating a predictive model using Neural Network Artificial Intelligence would be helpful in solving this issue. In particular, the predictive model will generate an equation that can predict compressive strength values based on the physical properties of the mixture (even prior to making the concrete). By doing so, engineers would be able to manipulate the physical properties amounts and ratios in order to adjust the compressive strength values as desired in projects, thus, optimizing the compressive strength. Also, it would reduce the cost and effort required in labs to check the resulting compressive strength that is usually random.

It is expected that once the compressive strength is predicted by the Neural Network Artificial Intelligence model, engineers can test the samples at the lab, and will obtain similar values (like those obtained from the model).

1.2 Research Objective

The primary objective of this research study is to develop and use Artificial intelligence Neural Network model to predict compressive strength of concrete samples that contain recycled aggregate as a component of the concrete mixture. The artificial intelligence model will predict compressive strength values of concrete samples and compare it to the experimental compressive strength values. The evaluation of the model's success is based on the following critical points. First, the training of any model of the similar purpose would provide a "Best Training Performance" graph which includes a dotted line and a circle at the location of the performance at the dotted line. Either of the fitting or training lines should pass through the circle to show that the model processed correctly and does not need to be rebuilt using different parameters. Also, on the same graph, the fitting and training line should decline in a similar pattern until one of each reaches the dotted line which indicates that errors of the data have been declining to a minimum value. The regression graph of the matrix dataset should have a fitting close to that of the regression of the data being trained. The number of constants, biases, and weights should result to the expected number, which was 145. The regression progress diagram must show that not all of the constants were used in the model.

1.3 Research Scope

This research investigates the effect of recycled aggregate on the compressive strength of concrete using Artificial Intelligence Neural Network. The model predicted results will be compared to the experimental data collected from previous research literature. Apart from the amount of RCA, the research also considers other physical properties of the concrete mixture that are known to affect the final compressive strength of concrete. Here, the work only accounted physical properties but excluded the influence of any chemical properties which might affect the strength of concrete. Also, parts of this research focus on how the success of this model can be beneficial on both of the economy and the environment.

1.4 Research Methodology

To achieve the stated objective, a matrix dataset was to be created by collecting enough data from previous research literature. The choosing of a previous research required specific criteria described in section 3.1, and it can be briefly explained as the following. The researchers must have accomplished their results experimentally by including the components of the concrete mixtures, and their samples must include recycled concrete aggregate. The testing of the mechanical properties or compressive strength of concrete must have been done after 28 days of samples' curing. Each of the samples must include the following physical properties:

- Replacement Level (%)
- Cement (Kg/m^3)
- Water (Kg/m^3)

- Effective Water to Cement Ratio (**w/c**)
- RCA Water Absorption (%)
- NA Water Absorption (%)
- RCA Bulk Density (Kg/m^3)
- NA Bulk Density (Kg/m^3)
- RCA Aggregate Size
- NA Aggregate Size

Replacement level, cement density, water density, effective water-cement ratio, and absorption levels of both of the recycled and natural aggregate have the highest effect on reducing compressive strength of the samples as explained in the literature. The other four physical properties which are the bulk densities of recycled aggregate and natural aggregate, and the size of recycled and natural aggregate are included because they would exist in the concrete mixture even if they are not considered in the model.

Artificial Intelligence Neural Network is a complex computational system, cerebral inspired from human beings and living creatures. Neural Network (NN) functions by connecting multiple input variables (by several hidden layers that can be determined based on the workability of the overall model and results) to generate an output or outputs. MATLAB is the programming platform used in this work. MATLAB allows engineers to create their individual codes that matches their job or task requirements. In addition, it offers built-in algorithms that is ready to be used which reduces time and effort. MATLAB was chosen to build the prediction function and model, Bayesian Regularization Backpropagation algorithm was coded and used because it uses both regularization and generalization. Generalization is the task of creating a pattern between the data assuming the data is nonlinear, and regularization diminishes any possible issue of data overfitting. In this work, the model considered the ten different physical properties as input parameters, and one hidden layer was chosen to reduce overfitting issues as well. Amongst the dataset, the training data constituted the highest because training always requires more data to generate a more accurate general model. In particular, the training data in this research study formed about 70% which was found to be sufficient after several trials. The remaining data was used for model validation and testing. In summary, the distribution of the data was as the follows:

- 70% of the data has been selected randomly to be trained
- 15% of the data has been selected to be validated
- 15% of the data has been selected to be tested

1.5 Research Contribution

It is expected that the prediction model would allow engineers in the industry to manipulate the physical properties of the concrete mixtures to get a specific compressive strength value. In the future, this research can be improved to include optimization capability. This model allows engineers to predict compressive strength of recycled concrete, which is usually random and unpredicted, and encourage the consumption of construction and demolition waste (C&D) which would improve the environment and economy. Also, it would reduce the effort of testing samples that include recycled aggregate. Although this does not totally eliminate important empirical testing, it will significantly reduce the number of tests. The predictive model permits engineers and material scientists to obtain an initial prediction of what the compressive strength values would be (under the numerous input parameters), especially when the testing is done for industrial purposes, not educational. Subsequent to this work, reversal-prediction model can be created to determine the replacement level of recycled concrete based on the value of slump.

1.6 Thesis Arrangement

Chapter 1 includes an introduction of recycled concrete aggregate and its effects on the environment and economy. In that same chapter, a brief overview of artificial intelligence neural networks and the issues regarding compressive strength of samples containing recycled aggregate were given. Moreover, the problem statement of the research was described along with the model creation and its benefits in resolving the issue. Chapter 2 is the literature review of this research, which includes explanation of the physical properties of concrete that were used as input parameters in the model, and it includes explanation of previously published prediction models and their differences with the created model for this research. Chapter 3 presents the methodology of creating the matrix dataset, the MATLAB function, and the model (including detailed explanation of the evaluation criterion). Chapter 4 describes the training results and the analysis of the results; it also has the evaluation of the model. The last Chapter is the conclusion of the research and possible future work.

CHAPTER II

LITERATURE REVIEW

In general, concrete mixtures that are prepared in laboratories include natural aggregate that can be coarse aggregate or fine aggregate, water, cement, and other chemical admixtures based on the requirements of the projects. The properties of concrete mixtures can affect the mechanical properties once tested. Those properties can be related to the ratio of the amounts being used in the mixture or its physical properties.

2.1 Physical Properties

This section will include the physical properties that are being studied in this research, and how it affects the compressive strength values. Each subsection will include one physical property, its definition, and how it affects mechanical properties of concrete. The physical properties that were considered in this research are natural aggregate water absorption, recycled aggregate water absorption, effective water-cement ratio, cement density, water density, natural aggregate size, recycled aggregate size, recycled and natural aggregate bulk densities, and the replacement level of natural aggregate by recycled aggregate.

2.1.1 Natural Aggregate Water Absorption Percentage

Water absorption of the aggregates can be defined as the aggregates' maximum capacity of water which the aggregate particles can absorb. Generally, water absorption correlates with the aggregates porosity which is defined by the ratio of the weight of the voids between the aggregate particles due to water saturation to the total volume; porosity can be calculated by equation 1 (Das and Sobhan 67-68).

$$\eta = \frac{V_v}{V} \qquad \text{equation (1)}$$

Where,	η	= Porosity
	V_v	= Volume of void
	V	= Total volume

Theoretically, normal aggregates vary in absorption level based on the type of the aggregate, fine aggregates have a lower absorption level when compared to coarse aggregate. According to testing specifications by *AASHTO T 84* and *AASHTO T 84*, the measured water absorption percentage for fine aggregate based on an experimental study of oven-dried aggregate that were soaked in water for 15 days varied between 0.3% and 3.4% (Tran et al. 32-40). According to the same specifications, coarse aggregate recorded higher water absorption levels which varied between 1.1% and 4.4% (Tran et al. 32-40). However, natural aggregate particles can record higher water absorption levels which explains the high porosity leading to durability issues.

Water absorption is a physical property of the aggregates and the value or the percentage of the water absorption is obtained in a qualified lab through a specific procedure. Usually, the moisture content is determined in a lab by measuring weights of the aggregates in three different states:

- Saturated surface dry (SSD): the weight of the particles in which the surface is dry, but the inner pores are filled with water
- Oven dry (OD): the weight of the particles after exposing them to a specific temperature until the particles are desiccated
- Wet surface: the weight in which the particles surface and pores are filled up and covered with water

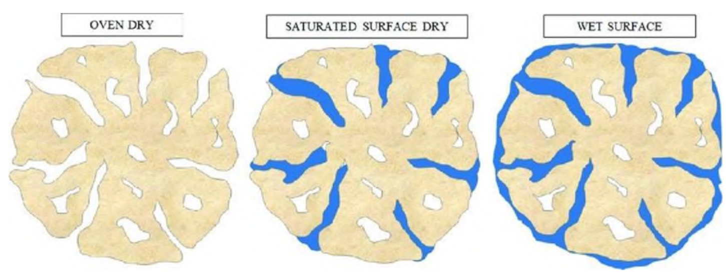

Figure 2: An Illustration of the Particles Three States of Weight (Hunce et al. C).

Even though three weights are recorded from the procedure above, two weights would be used for calculating water absorption level, which are oven dry (OD) and saturated surface dry (SSD). Wet surface is not used yet cannot be ignored because of a sequential purpose. Water absorption can be calculated by equation 2.

$$A = \frac{W_{SSD} - W_{OD}}{W_{OD}} * 100\% \qquad \text{equation (2)}$$

Where, A = Absorption level

W_{SSD} = Weight of saturated surface dry particles

W_{OD} = Weight of oven dry particles

Scholars have explained that water absorption level of natural aggregates does not directly affect the value of compressive strength in concrete. Nonetheless, they empirically are correlated. An experimental research by S. P. Zhang and L. Zong showed that water absorption level of aggregates only affects the cover of the concrete. The experiment manifests a lower compressive strength values of the concrete cover only when the water absorption level is high (Zhang and Zong 4).

2.1.2 Recycled Aggregate Water Absorption Percentage

Water absorption level does not differ in definition when compared between either natural or recycled aggregate, the process of determining the values remains the same experimentally and computationally. Although, what differs is the following: old aggregates recorded much higher values of water absorption levels and extreme capability of absorbing water (Şahin and Tarhan 996-999). Researchers discussed that time might be a factor in changing the aggregates capability of absorbing water. It is discussed that the following properties of the parent rocks plays a significant role as well:

- Rock type of parent rock.
- Aggregate size of parent rock; and
- Compressive strength of parent rock.

The qualities listed above significantly increases the porosity of the aggregates, which leads to higher water absorption levels in the recycled aggregates. It has been reported multiple times that water absorption percentage for recycled concrete aggregate is much higher than natural aggregate, and often, it is difficult to predict the increase amount before testing compared to the natural aggregate that rarely exceeds 1% water absorption level. Levels used in this research fluctuates between 0-7%, and some data points levels recorded as high as 14.9%. The higher water absorption levels in recycled aggregate lead to decreasing the compressive strength by unit area in concrete samples containing recycled aggregate. Table 2 shows different water absorption levels of recycled concrete aggregate RCA used in this research that were obtained by different researchers.

Table 2: Water Absorption Levels of RCA by Different Researchers

Water Absorption Level of RCA	Researcher
5.3	N. Fonseca a, J. de Brito a, L. Evangelista
7.5	Woubishet Zewdu Taffese
6.4	Job Thomas, Nassif Nazeer Thaickavil, P.M. Wilson
2.7	Chaocan Zheng, Cong Lou, Geng Du, Xiaozhen Li, Zhiwu Liu, Liqin Li
14.9	Chaocan Zheng, Cong Lou, Geng Du, Xiaozhen Li, Zhiwu Liu, Liqin Li

2.1.3 Effective Water-Cement Ratio

Effective water to cement ratio or as usually referred to as w/c ratio is the amount of water used in a specific concrete mix to the amount of cement used in the same mixture. This one single property affects multiple mechanical properties of the resulting concrete mixture, such as, compressive strength, tensile strength, and flexural strength. According to *Concrete Network*, effective water-cement ratio is calculated by dividing the weight of water used in a mixture in pounds by the cement weight in pounds as well, which results in a unitless ratio. For instance, if a w/c value is equal to 0.5, it means that for every 100 lbs. of cement used in the mixture, 50 lbs. of water is used to mix. According to *The Concrete Countertop Institute*, effective water to cement ratios range between 0.4-0.8 (The importance of water cement ratio, concretecountertop.com). While the lower ratios indicate higher strength and quality concrete, in some cases the ratio might be as low as 0.3. This requires the use of super-plasticizer which is a water content reducer admixture used in the cases where water in mixtures is relatively high compared to the amount of cement, "*Chemical Admixtures for Concrete ACI*". Effective water to cement ratios are inversely proportional to the compressive strength of the resulting concrete. For high w/c values the strength is low due to the diluted concrete paste containing high water levels. Other than that, high w/c values are quality reduction factor because it leads to shrinkage and cracking in the concrete. Effective w/c ratio is dependent on the weights of water and cement used to produce the mixture. Recycled aggregates have higher water absorption capacity than natural aggregate which would affect the w/c ratio, thus resulting in higher effective water-cement ratio for samples containing recycled aggregate. Table 3 shows the difference in the w/c ratios for different recycled concrete replacement levels. It also shows the consistency in the w/c ratios for similar mixtures that does not contain any replacement levels.

Table 3: Compressive Strength Values Compared to Replacement Level % and Water-Cement Ratio in Multiple Samples

Sample	Replacement Level %	Effective Water-Cement Ratio	Compressive Strength Mpa	Researcher
A1	0	0.4	34.8	Job Thomas, Nassif Nazeer Thaickavil, and P.M. Wilson
A2	0	0.4	41.2	Job Thomas, Nassif Nazeer Thaickavil, and P.M. Wilson
A3	0	0.4	52.8	Job Thomas, Nassif Nazeer Thaickavil, and P.M. Wilson
P18	50	0.52	35.4	Emilio Garcia Taengua, Vivian A Ulloa, Maria J. Pelufo, and Alberto Domingo
P19	100	0.5	31.4	Emilio Garcia Taengua, Vivian A Ulloa, Maria J. Pelufo, and Alberto Domingo
P20	20	0.42	48.5	Emilio Garcia Taengua, Vivian A Ulloa, Maria J. Pelufo, and Alberto Domingo

2.1.4 Cement Density

Cement is one major component in any concrete mixture, it can be imagined as the paste that coalesces the aggregates together fusing them into one structure. Cement itself consists of multiple components; it cannot be found from natural sources but needs different raw materials to be combined together. The components are chemically combined together through a process which generates cement as a substance; the components are but not limited to, limestone, shells, sand, clay, iron ore, silica sand, etc. Furthermore, those ingredients are chemically combined by the use of calcium, silicon, aluminum, iron, etc., and exposed to extreme heat temperatures after being crushed several times. The temperatures can reach 2,700 degrees Fahrenheit, then left to cool down, and finally, the resulting material is being grounded again to generate cement in the usual powdery form. It has been explained previously the relationship between compressive strength and effective water to cement ratio; also, cement as a chemical component in concrete mixtures can affect compressive strength levels. Cement contains lime (CaO) that affects the strength of concrete, the relationship has been proven to be proportional which means the higher the lime (CaO) in the cement, the lower the compressive strength of the resulting concrete (Thongsanitgarn et al.).

2.1.5 Water Density

Water is an indispensable component in making concrete mixtures as well. It is the component that helps change cement from the dry powder phase into the paste phase that holds the aggregate and mixture together. Nonetheless, water can lead to compaction and reduction in mechanical properties of concrete. Thus, excessive water levels increase the vacuum between the aggregate particles that would eventually evaporate when exposed to the surrounding environment. The gaps would fill up with air as a replacement for the evaporated water which would lead to reduction in the compressive strength of the concrete. Water density is an important component in generating concrete, and it is also an important factor in projects and as such should be controlled under project's criterion. A solution to reduce water content in existing and ready to use concrete mixtures is the use of super-plasticizer or moisture reducer admixtures. Also, it is important to consider the type of water used in concrete mixtures, previous research studies explained that concrete mixtures prepared with wastewater caused the reduction of compressive strength significantly when compared to other samples prepared with ground water (Doddagoudara et al.). Table 4 below shows the results of the experimental study and how the water source can reduce compressive strength, the samples were tested after 28-day curing age.

Table 4: Effect of Water Source on Compressive Strength (Doddagoudara et al.)

Type of Water	Compressive Strength (N/mm^2)
Sewage Water	18.75
	19.2
	18.75
Tap Water	25.92
	21.8
	23.98
Bore Water	27.4
	24.4
	25.28

2.1.6 Natural Aggregate Classifications

Natural aggregate is an essential ingredient in producing concrete mixtures that can be used in structural projects, infrastructure, highways pavement, etc. Natural aggregates can be classified in two different categories as the following:

- Classification of aggregates based on shape; and
- Classification of aggregates based on size.

Natural aggregates shapes vary from the defined shapes into the amorphous shapes. Figure 3 shows four different aggregate types classified based on shape.

Figure 3: Aggregate Categories Based on Shape

Rounded shaped aggregates is the first category based on shape; the spherical shape is naturally occurring due to erosion by running water, and this specific shape has the least surface area. Lower area means lower water absorption while preparing the concrete mixture, thus, higher compressive strength values. The second category is the irregular shaped aggregate. Although this type might have a relatively higher surface area, the irregularity in shape requires more cement in the mixture which sustains an acceptable effective water to cement ratio. The sharped edges of the aggregate increase the bond between the aggregates when the cement paste is formed. The angular shaped aggregate results from crushing or drilling large rocks; the shape characteristics of this type might be a cause of decreasing compressive strength of concrete due to the 40% increase between the aggregate particles which lead to increase in water absorption. The last category shape classification is flaky aggregates which has the least thickness; although, on the other hand, it has the highest surface area compared to the other types. This research study focuses on the size of the natural or crushed aggregate particles used in the dataset; classifying aggregates based on size subcategorizes into either fine aggregates or coarse aggregates. The process of defining a sample into one of the categories can be done by grading based on "*AASHTO T 27*" limitations; sieve analysis test can be done in geotechnical engineering lab. Based on the *American Association of State Highway and Transportation Officials AASHTO*, there are seven sieve sizes for fine aggregates that range from 150 μm to 9.5 mm, and thirteen other sieve sizes for coarse aggregates that range from 1.18 mm to 100 mm. Based on a research done by *Rozalija Kozul* and *David Darwin*, the increase in the aggregate size could decrease the mechanical properties of the concrete, especially flexural strength (Kozul et al.).

2.1.7 Recycled Aggregate Size

Recycled aggregate does not differ in size classification than the natural aggregate; same specifications by AASHTO applies on recycled aggregate as well. Usually, it depends on the size of the parent mixture aggregate; it is preferred to have recycled aggregate in the size of coarse aggregate. Therefore, after extracting the aggregate from demolished samples, it is crushed to have it in a specific size; Table 5 shows standard sieve sizes in the United States.

Table 5: Sieve Sizes

Sieve Number	Opening (mm)	Sieve Number	Opening (mm)
4	4.75	35	0.5
5	4	40	0.425
6	3.35	50	0.355
7	2.8	60	0.25
8	2.36	70	0.212
10	2	80	0.18
12	1.7	100	0.15
14	1.4	120	0.125
16	1.18	140	0.106
18	1	170	0.09
20	0.85	200	0.075
25	0.71	270	0.053
30	0.6		

2.1.8 Aggregate Bulk Density

The bulk density is different than relative density, which is referred to as specific gravity, bulk density is the mass of the concrete divided by the volume of a container that needs to be filled by aggregates, bulk density can be calculated by equation 3

$$\text{Bulk Density} = \frac{\text{Mass}}{\text{Volume}} \qquad \text{equation (3)}$$

Density of the overall concrete mixture which is correlated to the bulk density of the recycled or natural aggregate used in the same mixture can affect the resultant compressive strength of concrete. According to *American Association of State Highway and Transportation Officials, AASHTO*, there are three methods explained in section "*ASTM C 29 (AASHTO T 19)*" that are used in consolidating the aggregates while placed in the container to help calculate the bulk density.

2.1.9 Aggregate Replacement Level

Aggregate replacement level is the amount of natural aggregate replaced by recycled aggregate in concrete mixtures. Not necessarily true, but scholars think that the increase in replacement level of natural aggregate would decrease the compressive strength of concrete because of the high level of recycled concrete aggregate. Although, some data points used in this research that have been collected by multiple scholars worldwide showed some outlier, multiple samples that included a full replacement level equal to 100% of recycled aggregate sustained compressive strength values within an accepted range.

2.1.10 Slump

Slump is a test being performed after the concrete mixture is being prepared and prior to its direct use in projects. By definition, slump is a test used to determine the quality of concrete, by measuring the water in content in a specific batch of concrete. By doing so, it can be determined how moldable that concrete sample is (Tran et al. B-6). In general, a lower slump means a higher quality concrete; as discussed earlier, the increase in water in the mixture would reduce the mechanical properties of concrete by increasing the voids, especially compressive strength.

To perform a slump test, a metal cone with 8 inches diameter base and 4 inches diameter top is needed. The concrete is filled in the cone by a three-stage process; the first stage is to fill one-third of the cone by concrete then use a steel rod to stroke the cone 25 times to let the concrete settle. The second stage is repetitive of the first one until two-thirds of the cone is filled. The last stage is to fill up to the surface of the cone. Once the cone is removed, the distance between the top of the cone and the top of the concrete is measured, an acceptable slump value is within the range of four inches which means good workability for the concrete. Hypothetically, due to the high absorption of water in recycled concrete, the slump of recycled aggregate concrete is higher than the natural aggregate concrete which is a main factor of reducing compressive strength in recycled concrete (Nagaraja et al. 3).

2.2 Recycling Concrete Aggregates as an Alternative

A common method used to reduce Construction and Demolition waste (C&D) is recycling concrete aggregate and reusing it in different projects. Recycling concrete is defined by crushing concrete structures, removing steel or any unnecessary components using multiple methods such as electromagnets or screening. Furthermore, the concrete is then crushed into a smaller size, and usually recycled coarse aggregate is similar in mechanical properties to natural coarse aggregate which can be used in concrete or any other structure as a component. Ecological and economic benefits shall result from recycling concrete. In addition, the recycled concrete would not affect projects negatively. According to *Concrete Network*, it costs almost one hundred dollars per ton to transport the debris waste to landfills besides the cost of dumping the waste in landfills where it is no longer used or beneficial (Concrete Recycling vs. Disposal, concretenetwork.com). It increases the pollution levels of the lands and reduces their fecundity. Recycling construction waste guarantees an economical boost due to the reduction in the overall project cost. It also generates more employment levels that are needed in the recycling process, especially in the component's removal phase (Suitable Management of Construction and Demolition Material, epa.gov). Fundamental natural resources are being consumed as a result of producing natural aggregate. On the contrary, recycling aggregate would significantly reduce the consumption of natural resources. Recycling concrete can be beneficial in a comprehensive way, summarized in the following:

- Reduction in landfill and waste transfer costs
- Generating new jobs related to the waste management and sustainability field which would enhance the economy
- Decreasing levels of mining natural resources, and using existing ones that are not used
- Using the recycled materials as a component in multiple projects related to infrastructure, roadways and bridges or even structural premises.

2.3 Prediction by Artificial Intelligence

Recycling concrete starts from the phase of infrastructure demolition and crushing the waste by multiple methods defined by the country's regulations or the project's criteria. Methods of extracting the raw aggregates might differ but they all lead to the same purpose. Later, manufacturers work on using the recycled aggregates in a new concrete production with the focus on having adequate practical mechanical properties such as compressive strength. Compressive strength is one of the most important mechanical properties of concrete as it specifies the concrete capacity of resisting the external and internal applied forces. It is usually determined from 28-day old concrete cylindrical specimens that are crushed by a testing machine. Many scholars have explained that recycled aggregate could possibly lower the compressive strength of concrete based on the physical properties of the recycled aggregate and natural aggregate. This research focuses on how physical properties could affect the compressive strength of concrete using Artificial Intelligence. Obviously, this could reduce the empirical method of creating new concrete cylinders and experimentally testing possible values of compressive strength. When recycled aggregate are added to specific concrete mixture, the resulting compressive strength values would not be predicted because the replacement of natural aggregate by recycled aggregate can highly affect mechanical properties in general. The creation of model would help predict compressive strength values by including the physical properties of the aggregate and the mixture used as input parameters. In principle, if the predicted results are not within the expected range, the mixture proportions can be manipulated to achieve desired compressive strength values. Once the results given by the model satisfy the project compressive strength, the lab testing can then take place, thus, reducing the number of experimental tests needed. Neural Networks (NN) or Artificial Intelligence is a highly advanced technique that can help predict the compressive strength of concrete by the use of a programming model that connects input and output values (Kozma et al. 46).

Artificial Intelligence Neural Network can work as a pattern recognition or a prediction and forecasting indicator. Neural Network has been beneficial in project management by statistically predicting projects costs; by collecting the role factors that could affect the overall cost, deep learning can produce an outcome underscoring a possible overall cost. Other examples on the application of Neural Network in Engineering and Science are the following:

- According to Bo Li, neural Network has been used in 3D Printing Additive Manufacturing; it reduces the systematic errors that could possibly being produced or the glitches in the final outcome by predicting what the final shape could be and represent it in a CAD file (Li et al.).

- According to Albert T. Young, deep learning has a promising future in medicine; its efficiency has already been tested to declare accurate results in regards of diagnosing diseases by analyzing the entered symptoms or even translating patients' images in Dermatology to predict expected illness (Young et al.).
- According to Giada Arney, an astrobiologist at NASA, Artificial Intelligence has been beneficial in analyzing large data related to space science. Focusing on its ability to reduce the time and effort of manually computing and analyzing data; although, eliminating the option of replacing human brains by Artificial Intelligence (Giada Arney, NASA Applying AI Technologies to Problems in Space Science, nasa.gov)

The successful use of artificial intelligence in multiple industrial, medical, and science proves its efficiency in analyzing problems if used correctly.

2.4 Existing Prediction Models

This section of the research will present a few studies on the use of Artificial Intelligence Neural Network or Deep learning models to predict concrete compressive strength of concrete samples that contain recycled aggregate. The challenging aspects of this research topic include accurate determination and representation of the input parameters or the predictors of the compressive strength and selection of the proper prediction algorithm or function.

2.4.1 Model 1

A work on a similar topic was published on January 2000 which was "*Strength Characteristics of Recycled Aggregate Concrete by ANN*". The researchers aim was predicting compressive strength values of recycled concrete by using Deep Learning and compare their results with the obtained experimental test they performed initially on their collected samples. The prepared samples included cement of 53 grade, recycled aggregate of 53 grade, sand, and natural aggregate (Haripriya et al.). Their work did not report the values of the tested mechanical properties. It did not state or account for concrete mixture physical properties, or the total number of the tested samples.

The training progress of the programming software which indicates all of the information included in the used model is included in their research. The used training algorithm was Levenberg-Marquardt (trainlm) which is a built-in function in MATLAB. This algorithm uses the performance equation of Mean Squared Error (MSE). The number of epoch iterations was 66 iterations (Haripriya et al.). The researchers only used one input parameter which was replacement level of natural aggregate by recycled aggregate, one hidden layer, and one output which was compressive strength of the samples.

The regression fit of the validating, testing, and training data is also included in their research. According to the researchers, their model was assumed to be nonlinear due to the unclear relationship between the input and output parameters. The non-linear regression fit in the figure below basically plots the experimental data on the y-axis and the examined data on the x-axis which allows the research to determine an equation that describes the relationship between the experimental and predicted data .

This thesis research differs from the explained research above in many different aspects. First, the researchers indicated the components of their mixtures without including one important parameter which is water density. Water density itself controls other independent variables which are the effective water-cement ratio, the amount of cement to be added, and the necessity of adding chemical components such as concrete super-plasticizer. The thesis research would include all of the physical properties that are included in the concrete mixtures. Nonetheless, the addition of chemical components will be ignored because it would require lab testing which is not available in the thesis research. Those ignored variables control the resultant mechanical properties of the samples. Also, the number of the tested dataset was not included which makes it harder for the reader to judge on the success of the model. The thesis research will include a total of 201 datapoints that were collected based on a specific criterion that was discussed in previous sections in Chapter 2. The used algorithm in their research, which was Levenberg-Marquardt (trainlm), is as explained earlier a built-in function in MATLAB. This function is not efficient due to its speed of obtaining the highest convergence, and it can be seen in the training time included in their research, which was close to zero seconds. Also, it would reduce the square mean errors which would result in using the highest capacity of the weights and biases in the model. Thus, the pattern recognition of the data would not be accurate by the training algorithm. The model indicated also that the used input parameter was only the replacement level which was used as a predictor of the compressive strength. Irrespective of the type of the model (that is either as linear or non-linear), it would generate a linear best fit line to predict values closer to the actual experimental value. The thesis model would be built upon using many different independent variables that would be all considered as predictors of the compressive strength. Also, the training function would be coded in order to determine the randomness of the pattern between the data (if existed) and create the best fit of the data.

2.4.2 Model 2

This second model to discuss is a research work named *"Predicting strength of recycled aggregate concrete using Artificial Neural Network, Adaptive Neuro-Fuzzy Inference System and Multiple Linear Regression"*. The research paper discussed multiple methods used to predict compressive strength values of 257 different prepared samples (Khademi et al.). Both of the adaptive neuro-fuzzy inference system and the multiple linear regression are not to be discussed in this research, although, explanation of the artificial neural network will be provided. The 28-day compressive strength to be predicted was built on 14 different input parameters which were cement, natural fine aggregate, recycled fine aggregate, natural coarse aggregate 20 mm, natural coarse aggregate 10 mm, recycled coarse aggregate 20 mm, recycled coarse aggregate 10 mm, water, admixture, aggregate to cement ratio (A/C), water to cement ratio (W/C), sand to aggregate ratio (S/A), replacement ratio, and water to total material (W/T).

The physical properties or the independent variables are wider than what is included in this thesis research. Although, their training algorithm was Levenberg-Marquardt (trainlm) similar to the previous research (Khademi et al.). Concerns regarding Levenberg-Marquardt has been discussed previously, although, the researchers are not including their training progress window which would allow the reader to understand the performance of the model. The distribution of the datasets was 70% of the data for the training and 30% divided equally for validating and testing which is identical to the thesis research.

The neural network model of their model is included in their published research, and it indicates the number of the input parameters which was 14, the hidden layer, and the output layer. It also shows the number of the chosen nodes in the hidden layer, which was 29, this number is considered relatively high when compared to the number of nodes chosen for the model used in the thesis research.

Other publications might be found that studied the same issue of compressive strength prediction, the research done about this topic is not high, but most of the available work is similar in the work process. The difference in the thesis research is the use of a different prediction algorithm, which is Bayesian Regularization Backpropagation. It has not been used to predict the compressive strength alongside the Mean Squared Error function to reduce the error.

CHAPTER III

MODEL DEVELOPMENT

The preliminary stage in this research study was to collect data and create a data matrix to which the artificial intelligence neural network can be applied. First, in order to collect data from previous research work and experiments, their datasets must include variables that can serve as data fields in the dataset or the data matrix. As explained in the methodology section in chapter 1, the created data matrix needed to include ten different physical properties that were treated as the input parameters or the independent variables of the function. Chapter 2 included a literature overview of the physical properties of concrete in general, whether it included recycled aggregate or natural aggregate, and its relationship with compressive strength, and how it could possibly affect the resulting mechanical properties values.

The selection of physical properties was determined based on theoretical and experimental results explained in research papers that are used in this research. Although, properties that include the addition of chemical components or admixtures are ignored due to the relative purposes of primarily working on this research, which are maintaining a sustainable environment, recycling the existing construction and demolition wastes

(C&D), and consuming less. The following are the physical properties that are being used as independent variables:

- Replacement Level (%)
- Cement (Kg/m^3)
- Water (Kg/m^3)
- Effective Water to Cement Ratio (**w/c**)
- RCA Bulk Density (Kg/m^3)
- NA Bulk Density (Kg/m^3)
- RCA Aggregate Size
- NA Aggregate Size
- RCA Water Absorption (%)
- NA Water Absorption (%)

Using additional components would increase the cost of the concrete mixtures; therefore, the considered physical properties are the properties that highly affects compressive strength values. The physical properties are replacement level of natural aggregate by recycled aggregate and water-cement ratio. The other eight physical properties are being considered due to the fact that they would exist in a concrete mixture. For instance, for a water-cement ratio to exist in a concrete mixture, there should me some amount of water and cement to be used which creates water density and cement density. The same theory applies on recycled concrete aggregate bulk density, natural concrete aggregate bulk density, recycled concrete aggregate size, and natural concrete aggregate size. Water absorption is a very important parameter to be included when studying the effects of recycled aggregate on the mechanical properties of concrete. As explained in chapter 1, the main issue of recycled aggregate that it absorbs water in higher rate and capacity when compared to natural aggregate.

3.1 Evaluating Research Papers

A comprehensive review of published articles is the foundation of this research, in order to complete this theoretical thesis, a sufficient amount of data needed to be extracted. A total of 15 research papers of previous work have been used in this research; each of the fifteen papers was published and found from different sources. Each of the papers was evaluated on whether to be used or not in creating the dataset based on the following criteria:

- Must contain experimental work specifying number of specimens were used.
- The created samples must contain recycled aggregate concrete (RCA), and if any of the samples does not include recycled concrete aggregate (RCA), it should have been created for a comparison factor with (RCA) samples. This point would guarantee the direction and purpose of the used research papers is similar to this research. Many different papers have been found which included projects relating the subject of mechanical properties and compressive strength of concrete. Although, not all of them can be used, the targeted data must contain recycled aggregate as a component of the tested materials.
- Each research must include the ten physical properties that are used as input variables in this research and the dataset and the objective of this research are built on.

- It was preferred that published data are on engineering sources, if not, the publisher is identified as a person working for an engineering academic institution.
- Each of the research papers must show a recorded table of the mechanical properties results focusing on Compressive Strength. If a paper does not include compressive strength values for any of the tested samples, it may not be used. Other mechanical properties were recorded for future work related to this research, while this research focuses only on compressive strength. All of the fifteen papers included a sufficient amount and an initial purpose of either studying the mechanical properties of recycled concrete, or the effect of the physical properties on the resulting mechanical properties of the recycled concrete.
- Due to the possible change of compressive strength values between different curing time periods, the collected compressive strength values should have been tested at 28-day curing period.

Data analysis in this research is the process of reading through the published research papers by scholars to conduct data and parameters that were not summarized in conspicuous calculations tables. Also, it was important to indicate the parameters each researcher indicated while doing experimental work. As a result, a total of 10 variables were collected from each scientific paper as input variables which was included in the paper selection criteria, besides the mechanical properties that are being treated as an outcome, especially the compressive strength value for each data-point. Tables 6 and 7 below summarized the name of each research paper was used in this research, the name and occupation of the researchers, and a brief purpose of each research paper, the reference column includes the reference letters for the papers' names used in the dataset.

Table 6: Description of the First 8 Research Papers

Research Name	Researcher Name and Occupation	Research Purpose	Reference Letter
"The influence of curing conditions on the mechanical performance of concrete made with recycled concrete waste"	N. Fonseca and J. de Brito are faculty members at Instituto Superior Técnico. L. Evangelista is a faculty member at Instituto Superior de Engenharia de Lisboa	To study how mechanical properties of recycled aggregate would change under curing conditions	A
"Suitability Investigation of Recycled Concrete Aggregates for Concrete Production: An Experimental Case Study"	Woubishet Zewdu Taffese is a faculty member at Aalto University	To study the effects of recycled aggregate on the workability and performance under different replacement levels	B
"Strength and Durability of Concrete Containing Crushed Concrete Aggregates"	Job Thomas, Nassif Nazeer Thaickavil, and P.M. Wilson are faculty members in Cochin University of Science and Technology	To evaluate the possibility of replacing natural aggregate by recycled aggregate	C
"The influence of recycled concrete aggregate on the properties of concrete"	Nisreen Mohammed, Kaiss Sarsam, and Mazin Hussien are faculty members at University of Technology, Baghdad	To study the change in mechanical properties of recycled concrete aggregate under different replacement levels	D
"Mechanical properties of recycled concrete with demolished waste concrete aggregate and clay brick aggregate"	Chaocan Zheng, Cong Lou, Geng Du, Xiaozhen Li, Zhiwu Liu, Liqin Li are faculty members at College of Civil Engineering and Architecture, Jinhua Polytechnic	To investigate the effects replacing natural coarse aggregate with either recycled concrete aggregate or recycled clay brick aggregate on the compressive strengths of the hardened concrete	E
"Preparation and properties of high-strength recycled concrete in cold areas"	Y. Hai-tao is a faculty member at Harbin Institute of Technology. T. Shi-zhu is a faculty member at Suzhou University of Science and Technology	To prepare concrete with recycled aggregate with high strength for cold areas	F
"Recycled Aggregate Concrete as Structural Material"	M. Etxeberria, R. Marı´, and Va´zquez are faculty members at Universitat Politècnica de Catalunya	To study the possibility of using RCA as a structural material	G
"Influence of water-reducing admixtures on the mechanical performance of recycled concrete"	A. Barbudo is a faculty member at University of Cordoba. Jorge de Brito is a faculty member at University of Lisbon. Luis Evangelista is a faculty member at Instituto Politécnico de Lisboa. Miguel Bravo is a faculty member at Technical University of Lisbon	To determine the suitability of using two types of water-reducing admixtures to improve the characteristics of concrete made with recycled aggregates.	H

Table 7: Description of the Second 7 Research Papers

Research Name	Researcher Name and Occupation	Research Purpose	Reference Letter
"Short and long-term behavior of structural concrete with recycled concrete aggregate"	S. Manzi, C. Mazzotti, and M.C. Bignozzi are faculty members at Università di Bologna	To study the effects of fine and coarse recycled concrete aggregates on short and long-term mechanical and physical properties of concrete	I
"Influence of curing conditions on recycled aggregate concrete"	Carlos Thomas, Jesús Setién, and Ana Cimentada are faculty members at Universidad de Cantabria. César Medina Martínez is a faculty member at Universidad de Extremadura. J.A. Polanco is a faculty member at Instituto Superior Politécnico	To study the influence of permeability on durability of recycled concrete exposed to an aggressive environment.	J
"Mix Design and Properties of Recycled Aggregate Concretes: Applicability of Eurocode 2"	George Wardeh, Elhem Ghorbel, and Hector Gomart are faculty members at Université de Cergy-Pontoise	To study of fresh and hardened properties of concrete containing recycled gravel	K
"Properties of recycled aggregate concrete made with recycled aggregates with different amounts of old adhered mortars"	Zhenhua Duan is a faculty member at at Tongji University. Chi Sun Poon is a faculty member at The Hong Kong Polytechnic University	To compare the difference in properties of recycled aggregates (RA) with varying amounts of old adhered mortar on mechanical properties of recycled concrete	L
"Influence of silica fume on mechanical and physical properties of recycled aggregate concrete"	Özgür Çakır and Ömer Özkan Sofyanlı are faculty members at Yıldız Technical University	To study the effects of silica fume (SF) in the concrete mix design on the quality of recycled aggregates in concrete	M
"Bond of Reinforcement in Concrete Incorporating Recycled Concrete Aggregates"	Liam J Butler is a faculty member at York University. Susan Tighe and Jeffrey S. are faculty members at University of Waterloo	To study the bond of reinforcement in concrete produced using RCA as coarse aggregate.	N
"New Views on Effect of Recycled Aggregates on Concrete Compressive Strength"	Emilio Garcia Taengua is a faculty member at University of Leeds. Vivian A Ulloa is a faculty member at Pontificia Universidad Javeriana. Maria J. Pelufo and Alberto Domingo are faculty members at Universitat Politècnica de València	To study the composition and properties of recycled coarse aggregates from previous concrete structure and w/c ratio on compressive strength	O

3.2 Research Papers Analysis

The first paper to be analyzed and data extracted was "*The influence of curing conditions on the mechanical performance of concrete made with recycled concrete waste*". The aim of this research was to conduct how different curing conditions and temperatures of concrete samples that contain recycled aggregate at different replacement levels would affect the mechanical properties of the prepared concrete samples. The samples were prepared and kept in a humid atmosphere and non-standard temperatures corresponding to the season being prepared in. After that, it was tested for different mechanical properties including compressive strength and tensile strength at 3 different curing periods, although, the extracted data was the data tested at 28-day period (Fonseca et al.). The extracted data can be summarized as the following:

- Four data points were extracted from this research.
- Three samples included recycled concrete aggregate (RCA) at three different replacement levels there were increased gradually as 20% replacement level, 50% replacement level, and 100% replacement level. The fourth sample did not include recycled aggregate and was prepared for a comparison purpose to study the difference in the mechanical properties when compared to samples that include recycled concrete aggregate (RCA).
- All of the four samples mixtures were maintained to have the same water-cement ratio that was equal to 0.43 and cement density that was equal to 446 (Kg/m^3). Water density was increased when increasing the replacement levels, and it ranged between 191.6 (Kg/m^3) and 198.7 (Kg/m^3).

- Recycled concrete aggregate bulk density was fixed for samples that included replacement levels which was equal to 2310 (Kg/m^3). Recycled concrete aggregate size was also fixed for samples that included replacement levels.
- Natural aggregate bulk densities were equal to 2510 (Kg/m^3) in the three different samples that included natural aggregate, and the used natural aggregates had the same size.
- Recycled concrete aggregate had higher absorption levels than natural aggregate.
- Compressive strength recorded its highest value for the sample that did not include any replacement levels, and it started to reduce gradually while adding and increasing replacement levels.

The second paper was "*Suitability Investigation of Recycled Concrete Aggregates for Concrete Production: An Experimental Case Study*". The paper's aim was investigating the productivity of recycled aggregate used in concrete samples; focusing on the possibility of recycling construction and demolition waste (C&D) into new concrete that can be used to maintain the sustainability of construction in the country (Taffese). The used prepared samples included different concrete mixtures and all of them were tested for compressive strength at a 28-days period. The research paper can be summarized as the following:

- A total of five points were extracted from this research. Two samples had 0% replacement level, another two samples had 10% replacement level, and the last sample had a 20% replacement level.

- Two different w/c ratios were used for the 5 different samples which were equal to 0.61 in three samples which were categorized in one group, and the other two samples had a ratio of 0.55 and they were in a different group.
- The first group of the three samples had a cement density of 296.72 (Kg/m^3) and water density of 230.51 (Kg/m^3). The second group had a cement density of 329.1 (Kg/m^3) and water density of 212.67 (Kg/m^3).
- Bulk density of natural aggregate in concrete samples that included natural aggregate was equal to 2700 (Kg/m^3), while in recycled aggregate samples was equal to 2170 (Kg/m^3) excluding the samples with 0% replacement level.
- Aggregate size was similar for both types and equal to 38 in either.
- Recycled aggregate absorption levels were higher than the natural aggregate as anticipated.
- Compressive strength values were the highest for the two samples with a 0% replacement level, and it was higher in the concrete sample that included a lower water density.
- The results prove that increasing the replacement level and water density would reduce the values of mechanical properties of concrete.

The third paper was *"Strength and Durability of Concrete Containing Crushed Concrete Aggregates"*. This purpose of this research was to study the effects of replacing natural aggregate by crushed recycled concrete aggregate of the same size and analyze the data by regression analysis to understand the effects of aggregate replacement on the mechanical properties of concrete (Thomas et al.). The research study can be summarized as the following:

- A total of 36 datapoints were extracted from this research, the data were divided into three different groups, each group included 12 different points.
- The samples in the first group were subdivided based on replacement levels; 3 samples with 0% replacement level. 3 samples with 25% replacement level, 3 samples with 50% replacement level, and the last 3 samples with 100% replacement level. Water-cement ratio was the same for the 12 samples and equal to 0.4, the cement density was increased on a 50 (Kg/m^3) increments where the densities ranged between 300(Kg/m^3) and 450 (Kg/m^3). Water density started at 120 (Kg/m^3) and increased to reach 180 (Kg/m^3). Recycled concrete (RCA) and natural aggregate bulk densities were fixed for all of the samples in this group and equal to 2340 (Kg/m^3) and 2720 (Kg/m^3) respectively.
- Group number two had another 12 samples that were subdivided based on replacement levels also: 3 samples with 0% replacement level. 3 samples with 25% replacement level, 3 samples with 50% replacement level, and the last 3 samples with 100% replacement level. Water-cement ratio was equal to 0.45 in the twelve different samples, the cement density was increased on a 50 (Kg/m^3) were the densities ranged between 300 (Kg/m^3) and 450 (Kg/m^3). Water density ranged between 135 and 202.5 (Kg/m^3). Recycled concrete (RCA) and natural aggregate bulk densities were similar to the first group.
- The third group also had 12 different samples that were subdivided similarly to the first and second groups. The w/c ratio for the twelve samples in this group was equal to 0.5. The cement density did not change from the first two groups, although, water density had a range of 175-225 (Kg/m^3).

- Compressive strength values varied based on the replacement levels, water-cement ratio, and water and cement densities.

Paper number four was *"The influence of recycled concrete aggregate on the properties of concrete"* which aimed to study the physical and mechanical properties of recycled concrete containing recycled coarse aggregate from previous projects (Mohammed et al.). It can be summarized as the following:

- The total datapoints that had been extracted were six points.
- The six samples were divided into two groups based on w/c ratio.
- The first group with three samples had a 0.46 w/c ratio while the second group had a 0.28 w/c ratio.
- The cement density and water densities were equal to 400 (Kg/m^3) and 185 (Kg/m^3) respectively for the first group, while they were equal to 450 (Kg/m^3) and 126 (Kg/m^3) for the second group.
- Recycled aggregate and natural aggregate bulk densities and particle sizes were fixed for all of the prepared mixtures.
- Increasing the replacement level of archaic aggregates would reduce the compressive strength values, nonetheless, the reduction is not accounted for.
- Increasing the cement and water densities by increasing amounts instead of reducing a component against the other, would significantly increase the compressive strength values in a comparable view with other samples with similar replacement levels.

Paper number five was *"Mechanical properties of recycled concrete with demolished waste concrete aggregate and clay brick aggregate"* which had a similar aim of previously listed research papers by many other scholars which evaluated the internal effect of the physical properties on mechanical properties. In addition, the researcher was not only using recycled concrete aggregate (RCA), but recycled brick aggregate was also used in the samples to test its effect on the final strength of concrete (Zheng et al.). The research can be summarized as the following:

- Twenty different datapoints were used from this research.
- The samples were divided into four groups based on physical properties of the concrete mixtures with five samples in each.
- The samples in each group had different replacement levels including 0%, 25%, 50%, 75%, and 100% replacement level.
- Group 1 and group 3 had a water-cement ratio of 0.55, cement and water densities of 437 (Kg/m^3) and 244 (Kg/m^3) respectively. The recycled aggregate had a bulk density equal to 2214 (Kg/m^3), and the bulk density of the natural aggregate was equal to 2687 (Kg/m^3).
- Group 2 and 4 had a water-cement ratio of 0.35, cement and water densities of 528 (Kg/m^3) and 185 (Kg/m^3) respectively. The recycled aggregate and natural aggregate bulk densities were similar to groups 1 and 2.
- The particles sizes were fixed for all of the samples in either of recycled aggregate type or the natural aggregate type.
- The compressive strength was recorded based on 28-day curing period.

Paper number six was *"Preparation and properties of high-strength recycled concrete in cold areas"* which aimed to introduce recycled concrete with high mechanical properties produced to withstand atmospheric conditions in cold areas (Haitao and Shizhu). The following points are a summary of the research paper:

- 20 datapoints were extracted from this research. The samples were divided into 4 groups, each group had 5 different samples based on various replacement revels starting from 0% and ending in 100% replacement level.
- All of the 20 concrete mixtures included water density equal to 195 (Kg/m^3).
- Recycled concrete aggregate and natural aggregate bulk densities were fixed in all samples and equal to 2492 (Kg/m^3) and 2780 (Kg/m^3) respectively. As well as the aggregates sizes were similar in the twenty samples.
- Samples in the first group had the following physical properties: w/c ratio was equal to 0.3, cement density was equal to 650 (Kg/m^3).
- Samples in the second group had the following physical properties: w/c ratio was equal to 0.35, cement density was equal to 557 (Kg/m^3).
- Samples in the third group had the following physical properties: w/c ratio was equal to 0.4, cement density was equal to 488 (Kg/m^3).
- Samples in the fourth group had the following physical properties: w/c ratio was equal to 0.45, cement density was equal to 433 (Kg/m^3).
- Groups with lower water-cement ratios recorded higher compressive strength values than groups with higher ratios.

The seventh paper was *"Recycled aggregate concrete as structural material"* where the scholar's purpose was studying the effect of recycled aggregate used with structural beams and its effect on shear and compressive strength. As expected, the eight extracted data points results are as explained in the second chapter, i.e., literature review. The eight data points with different replacement levels ranged in compressive strength values with the highest recorded value for samples excluded recycled aggregate in their mixture; the values decreased when recycled aggregate used or increased (Etxeberria et al.). The following points are a summary of the physical properties of the concrete samples included in this research:

- The first two samples had the following physical properties: 100% replacement level, 0.5 w/c ratio, 325 (Kg/m^3) cement density, and 162 (Kg/m^3) water density.
- The second two samples had the following physical properties: 50% replacement level, 0.52 w/c ratio, 318 (Kg/m^3) cement density, and 165 (Kg/m^3) water density.
- Another two samples had the following physical properties: 25% replacement level, 0.55 w/c ratio, 300 (Kg/m^3) cement density, and 165 (Kg/m^3) water density.
- The last two samples had the following physical properties: 0% replacement level, 0.55 w/c ratio, 300 (Kg/m^3) cement density, and 165 (Kg/m^3) water density.
- Recycled concrete aggregate and natural aggregate had bulk densities of 2430 (Kg/m^3) and 2670 (Kg/m^3) respectively.

Twelve data points were used from the eighth paper, *"Influence of water-reducing admixtures on the mechanical performance of recycled concrete"*. This research focused on using two types of water-reducing admixtures to improve the physical and mechanical properties of concrete made with recycled aggregates (Barbudo et al.). The pivot points of this research are the following:

- The twelve different concrete samples were divided into 3 different groups.

- The cement density of the 12 samples was equal to 350 (Kg/m^3).
- The recycled concrete aggregate and natural aggregate bulk densities were equal to 2451 (Kg/m^3) and 2581 (Kg/m^3) respectively.
- The water-cement ratios were as the following: 0.4 in the first group, 0.45 in the second group, and 0.54 in the last group.
- The water density differed between the groups as the following: equal to 140 (Kg/m^3) in the first group, 157.5 (Kg/m^3) in the second group, and 189 (Kg/m^3) in the third group.

The ninth paper to have read and analyzed is "*Short and long-term behavior of structural concrete with recycled concrete aggregate*". The researchers tried to analyze the effects of both recycled concrete aggregate and natural aggregate on multiple mechanical properties of the concrete including its strength (Manzi et al.). The research paper can be summarized as the following:

- Five different points were used from this research.
- The replacement levels varied and included irregular values such as 63.5% and 36.5%.
- All of the other physical properties were fixed in the five different samples and can be listed as the following: w/c equal to 0.48, cement density equal to 350 (Kg/m^3), water density equal to 168 (Kg/m^3), recycled aggregate bulk density equal to 2250 (Kg/m^3), and natural aggregate bulk density equal to2570 (Kg/m^3).

Paper number ten to have analyzed and data extracted was "*Influence of curing conditions on recycled aggregate concrete*". The objective of this research work is studying the effects of permeability on the recycled concrete compressive and tensile strengths; the data was beneficial due to the profuse of samples being tested (Thomas et al.). A total of 24 specimen samples were tested in which each of the samples included different physical properties resulting from changing the mixture ingredients ratio, as well as the heterogeneity of the replacement levels of the recycled aggregates in each sample. Replacement levels varied from zero, which means using a complete natural or crushed aggregate, to a hundred percent, which is the ultimate capacity of the use of recycled aggregate in that mixture. Also, the researchers (Thomas et al.) have listed the mixture proportions in regards of natural and recycled aggregate bulk densities (Kg/m^3), as well as the size of aggregates that have been used, and the water absorption levels for both of the natural aggregate concrete samples and the recycled concrete aggregates. The 24 datapoints were all considered in this research due to the matching research criteria as the following:

- Compressive strength values decreased gradually with increasing replacement levels of the natural aggregates.
- Samples with natural aggregates recorded highest mechanical properties values.
- Effective water-cement, which will be shown in later sections how to have had it calculated, ratio has affected the compressive strength values alongside the other physical properties of the aggregate.
- Bulk densities of either natural or recycled aggregate were fixed and similar in samples containing them showing that their effect on outcomes is negligible; natural aggregate bulk density was equal to 2540 (Kg/m^3), and 2320 (Kg/m^3) for recycled aggregate samples.

Paper number eleven was "*Mix Design and Properties of Recycled Aggregate Concretes: Applicability of Eurocode 2*". This research work focused on studying the fresh and hardened properties of concrete containing recycled gravel and how it reflects on the strength of concrete (Wardeh et al.). The research work can be summarized as the following:

- Four different datapoints were used from this research
- The replacement levels were 0%, 30%, 65%, and 100%.
- Water-cement ratios were equal to 0.5, 0.5, 0.42, and 0.4, while the water density was equal to 180 (Kg/m^3).
- Cement densities in the four samples were 360 (Kg/m^3), 360 (Kg/m^3), 427(Kg/m^3), and 448 (Kg/m^3).
- Recycled concrete aggregate (RCA) and natural aggregate bulk densities were equal in the four samples and were equal to 2240 (Kg/m^3) and 2510 (Kg/m^3) respectively.

The twelfth paper was "*Properties of recycled aggregate concrete made with recycled aggregates with different amounts of old adhered mortars*" which studied the difference in properties of recycled aggregates (RAs) with varying amounts of old adhered, and the influence of the different RAs on the mechanical and properties of recycled concrete (Duan and Poon). The paper can be summarized as the following:

- 16 datapoints were extracted from this research work. The samples were divided into four different groups including four samples in each group.
- Each group had two different replacement levels which were 0% for one sample and 100% for the other three samples in the same group.

- Water-cement ratios were different from one group to the other; w/c ratio was equal to 0.34 in the first group, 0.44 in the second group, 0.51 in the third group, and 0.68 in the last group.
- Cement densities differed also as the following: it was equal to 485 (Kg/m^3) in the first group, 425 (Kg/m^3) in the second group, 350 (Kg/m^3) in the third group, and 300 (Kg/m^3) in the last group.
- Different amounts of water were used in the four groups which resulted in a water density difference as the following: 165 (Kg/m^3) used in the first group, 185 (Kg/m^3) in the second group, 180 (Kg/m^3) in the third group, and 205 (Kg/m^3) in the last group.
- Natural aggregate bulk density was equal to 2600 (Kg/m^3) in the samples that did not include any recycled aggregate, while three different recycled aggregate bulk densities were used in each group, and they were equal to 2450 (Kg/m^3), 2370 (Kg/m^3), and 2360 (Kg/m^3).

Paper number thirteen was "*Influence of silica fume on mechanical and physical properties of recycled aggregate concrete*". The researchers aimed to study the effects of Silica fume on the recycled aggregate used in concrete samples and its effect on the strength of the concrete (Çakır and Sofyanlı). The paper can be summarized as the following:

- Four datapoints were used from this research.
- Replacement levels were as the following: 0%, 50%, 50%, and 100%.
- Water-cement ratio was fixed in all of the samples and equal to 0.5.

- Cement and water densities were also fixed in all of the samples and equal to 380 (Kg/m^3) and 190 (Kg/m^3) respectively.
- Recycled aggregate and natural aggregate bulk densities were also similar in all of the samples and equal to 2380 (Kg/m^3) and 2670 (Kg/m^3) respectively.

Paper number fourteen was "*Bond of Reinforcement in Concrete Incorporating Recycled Concrete Aggregates*". In this research, the engineers tried to study the bonds of reinforcement in concrete samples produced by using recycled concrete aggregate. The study included both of the replacement level of the natural aggregate by recycled aggregate and the mechanical properties testing of the resulting concrete samples which were necessary to be considered in this research (Butler et al.). The research can be summarized as the following:

- 12 different data points were extracted and used in this research.
- Two different replacement levels were used in the concrete mixtures. The first replacement level was equal to 0% and it was used in four different samples, the second replacement level was equal to 100% and it was used in the eight different concrete mixtures.
- The water-cement ratio in the samples differed between one sample and the other where no mixtures matched in their ratios. The ratios ranged between 0.3 and 0.64. The difference in water-cement ratio is a result of not using similar amounts of water and cement, cement density ranged between 262 (Kg/m^3) and 600 (Kg/m^3). While water density ranged between 160 (Kg/m^3) and 190 (Kg/m^3).

- Recycled aggregate bulk density ranged between 2380 (Kg/m^3) and 2480 (Kg/m^3), while natural aggregate bulk density was fixed for all of the samples and was equal to 2710 (Kg/m^3).

Paper number fifteen, which was the last paper to be analyzed, was "*New Views on Effect of Recycled Aggregates on Concrete Compressive Strength*" which aimed to study the effect of the recycled aggregate composition that was used in concrete mixtures on the mechanical properties and strength of the resulting concrete samples (Ulloa et al.). The paper can be summarized as the following:

- 25 datapoints were extracted and used from this research.
- Three different replacement levels were used in the 25 different samples, and they were equal to 20%, 50%, and 100% replacement level.
- Water-cement ratios ranged between 0.4 and 0.61, and water density ranged between 152 (Kg/m^3) and 235.6 (Kg/m^3).
- The used cement amount was fixed in all of the samples and was equal to 380 (Kg/m^3).
- Recycled concrete aggregate bulk density did not change in all of the samples and was equal to 2350 (Kg/m^3), and the same applies on natural aggregate bulk density that was equal to 2590 (Kg/m^3).

3.3 Data Extraction Using Microsoft Excel

All of the data that have been selected to be used from the papers in the previous section 3.1 where extracted and added to a data matrix on Microsoft Excel, the created dataset can be found in APPENDIX C. The table was labelled in proper names that the programming software would easily understand in order to avoid any possible errors while moving forward to different steps of this research.

Calculating data is the third process of creating the data matrix; some of the published papers did not include the effective water to cement ratio listed with the numbers for each of the samples. The total number of the collected data points is 201 points, and in order to consider the effective water to cement ratio an effective parameter that could possibly affect the resulting outcome, each of the data points must include an individual value of the w/c ratio. The effective water to cement ratio is unit less and can be calculated by dividing the density of the concrete used in one specific mixture for one sample by the density of the water used in that sample as shown in equation 4.

$$\frac{w}{c} = \frac{Cement\ Density}{Water\ Density} \qquad \text{equation (4)}$$

Table 8 shows different calculated effective water to cement ratios for multiple concrete samples from different papers:

Table 8: Calculated Effective Water to Cement Ratios

Mix. Designation	Cement (Kg/m3)	Water (Kg/m3)	Effective w/c Ratio
RC-XS3-SR-1	385	173	0.42
Ref-II	329.1	212.67	0.55
RC-20	329.1	212.67	0.55
A1	300	120	0.4
70N.C	450	126	0.28
RCA2-00	528	185	0.35
RCA2-25	528	185	0.35
RCA2-50	528	185	0.35
RCA2-75	528	185	0.35
RCA2-100	528	185	0.35
H$S1	650	195	0.3
C30RA2	300	205	0.68
C30RA3	300	205	0.68
CS1	380	190	0.5
P1	380	159.6	0.42

3.4 MATLAB

MATLAB is one accessible coding software to be used regarding generating or even using a built-in code or an algorithm to generate a specific fitting linear or non-linear function between dependent variables and one or more independent variables.

To get started with MATLAB, and as a first step, the data matrix that was created previously on Microsoft Excel needed to be exported to MATLAB. The software offers two or more methods to do so, the first one is by converting the Microsoft Excel file into a text file and transfer it to MATLAB which is a convoluted method in this research. To save time, effort, and any unexpected issues resulting from transferring the file from one format to the other, the Microsoft Excel was transferred in the same format it was created. Although, a brief procedure had been done before transferring the data matrix, in which the data matrix was divided into two files labeled with 'Features' and 'Labels'. The Features file which includes all of the collected data concerning the 201 data points in a matrix format. The second file is named Labels, which includes the compressive strength values or the targeted values. MATLAB is a programming software that functions in an array format which means the inserted data should be in two-dimensions, including matrices.

3.5 MATLAB Function and Model

As explained previously, MATLAB offers multiple built-in functions that can be used to predict an output value for a certain range of inputs. Although, the selection of a model was more complex and needed the coding of new function that is not built-in in MATLAB. If the correlation between the variables was to be determined by Microsoft Excel, or any other software that offers a linear regression tool, the results might show a need of deleting one or more of the variables. Table 9 below is part of the results of a multiple regression test performed on Microsoft Excel. The table includes the coefficients and P-value results of each of the included independent variables or input parameters in the data matrix. The P-value of the effective water-cement ratio is 0.016, and when compared to other physical properties, the value indicates that other independent variables are better predictors in the indicated model. Many researchers explained in experimental and theoretical research work that water-cement ratio has the effect on compressive strength. In other words, and based on the coefficient result of the effective water-cement ratio, which is 52.446, if the w/c ratio is to be increased, the compressive strength would increase which is the opposite of what previous research works included. It was assumed in this work that the 201 datapoints are not sufficient to examine whether the relationship between compressive strength and physical properties is linear or not.

Table 9: Part of the Regression Analysis Results

	Coefficients	P-value
Replacement Level %	-0.118	0.028
Effective w/c Ratio	52.446	0.016
Cement (Kg/m^3)	0.157	2E-10
Water (Kg/m^3)	-0.360	4.1E-10
RCA Bulk Density (Kg/m^3)	0.002	0.408
NA Bulk Density (Kg/m^3)	-0.011	5.3E-09
RCA Aggregate Size	0.050	0.771
NA Aggregate Size	0.476	0.002
RCA Water Absorption %	-0.511	0.083
NA Water Absorption %	12.448	3.2E-10

As a result, Bayesian Regularization Backpropagation function was chosen, which would treat the relationship between input and output parameters as non-linear (Yang et al.). The details of the MATLAB function are given in APPENDIX A. The prediction of any subject using artificial intelligence is a challenging task when it comes to choosing the correct function, the selection must be built on logical reasons. The Bayesian nonlinear model was adopted because it diminishes the arrangement of squared errors and weights then it generates a new arrangement of the data, which is called generalization. Generalization can be defined by the task performed by the function to understand and create a specific pattern of the listed data so the loss of the training data, which is the error, decreases while more data is processed. If the error does not decrease during training, the model needs to be modified or changed.

The training of the non-linear model is accomplished by an approach known as Bayesian regularization. Bayesian regularization-based artificial neural networks (BRANNs) are stronger and more efficient than normal backpropagation networks, especially when the relationship between the data is non-linear or unspecified (random). It can minimize or omit the need of extensive cross-validation by changing the non-linear regression into a "well-posed" mathematical problem in the method of ridge regression. Also, Bayesian regularization are considered to have a lower chance of over fitting because they compute and train on an effective number of parameters or weights, efficiently turning off the neurons which are not relevant or do not contribute towards network performance (Yang et al.) and (Wagner et al.). Therefore, adopting Bayesian Regularization Backpropagation model for this research problem is an ideal selection due to the limited number of input parameters which can be reduced if another approach was to be used. The Bayes' rule in the neural network can be expressed by equation 5 (Hagan).

$$P(x|D,\alpha,\beta,M) = \frac{P(D|x,\beta,M)P(x|\alpha,M)}{P(D|\alpha,\beta,M)} \quad \text{equation (5)}$$

Where, x = The vector containing the weights and biases

D = The training dataset

α, β = Regularization parameters

M = Model selected

$P(D|x,\beta,M)P(x|\alpha,M)$ = Density functions

The density functions can be expressed also with equations 6 and 7 (Hagan).

$$P(D|x, \beta, M) = \frac{1}{Z_D(\beta)} \exp(-\beta E_D)$$ equation (6)

Where, β $= \frac{1}{(2\sigma_\varepsilon)^2}$

E_D = The sum squared error of the training dataset

Z_D $= \left(\frac{\pi}{\beta}\right)^{\frac{N}{2}}$

And,

$$P(x|\alpha, M) = \frac{1}{Z_w(\beta)} \exp(-\alpha E_w)$$ equation (7)

Where, α $= \frac{1}{(2\sigma_w)^2}$

E_W = The sum squared error of the network weights

Z_w $= \left(\frac{\pi}{\alpha}\right)^{\frac{n}{2}}$

One further step was still needed in the process of creating a model after the function was determined. A model on MATLAB requires the selection of a specific number of hidden layers. The complication of the system remains in its hidden layer. Researchers and neuroscientists feature the hidden layer or the hidden nodes layer as neurons that matches in function to analyze the input layer and connect the inputs by calculating the weights and biases of the input and convert it to an output. There are no lucid methods to pick a specific number of hidden layers, yet it is said to be determined by practice,

APPENDIX B includes the MATLAB model. The number of hidden layers cannot be determined without experimental testing resulting in accurate results. It is irresolute to specify the number of the nodes to be used due to the reason that hidden layers number cannot be determined. Nonetheless, scholars have defined ways of specifying the size of layers and number of nodes relating to the size of the matrix dataset of the linearity of the relationship between the inputs, but there has not been any consensus by researchers on the criterion above (Sheela and Deepa).

A selection of one hidden layer was made where a weight value is attached to each of the input parameters. The single hidden layer is used to prevent the model from over fitting. As there are only 10 inputs to the model that means there are very limited neurons available in the input layer. The selection of multiple layers would result in an over fitted model which will lead to a bad performance by the model (Roelofs et al.). The similar conditions apply in choosing the number of the nodes in the hidden layer; therefore, twelve nodes were selected. According to Roelofs et al., the number of nodes should be close to the number of input parameters.

Figure 4 is an illustration of what the nonlinear model looks like, including only one hidden layer and 12 neurons in that layer. As a brief recap, the red circles in the input layer in the illustration above represent the ten input parameters or dependent variables (X_i); mathematically, the input parameters are connected to the hidden layer via activation nodes that generate each a numerical value called weight or (W_{ij}). Since the model contains 10 input parameters and 12 other nodes.

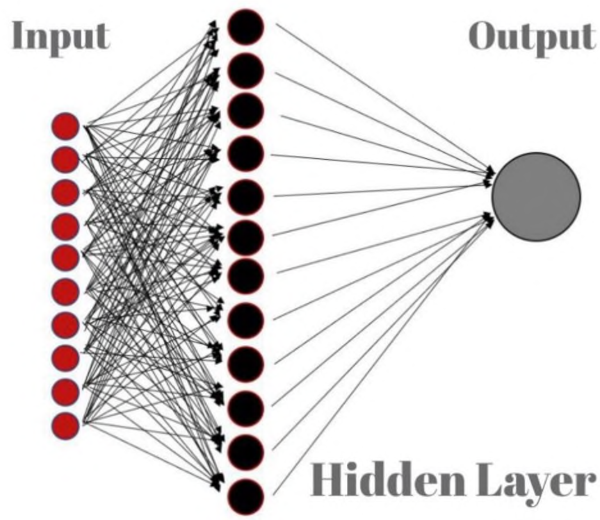

Figure 4: An Illustration of the Neural Network

Twelve other expected weights {W1…W12} are resulting from connecting the hidden layer's nodes to the output which is compressive strength. Another constant value is added to each node connected to the hidden layer called bias or (b_i). Bias constant theoretically stores the value of 1 or any other resulting value, and this value helps in interpreting the activation function in different locations of the neural network. In this research, twelve biases are expected from the neurons or nodes connected to the hidden layer, and one more bias value is expected to be connected to the output value, resulting in 13 possible constant biases {b1…b13}.

The criteria to determine if the model has been trained successfully are the following:

- The testing loss and the training loss, which are the declines of the errors, reduces in a similar pattern.
- Either of the testing loss or training loss lines need to go through the "best performance" line specified by the plot on MATLAB

CHAPTER IV

RESULTS AND ANALYSIS

Previous chapters indicated the nature and background of Artificial Intelligence Neural Network and history of its appearance until its recent widespread use in solving multiple real-life problems. Also, the first and second chapters indicated what could possibly affect the final resulting mechanical properties values in general or the compressive strength value specifically. Chapter 3 indicated the matrix dataset creation process and how it had been transferred to MATLAB in an array format in two discrete MATLAB files. In the previous chapter also, the reasons for choosing Bayesian Regularization Backpropagation Nonlinear model were discussed, and how it was written in a function format using multiple different equations so MATLAB can easily understand it. This chapter would discuss the training results and further analysis.

4.1 Training Results

The proposed model included 10 inputs which are different properties used to predict the compressive strength. The inputs are replacement level of natural aggregate by recycled aggregate, effective water-cement ratio, cement density, water density, recycled concrete aggregate bulk density, natural aggregate bulk density, recycled concrete aggregate size, natural aggregate size, recycled concrete aggregate water absorption, and natural aggregate water absorption.

The final stage of working on the MATLAB programming software is training the model and collecting the final results. Figure 5 shows an actual representation of the neural network Bayesian model which consists of the input layer that included the ten different input parameters. It also shows the hidden layer that consists of the twelve hidden nodes which connect the input layer to the output layer.

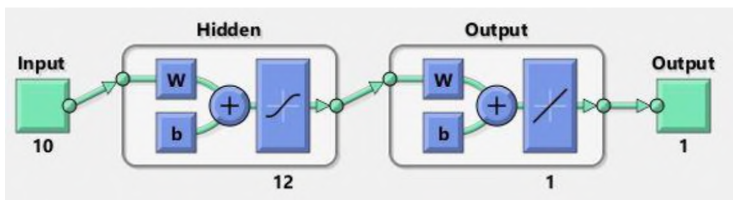

Figure 5: Representation of the Neural Network

The hidden layer uses tangent hyperbolic (Tanh) activation function while the output layer uses rectified linear (ReLU) activation function; both activation functions can be expressed by equation 8 and equation 9, respectively.

$$X = \tanh(x) \qquad \text{equation (8)}$$

$$X = \max(0, x) \qquad \text{equation (9)}$$

When a neural-network is trained on the training-set, it is set with established weights. Furthermore, these weights are improved throughout the training epoch and the optimal weightiness are produced. For carrying out the evaluation of the proposed model, 201 samples are considered. The 201 samples were divided into 3 sets which are training, testing and validation. 70% of the samples are kept for training purpose because the training process always requires a greater number of samples, as weights are finalized during the process. The remaining 30 % samples are divided equally between validation and testing sets. In the proposed model we have updated the weights till 896 iterations till the point weights got optimal. Figure 6 shows the summary of the model training. The samples were divided randomly to avoid any resemblance within the same set.

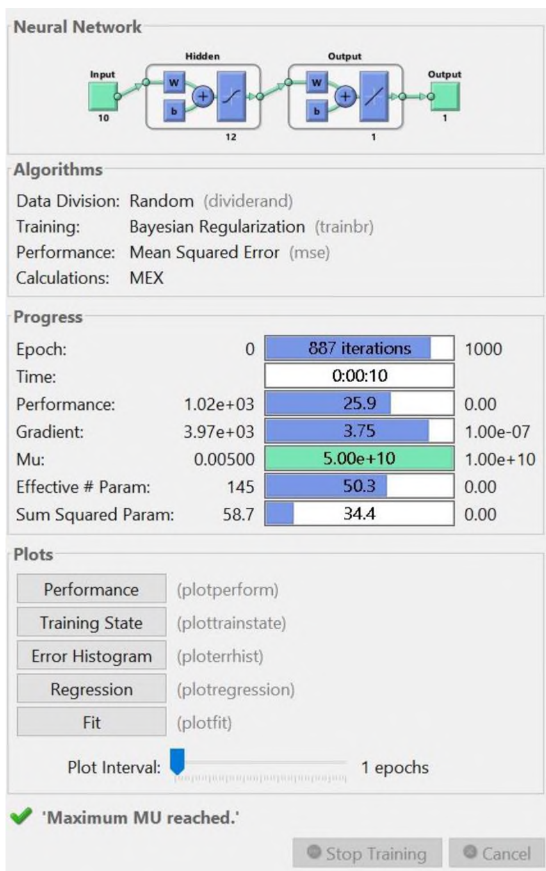

Figure 6: Training Summary

The performance is evaluated using Mean Square Error (MSE) which is shown in equation 10. Training is carried out using 887 iterations, while at the beginning the total number of weights and biases was 145. Whereas after the training process only 50% of the constants which is denoted by (Effective # Param). That means the turned off neurons do not contribute towards the betterment of system performance.

$$Mean\ Square\ Error\ = \frac{1}{n}\sum_{i=1}^{n} E_i^2 \qquad \text{equation (10)}$$

In other words, Mean Squared Error (MSE) is the training loss of the data, which has been explained previously in Chapter 3. Mean Squared Error does not have an optimal value that would justify the success of the training model due to the size of the model. Although, it has been discussed previously, if the testing loss declines in a similar pattern of the declination of the training loss, that would be a sign of the model's success. The other indicator that the model is successful is that the training line below in Figure 7 went through the best training performance circle.

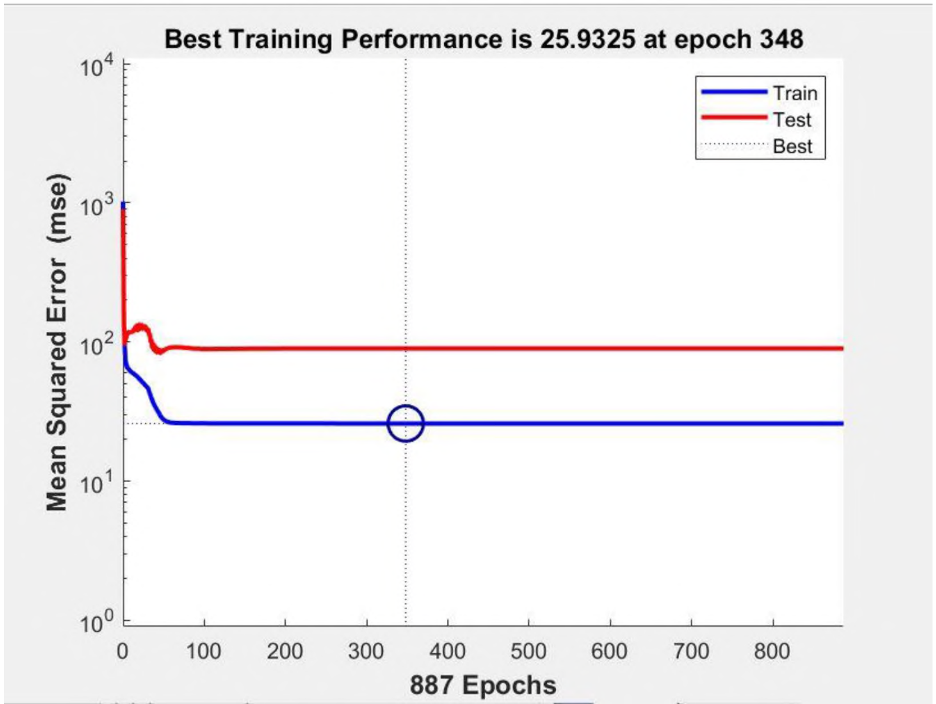

Figure 7: Best Training Performance Plot

Figure 8 shows the regression plots generated while training the model. The sample data across the Fit line shows that model is set to an optimal state where it remains at its best fit order. The regression lines present the relationship between the predicted compressive strength values and the experimental compressive strength values. For the training dataset, the relationship between the predicted compressive strength and the experimental compressive strength values is linear and can be presented by equation 11 below:

$$y_p = 0.84 * y_\epsilon + 7.2 \qquad \text{equation (11)}$$

The overall relationship between the predicted compressive strength values of the whole dataset of the 201 data points and the experimental values of the same points is also linear and can be concluded in equation 12 below. It is important to address that the relationship between the predicted and experimental outcomes is linear which is totally different than the non-linear model to predict the values. The Bayesian Regularization Backpropagation is a non-linear model used to predict the values of compressive strength specifically, although, the presented regression lines show the relationship between the type of the data, which is in this case predicted versus experimental, and that was determined after the training was completed in a separate step.

$$y_p = 0.84 * y_e + 7.7 \qquad \text{equation (12)}$$

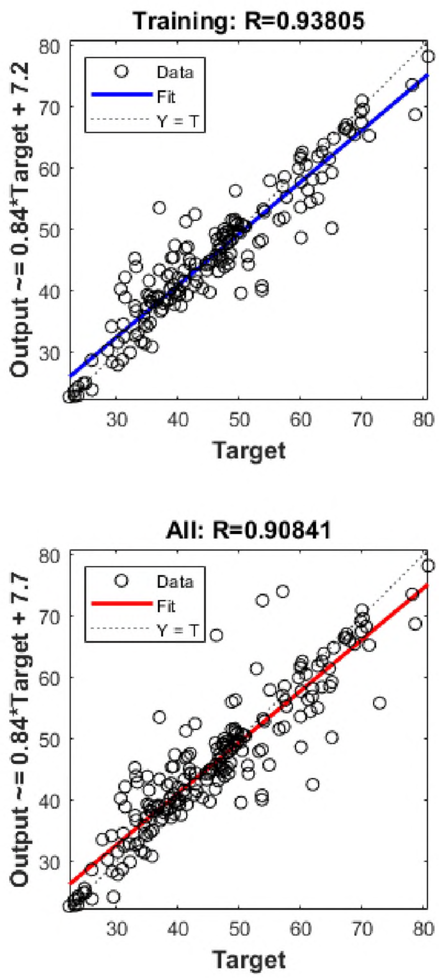

Figure 8: Regression Fitting Lines

To further evaluate the model an error histogram can be used. In error histogram, the test set is also used. The distribution of both the training and testing is being compared to analyse the model. Higher the similarity between the test and train distribution shows better performance by the model. Moreover, if the certain distribution is followed it depicts information about the model itself as well. Figure 9 shows the error histogram with 20 bins for training and test set. As can be seen, both training and test set follows the

Gaussian distribution. So that indicates that a good training has been carried out for the model and it has depicted good results in return.

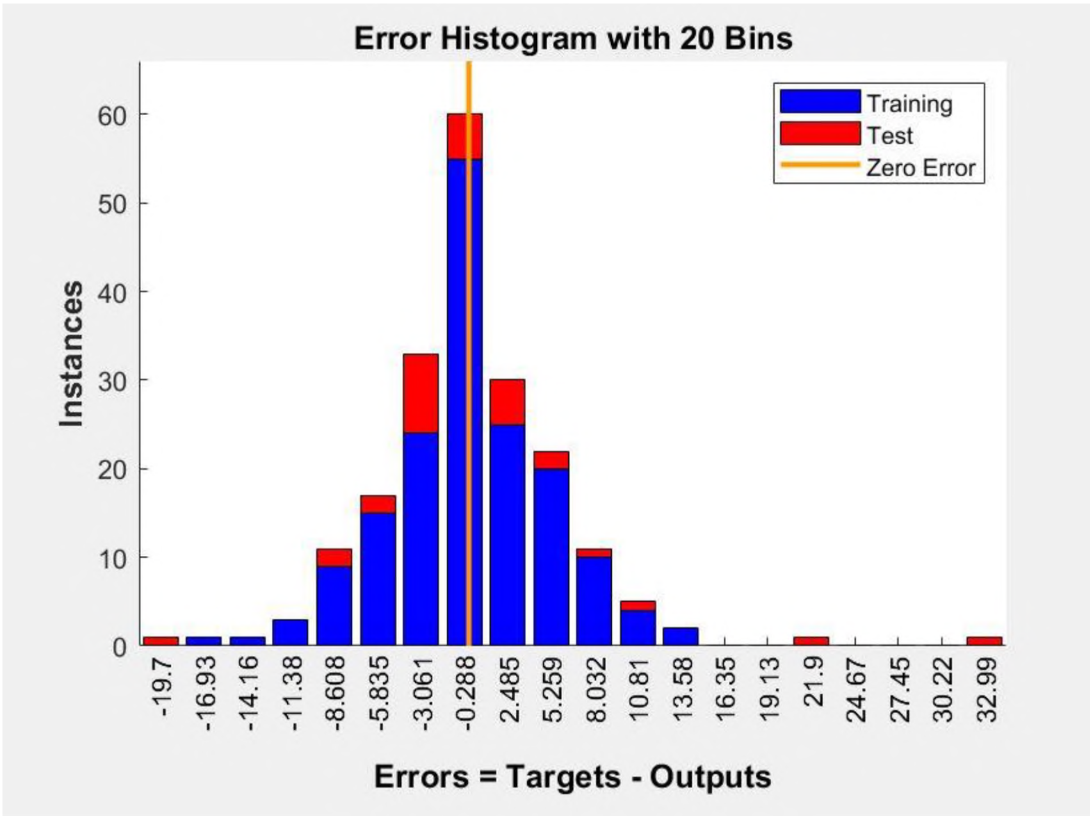

Figure 9: Error Histogram

Figure 10 shows the comparison between the experimental compressive strength and predicted compressive strength. The high similarity between the predicted and experimental values reflects the high performance by the proposed model. The long regression range was well tackled by the proposed model and especially after applying Bayesian regularization. The predicted compressive strength values can be found in APPENDIX D.

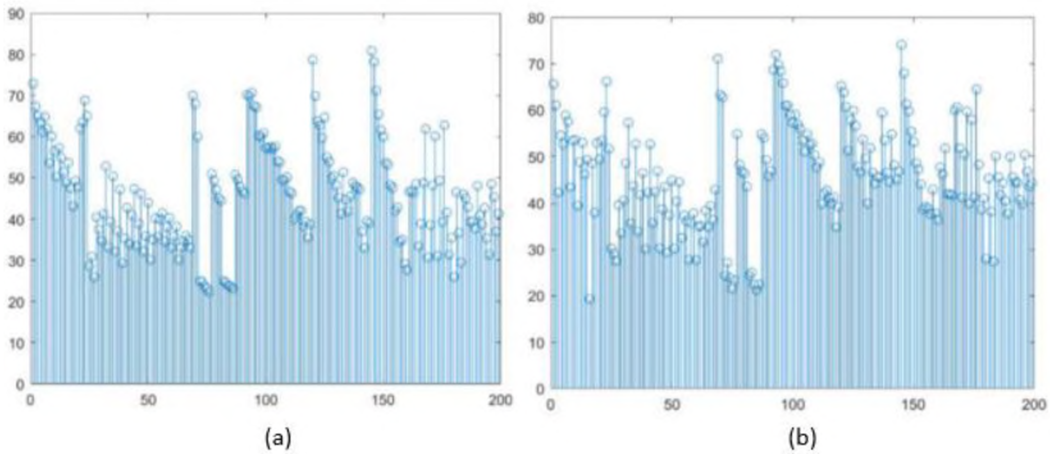

Figure 10: Comparison Between Experimental and Predicted Compressive Strength Values

4.2 Weights and Biases

Bias is just a constant-value or a constant-vector that is supplemented to the weighted sum achieved after multiplying the input with its corresponding weight. Bias is employed to offset the result. The bias is utilized to modify the result of activation-function in the direction of the positive or negative side. The weight and bias are equally dependent on the input, so it is equally important to study the data. Weights and biases can either have positive or negative values which are to be determined by the algorithm to best fit the data on the regression line.

Table 10 represent a 12x10 matrix that shows the 120 resulting weights values that are distributed from the input layer to the hidden layer and the number is matching what has been expected in Chapter 3.

Table 10: 12 x 10 Matrix, The Resulting Weights of Input-Hidden Layer Connection

	W_{i1}	W_{i2}	W_{i3}	W_{i4}	W_{i5}	W_{i6}	W_{i7}	W_{i8}	W_{i9}	W_{i10}
W_{1j}	0.04803	-0.9128	1.01271	-0.2246	-0.6025	-0.085	0.19696	-0.8722	-0.0696	-0.1426
W_{2j}	-0.4035	1.46857	-0.5956	-0.0805	0.76792	0.17649	0.02708	0.28367	-0.4964	1.53571
W_{3j}	0.05705	-1.6578	-0.1233	-0.1391	0.96177	0.99454	0.19941	-0.077	1.06371	1.05858
W_{4j}	-0.1501	-0.4153	0.88738	0.73195	0.04612	-0.804	0.42578	1.25781	0.10357	0.39534
W_{5j}	0.02708	0.81263	-0.4221	0.0606	1.08235	-0.7088	1.30259	0.03308	-0.3983	1.05836
W_{6j}	0.08242	2.80193	2.57075	-1.706	-0.0336	-0.7826	-0.1035	-0.6534	-0.1607	0.88043
W_{7j}	0.36797	0.19883	-0.2312	-0.5763	-0.0041	-0.516	-0.6078	-0.9059	-0.1272	1.25666
W_{8j}	-0.2459	-1.3262	-1.4555	0.78621	1.13797	0.8769	0.05107	-0.5792	-0.1274	-0.8764
W_{9j}	-0.806	1.15116	0.38454	0.2461	0.81733	-0.5215	-0.5706	0.45696	-0.0296	-1.055
W_{10j}	0.3202	0.86987	-1.7688	0.31549	-0.8483	0.48017	-0.8212	-0.2926	-0.7759	0.09498
W_{11j}	0.07397	0.90821	-1.2218	0.45106	0.60639	-0.0811	-0.3169	-0.4781	0.39675	0.70563
W_{12j}	0.15185	1.46715	2.44021	-1.2794	-0.3302	-0.3651	-0.2686	-0.2889	-1.2303	0.70233

Table 11 includes the 12 resulting weights values from the hidden layer to the output layer connection.

Table 11: 12 x 10 Matrix, The Resulting Weights of the Hidden Layer-Output Connection

W_1	W_2	W_3	W_4	W_5	W_6	W_7	W_8	W_9	W_{10}	W_{11}	W_{12}
-1.169	-1.8674	1.47609	-1.4639	1.80447	-3.0249	1.58139	-2.4499	1.44331	-1.9787	1.35444	2.80639

The hidden layer nodes' biases and the outcome bias are the listed in Table 12, and they are also equal to what has been assumed earlier, 13 constant bias values.

Table 12: The Total 13 Biases

b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	b_{11}	b_{12}	b_{13}
-0.2011	-0.3616	0.14966	-0.0862	-0.2786	1.23325	0.34521	-1.1467	0.03046	0.37735	-0.0573	0.08748	0.0898

4.3 Final Function

A recall from Chapter 3 that the probability function used is expressed in equation 13 below.

$$P(x|D,\alpha,\beta,M) = \frac{P(D|x,\beta,M)P(x|\alpha,M)}{P(D|\alpha,\beta,M)} \quad \text{equation (13)}$$

Where, P(x|D) is the subsequent likelihood of the weightiness vector 'x' provided the training dataset D. While P(x) is the prior likelihood of the weightiness vector and P(D|x) is the likelihood of the experimental data with weightiness vector being 'x'. The denominator is the integral of all possible weight vectors. This leads us to have a non-linear Bayesian which would result in having a resultant function of the compressive strength or the independent variable defined as a cost function expressed in equation 14 and 15. This function measures the performance of the ANN model for the given data.

$$Cost = -\log P(x) - \log P(D|x) + log\ P(D) \quad \text{equation (14)}$$

The final cost function with all the defined parameters would be

$$Cost = \frac{1}{\sigma_D^2}\left[\frac{\sigma_D^2}{2\sigma_x^2} * \sum XiW_{ij}^2 + b_i\right] \quad \text{equation (15)}$$

CHAPTER V

CONCLUSION

Previous chapters in this research discussed the economic and environmental benefits that can be achieved only if old aggregates were to be recycled and used more frequently in construction. The main objective of this research was to build a model using artificial intelligence that can predict compressive strength values of recycled concrete aggregate based on physical properties of concrete mixtures, and the goal was successfully achieved.

5.1 Prediction of Compressive Strength

The model could eventually be able to predict compressive strength values of the inserted matrix dataset. The results were discussed in the previous chapter, Chapter 4. By comparing the model to the previous models discussed in Chapter 2, this model that included the use of Bayesian Regularization Backpropagation can be considered to be more successful due to the selection of the algorithm (which was not determined randomly). Other built-in functions have many limitations and issues which would affect the pattern recognition between the data, even if the regression showed a high percentage of the data fitting the line. The results indicated that present ANN model is able to predict the compressive strength as function of multiple independent variables. It is worth mentioning that, if the number of parameters was minimal, or only one input parameter was used (similar to the model in section 2.4.1), the algorithm would fit the data in one clear step, which is translates into the simple linear model. There is presently no direct equation to calculate compressive strength as a function of multiples variables except through experiments, this emphasizes the numerous advantages of the developed ANN model.

5.2 Economical and Environmental Impact

The model can be used as a tool by engineers to calculate compressive strength when recycled aggregates are added by entering the physical properties of the mixture. Knowing what compressive strength values could be for recycled concrete aggregate (RCA) samples that are usually unpredicted would increase the use of construction demolition and waste (C&D). Moreover, if the compressive strength values are different from the strength required for a given project, it can be manipulated by changing the ratios of the physical properties of the concrete mixture. This process can be obtained prior to lab testing. The increase of using construction and demolition waste (C&D) would be economically beneficial by reducing the amount of money paid on renting landfills for the waste and would reduce the consumption of natural resources.

5.3 Future Research

Many research areas can be built on this project, compressive strength of concrete is not the only mechanical property of concrete, although, it is the one mechanical property that has been studied in this research. Similar methodology can be used to predict the other mechanical properties, either by using the same nonlinear model that has been used in this research, which has proven to be successful, or by building another model which indicates different function which requires programming expertise. The other mechanical properties that were not mentioned in this research are, flexural strength and tensile strength, and both properties need the collection of additional data as well. These two properties are also affected by the replacement level of recycled aggregate or the physical properties of the mixture's ingredients (but that was not the focus of this research).

Also, this research can be taken to a different level, which is optimization. Optimization of compressive strength can be simply explained by giving the programming software a specific value of compressive strength, and it would calculate the independent variables values, in other words, a value for each physical property.

Artificial Intelligence Neural Network has been evolving lately to involve multiple engineering or other real-life situations. Nonetheless, optimization or any other linear or non-linear regression models include many algorithms that can be used, and each needs to be studied and analyzed carefully to produce accurate and more suitable results.

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APPENDIX A

MATLAB FUNCTION

```
function [Y,Xf,Af] =
myNeuralNetworkFunction(X,~,~)

% [Y] = myNeuralNetworkFunction(X,~,~) takes
these arguments:
%
%   X = 1xTS cell, 1 inputs over TS timesteps
%   Each X{1,ts} = Qx10 matrix, input #1 at
timestep ts.
%
% and returns:
%   Y = 1xTS cell of 1 outputs over TS
timesteps.
%   Each Y{1,ts} = Qx1 matrix, output #1 at
timestep ts.
%
% where Q is number of samples (or series) and
TS is the number of timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.xoffset =
[0;0.28;243;120;0;0;0;0;0;0];
x1_step1.gain =
[0.02;4.54545454545455;0.00491400491400491;0.01
61290322580645;0.000802568218298555;0.000719424
460431655;0.0526315789473684;0.0526315789473684
;0.134228187919463;1];
x1_step1.ymin = -1;

% Layer 1
```

```
b1 = [0.12951062506819704945;-
0.080709949454657703427;0.46385460064547157089;
0.69813055119079903132;0.38142511613958296479;1
.0137170025392192585;0.68308117890422936913;-
0.12925280988185872122;-
0.57376499082986021083;-
1.0874593843885929909;0.12521492061037539645;-
0.078789186994432436341];
IW1_1 = [0.046380707783674667011 -
0.14588960389818686481 0.032561745046558711325
0.070400538064104289937 -0.11364376639969907268
0.064000279790021569193
0.0083686341436120786214 -
0.030396894602880485808 -
0.042890679338225989881
0.099409169549967646429;0.039161622122026278070
0.37245158007832401825 -0.81988247718361351168
-0.71941797073201274593 0.55006190554856460029
-1.0959036020449210991 -0.51346869316434340380
0.33960722284310307373 -0.30936299840658049165
0.18759607123241625604;0.15116098904418248661
0.16498297546316101347 0.90802881197931684110
1.4144434393126759097 -0.050111358374724315756
-0.61423762688487992811 -0.26276240676169626553
0.81214058157235069491 0.61230659141850329874
0.26071444944791322129;-0.15859308372888122896
-0.26348766885617880273 0.42749992344420406631
0.45086444612402998278 0.033494901145994855629
0.36181744116652775345 0.37775825161668380447
0.25339191246116166134 -0.35542847326769611005
0.34367481496710960975;0.018931932279857042328
0.62747766745026289925 -0.95522507189231165015
-0.46633139923245736647 -0.22845553067476098708
0.21059076503863102814 0.46919370452982345210 -
0.46839848208233753057 0.88416537398783323631 -
0.54448414786769661067;0.10434952229769307863
1.9724733544026544774 0.61177234965458160421 -
0.17018910852884419627 -0.38255806214992466030
```

```
0.28825496833495828364 0.09788316519199000143 -
0.49411839682137209673 -0.32625524393473032125
-0.10921163591411317539;-0.13337753678741881558
-0.48665724945964938808 0.19468350331233849615
0.2424174156968792182 -0.42032597631426549256 -
0.077979186003915290648 -0.35010527563834664688
-0.65737146968571336103 0.079103698534805241827
0.23104827198520572207;-0.045110840102196098078
0.14471455549765055437 -0.032904653169963042625
-0.069637465718775742873 0.11196625872020297965
-0.064383052965454767858 -
0.008496884076546131967 0.030111049792142817461
0.042288592074535884258 -
0.09995807541916097716;-0.051234890910338289072
-1.3082375694930143961 -1.0243366640686200064
0.4001362238570454477 0.89711534467408726723 -
0.14209066729393635131 -0.25599749038861940864
-0.6976958814014440069 -0.48030058811937892393
0.44278326145446422757;0.067160243892106216701
0.90610623486626618028 -0.39981170307582608592
0.4492049312070416911 1.4654882030367193391
0.1191136717062329653 0.6772167300403882928 -
0.34521583897861246593 0.90123107051091211339 -
0.201517895573572553;0.042579201929244039904 -
0.14108686539204606802 0.032978513926143739055
0.067843231865403058611 -0.10887010357162946184
0.063751993003985901742
0.0077347690620737166722 -
0.029171184594586296174 -
0.041409715091245594132
0.09762500799413834085;0.20873681092079976462
0.28213011414327227033 0.43908757121705821458
1.1796109611961673735 0.10733956053279873621 -
0.051222486327468980116 0.069313378070214898274
-0.48023720972349714931 0.05609068972291297861
0.026641955888136371888];
```

```
% Layer 2
```

```
b2 = 0.36972448227855936 32;
```

```
    % Layer 1
    a1 = tansig_apply(repmat(b1,1,Q) +
IW1_1*Xp1);

    % Layer 2
    a2 = repmat(b2,1,Q) + LW2_1*a1;

    % Output 1
    Y{1,ts} = mapminmax_reverse(a2,y1_step1);
    Y{1,ts} = Y{1,ts}';
end

% Final Delay States
Xf = cell(1,0);
Af = cell(2,0);

% Format Output Arguments
if ~isCellX
    Y = cell2mat(Y);
end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing
Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-
Processing Function
function x = mapminmax_reverse(y,settings)
```

```
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```

APPENDIX B

MATLAB MODEL

```
% This script assumes these variables are
defined:
%
%   features - input data.
%   label - target data.
clc
clear all
close all
load('feature')
load('labels')

x = feature';
t = labels';
% Choose a Training Function
% For a list of all training functions type:
help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for
challenging problems.
% 'trainscg' uses less memory. Suitable in low
memory situations.
trainFcn = 'trainbr';  % Bayesian
Regularization backpropagation.

% Create a Fitting Network
hiddenLayerSize = 12;
net = fitnet(hiddenLayerSize,trainFcn);

% Setup Division of Data for Training,
Validation, Testing
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Train the Network
```

```
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various
plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
%figure, plotregression(t,y)
%figure, plotfit(net,x,t)
```

APPENDIX C

DATASET

Table C 1: Dataset

Sample Number	Mix. Designation	Replacement Level %	Effective w/c Ratio	Cement (Kg/m^3)	Water (Kg/m^3)	RCA Bulk Density (Kg/m^3)	NA Bulk Density (Kg/m^3)	RCA Aggregate Size	NA Aggregate Size	RCA Water Absorption %	NA Water Absorption %	Compressive Strength (MPa)	Reference
1	RC-XS3-SR-1	0	0.42	385	173	0	2540	0	20	0	1.8	72.9	A
2	RC-XS3-SR-2	20	0.42	385	173	2320	2540	20	20	5.3	1.8	67.4	A
3	RC-XS1-DA-4	100	0.42	380	190	2320	0	20	0	5.3	0	65.1	A
4	RC-XS1-DA-3	50	0.44	380	190	2320	2540	20	20	5.3	1.8	63.5	A
5	RC-XS3-SR-3	50	0.44	385	173	2320	2540	20	20	5.3	1.8	61.2	A
6	RC-XS1-DA-2	20	0.45	380	190	2320	2540	20	20	5.3	1.8	64.8	A
7	RC-XS1-DA-1	0	0.46	380	190	0	2540	0	20	0	1.8	62	A
8	RC-XS3-SR-4	100	0.49	385	173	2320	0	20	0	5.3	0	53.7	A
9	RX-XC-SR-1	0	0.51	325	180	0	2540	0	20	0	1.8	60.1	A
10	RX-XC-SR-2	20	0.52	325	180	2320	2540	20	20	5.3	1.8	56.5	A

11	RC-XS1-SA-4	100	0.52	380	190	2320	0	20	0	5.3	0	50.3	A
12	RC-XS1-SA-1	0	0.53	380	190	0	2540	0	20	0	1.8	57.3	A
13	RC-XS1-SA-2	20	0.53	380	190	2320	2540	20	20	5.3	1.8	54.9	A
14	RC-XS1-SA-3	50	0.53	380	190	2320	2540	20	20	5.3	1.8	51.5	A
15	RX-XC-SR-3	50	0.54	325	180	2320	2540	20	20	5.3	1.8	48.9	A
16	RC-X0-DA-4	100	0.54	275	180	2320	0	20	0	5.3	0	53.7	A
17	RC-X0-DA-3	50	0.57	275	180	2320	2540	20	20	5.3	1.8	47.5	A
18	RX-XC-SR-4	100	0.58	325	180	2320	0	20	0	5.3	0	43.1	A
19	RC-X0-DA-2	20	0.59	275	180	2320	2540	20	20	5.3	1.8	49.3	A
20	RC-X0-DA-1	0	0.6	275	180	0	2540	0	20	0	1.8	47.8	A
21	RC-X0-SA-1	0	0.67	275	180	0	2540	0	20	0	1.8	62	A
22	RC-X0-SA-3	50	0.67	275	180	2320	2540	20	20	5.3	1.8	63.5	A
23	RC-X0-SA-2	20	0.68	275	180	2320	2540	20	20	5.3	1.8	68.8	A
24	RC-X0-SA-4	100	0.7	275	180	2320	0	20	0	5.3	0	65.1	A

25	Ref-I	0	0.61	296.72	230.51	0	2700	0	38	0	1.78	28.55	B
26	RC-10	10	0.61	296.72	230.51	2170	2700	38	38	7.5	1.78	30.95	B
27	RC-10*	10	0.61	296.72	236	2170	2700	38	38	7.5	1.78	25.95	B
28	Ref-II	0	0.55	329.1	212.67	0	2700	0	38	0	1.78	40.5	B
29	RC-20	20	0.55	329.1	212.67	2170	2700	38	38	7.5	1.78	37.5	B
30	A1	0	0.4	300	120	0	2720	0	20	0	0.7	34.8	C
31	A2	0	0.4	350	140	0	2720	0	20	0	0.7	41.2	C
32	A3	0	0.4	450	180	0	2720	0	20	0	0.7	52.8	C
33	A4	25	0.4	300	120	2340	2720	20	20	6.4	0.7	33.2	C
34	A5	25	0.4	350	140	2340	2720	20	20	6.4	0.7	39.4	C
35	A6	25	0.4	400	180	2340	2720	20	20	6.4	0.7	50.4	C
36	A7	50	0.4	300	120	2340	2720	20	20	6.4	0.7	32.1	C
37	A8	50	0.4	350	140	2340	2720	20	20	6.4	0.7	37.2	C
38	A9	50	0.4	450	180	2340	2720	20	20	6.4	0.7	47.2	C
39	A10	100	0.4	300	120	2340	0	20	0	6.4	0	29.3	C
40	A11	100	0.4	350	140	2340	0	20	0	6.4	0	35.3	C
41	A12	100	0.4	450	180	2340	0	20	0	6.4	0	42.8	C
42	A13	0	0.45	300	135	0	2720	0	20	0	0.7	34	C
43	A14	0	0.45	350	157.5	0	2720	0	20	0	0.7	41	C
44	A15	0	0.45	450	202.5	0	2720	0	20	0	0.7	47.4	C
45	A16	25	0.45	300	135	2340	2720	20	20	6.4	0.7	33.5	C
46	A17	25	0.45	350	157.5	2340	2720	20	20	6.4	0.7	38.9	C
47	A18	25	0.45	450	202.5	2340	2720	20	20	6.4	0.7	46.1	C
48	A19	50	0.45	300	135	2340	2720	20	20	6.4	0.7	32.2	C
49	A20	50	0.45	350	157.5	2340	2720	20	20	6.4	0.7	35.9	C
50	A21	50	0.45	400	202.5	2340	2720	20	20	6.4	0.7	44	C
51	A22	100	0.45	300	135	2340	0	20	0	6.4	0	30.2	C
52	A23	100	0.45	350	157.5	2340	0	20	0	6.4	0	35	C
53	A24	100	0.45	450	202.5	2340	0	20	0	6.4	0	40.2	C
54	A25	0	0.5	300	150	0	2720	0	20	0	0.7	35.8	C
55	A26	0	0.5	350	175	0	2720	0	20	0	0.7	40	C
56	A27	0	0.5	450	225	0	2720	0	20	0	0.7	41.5	C
57	A28	25	0.5	300	150	2340	2720	20	20	6.4	0.7	34.6	C
58	A29	25	0.5	350	175	2340	2720	20	20	6.4	0.7	38.1	C
59	A30	25	0.5	450	225	2340	2720	20	20	6.4	0.7	40.3	C
60	A31	50	0.5	300	150	2340	2720	20	20	6.4	0.7	33.1	C

61	A32	50	0.5	350	175	2340	2720	20	20	6.4	0.7	35.8	C
62	A33	50	0.5	450	225	2340	2720	20	20	6.4	0.7	38.2	C
63	A34	100	0.5	300	150	2340	0	20	0	6.4	0	30.2	C
64	A35	100	0.5	350	175	2340	0	20	0	6.4	0	33.2	C
65	A36	100	0.5	450	225	2340	0	20	0	6.4	0	34.6	C
66	35N.C	0	0.46	400	185	0	2650	0	14	0	0.7	36	D
67	50% R35	50	0.46	400	185	2400	2650	14	14	3.6	0.7	35	D
68	100 %R 35	100	0.46	400	185	2400	0	14	0	3.6	0	33	D
69	70N.C	0	0.28	450	126	0	2650	0	14	0	0.7	70	D
70	50% R70	50	0.28	450	126	2400	2650	14	14	3.6	0.7	68	D
71	100 %R 70	100	0.28	450	126	2400	0	14	0	3.6	0	60	D
72	RB A1-00	0	0.55	436	244	0	2687	0	7.1	0	1.2	25	E
73	RB A1-25	25	0.55	436	244	2214	2687	7.05	7.1	14.9	1.2	24.79	E
74	RB A1-50	50	0.55	436	244	2214	2687	7.05	7.1	14.9	1.2	23.76	E
75	RB A1-75	75	0.55	436	244	2214	2687	7.05	7.1	14.9	1.2	23.14	E
76	RB A1-100	100	0.55	436	244	2214	0	7.05	0	14.9	0	22.3	E
77	RB A2-00	0	0.35	528	185	0	2687	0	7.1	0	1.2	51	E
78	RB A2-25	25	0.35	528	185	2214	2687	7.05	7.1	14.9	1.2	49.36	E
79	RB A2-50	50	0.35	528	185	2214	2687	7.05	7.1	14.9	1.2	47.1	E
80	RB A2-75	75	0.35	528	185	2214	2687	7.05	7.1	14.9	1.2	45.1	E
81	RB A2-100	100	0.35	528	185	2214	0	7.05	0	14.9	0	44.54	E
82	RC A1-00	0	0.55	436	244	0	2687	0	7.1	0	1.2	25	E
83	RC A1-25	25	0.55	436	244	2214	2687	7.36	7.1	2.7	1.2	24.6	E
84	RC A1-50	50	0.55	436	244	2214	2687	7.36	7.1	2.7	1.2	23.9	E

85	RC A1-75	75	0.55	436	244	2214	2687	7.36	7.1	2.7	1.2	23.7	E
86	RC A1-100	100	0.55	436	244	2214	0	7.36	0	2.7	0	23.1	E
87	RC A2-00	0	0.35	528	185	0	2687	0	7.1	0	1.2	50.78	E
88	RC A2-25	25	0.35	528	185	2214	2687	7.36	7.1	2.7	1.2	49.66	E
89	RC A2-50	50	0.35	528	185	2214	2687	7.36	7.1	2.7	1.2	47.93	E
90	RC A2-75	75	0.35	528	185	2214	2687	7.36	7.1	2.7	1.2	46.9	E
91	RC A2-100	100	0.35	528	185	2214	0	7.36	0	2.7	0	46.2	E
92	H$S 1	0	0.3	650	195	0	2780	0	32	0	0.72	70.2	F
93	H$S 2	30	0.3	650	195	2492	2780	32	32	3.87	0.72	69.8	F
94	H$S 3	50	0.3	650	195	2492	2780	32	32	3.87	0.72	70.7	F
95	H$S 4	80	0.3	650	195	2492	2780	32	32	3.87	0.72	67.5	F
96	H$S 5	100	0.3	650	195	2492	0	32	0	3.87	0	67.1	F
97	H$S 6	0	0.35	557	195	0	2780	0	32	0	0.72	60.3	F
98	H$S 7	30	0.35	557	195	2492	2780	32	32	3.87	0.72	60	F
99	H$S 8	50	0.35	557	195	2492	2780	32	32	3.87	0.72	60.9	F
100	H$S 9	80	0.35	557	195	2492	2780	32	32	3.87	0.72	57.4	F
101	H$S 10	100	0.35	557	195	2492	0	32	0	3.87	0	57.1	F
102	H$S 11	0	0.4	488	195	0	2780	0	32	0	0.72	57.5	F
103	H$S 12	30	0.4	488	195	2492	2780	32	32	3.87	0.72	57.1	F
104	H$S 13	50	0.4	488	195	2492	2780	32	32	3.87	0.72	57.7	F
105	H$S 14	80	0.4	488	195	2492	2780	32	32	3.87	0.72	54.1	F
106	H$S 15	100	0.4	488	195	2492	0	32	0	3.87	0	53.8	F
107	H$S 16	0	0.45	433	195	0	2780	0	32	0	0.72	49.6	F
108	H$S 17	30	0.45	433	195	2492	2780	32	32	3.87	0.72	49.3	F
109	H$S 18	50	0.45	433	195	2492	2780	32	32	3.87	0.72	50.2	F
110	H$S 19	80	0.45	433	195	2492	2780	32	32	3.87	0.72	46.7	F
111	H$S 20	100	0.45	433	195	2492	0	32	0	3.87	0	46.3	F

112	RA CS M1	100	0.5	325	162	2430	0	25	0	4.4	0	40	G
113	RA CS M2	50	0.52	318	165	2430	2670	25	25	4.4	0.9	41	G
114	RA CS M3	0	0.55	300	165	0	2670	0	25	0	0.9	42	G
115	RA CS M4	25	0.55	300	165	2430	2670	25	25	4.4	0.9	42	G
116	RA CS M5	100	0.5	325	162	2430	0	25	0	4.5	0	38.3	G
117	RA CS M6	50	0.52	318	165	2430	2670	25	19	4.5	0.9	39.4	G
118	RA CS M7	0	0.55	300	165	0	2670	0	19	0	0.9	35.5	G
119	RA CS M8	25	0.55	300	165	2430	2670	25	19	4.5	0.9	38.8	G
120	B1	0	0.4	350	140	0	2581	0	22	0	1.2	78.7	H
121	B2	20	0.4	350	140	2451	2581	20	22	7.3	1.2	69.9	H
122	B3	50	0.4	350	140	2451	2581	20	22	7.3	1.2	63.8	H
123	B4	100	0.4	350	140	2451	0	20	0	7.3	0	62.8	H
124	B5	0	0.45	350	157.5	0	2581	0	22	0	1.2	59.7	H
125	B6	20	0.45	350	157.5	2451	2581	20	22	7.3	1.2	64.7	H
126	B7	50	0.45	350	157.5	2451	2581	20	22	7.3	1.2	55	H
127	B8	100	0.45	350	157.5	2451	0	20	0	7.3	0	53.9	H
128	B9	0	0.54	350	189	0	2581	0	22	0	1.2	49.8	H
129	B10	20	0.54	350	189	2451	2581	20	22	7.3	1.2	50.5	H
130	B11	50	0.54	350	189	2451	2581	20	22	7.3	1.2	48.1	H
131	B12	100	0.54	350	189	2451	0	20	0	7.3	0	45.2	H
132	CC	0	0.48	350	168	0	2570	0	20	0	1.2	41.3	I
133	RC1	27	0.48	350	168	2250	2570	25	20	7	1.2	51.4	I
134	RC2	63.5	0.48	350	168	2250	2570	25	20	7	1.2	44.7	I
135	RC3	36.5	0.48	350	168	2250	2570	25	20	7	1.2	41.9	I
136	RC4	36.5	0.48	350	168	2250	2570	25	20	7	1.2	45.6	I
137	RC	0	0.43	446	191.6	0	2510	0	25	0	1.3	48.8	J
138	C20	20	0.43	446	191.6	2310	2510	25	25	6.1	1.3	48	J
139	C50	50	0.43	446	194.4	2310	2510	25	25	6.1	1.3	47.7	J
140	C100	100	0.43	446	198.7	2310	0	25	0	6.1	0	47.2	J

141	NAC	0	0.5	360	180	0	2510	0	20	0	1.8	37	K
142	RAC30	30	0.5	360	180	2240	2510	20	20	6.5	1.8	33	K
143	RAC65	65	0.42	427	180	2240	2510	20	20	6.5	1.8	39.5	K
144	RAC100	100	0.4	448	180	2240	0	20	0	6.5	0	39	K
145	NC80	0	0.34	485	165	0	2600	0	20	0	0.9	80.8	L
146	C80RA1	100	0.34	485	165	2450	0	20	0	3.1	0	78.2	L
147	C80RA2	100	0.34	485	165	2370	0	20	0	7.1	0	71.2	L
148	C80RA3	100	0.34	485	165	2360	0	20	0	7.8	0	65.4	L
149	NC60	0	0.44	425	185	0	2600	0	20	0	0.9	61.6	L
150	C60RA1	100	0.44	425	185	2450	0	20	0	3.1	0	60	L
151	C60RA2	100	0.44	425	185	2370	0	20	0	7.1	0	53.7	L
152	C60RA3	100	0.44	425	185	2360	0	20	0	7.8	0	53.2	L
153	NC45	0	0.51	350	180	0	2600	0	20	0	0.9	48.3	L
154	C45RA1	100	0.51	350	180	2450	0	20	0	3.1	0	47.6	L
155	C45RA2	100	0.51	350	180	2370	0	20	0	7.1	0	42	L
156	C45RA3	100	0.51	350	180	2360	0	20	0	7.8	0	42.9	L
157	NC30	0	0.68	300	205	0	2600	0	20	0	0.9	34.5	L
158	C30RA1	100	0.68	300	205	2450	0	20	0	3.1	0	35	L
159	C30RA2	100	0.68	300	205	2370	0	20	0	7.1	0	29.2	L
160	C30RA3	100	0.68	300	205	2360	0	20	0	7.8	0	27.7	L
161	CS1	0	0.5	380	190	0	2670	0	22	0	2	46.7	M
162	CS2	50	0.5	380	190	2380	2670	12	22	7.4	2	46.9	M
163	CS3	50	0.5	380	190	2380	2670	22	22	5.1	2	46.4	M
164	CS4	100	0.5	380	190	2380	0	22	0	5.1	0	48.6	M

165	NAC-30	0	0.6	267	160	0	2710	0	19	0	1.52	33.4	N
166	NAC-40	0	0.59	271	160	0	2710	0	19	0	1.52	38.9	N
167	NAC-50	0	0.38	474	180	0	2710	0	19	0	1.52	48.8	N
168	NAC-60	0	0.37	487	180	0	2710	0	19	0	1.52	61.9	N
169	RAC1-30	100	0.72	243	175	2480	0	19	0	4.66	0	30.7	N
170	RAC1-40	100	0.64	281	180	2480	0	19	0	4.66	0	38.6	N
171	RAC1-50	100	0.47	404	190	2480	0	19	0	4.66	0	48.2	N
172	RAC1-60	100	0.41	463	190	2480	0	19	0	4.66	0	60.1	N
173	RAC2-30	100	0.63	262	165	2430	0	19	0	6.15	0	31.1	N
174	RAC2-50	100	0.38	500	190	2430	0	19	0	6.15	0	49.4	N
175	RAC3-40	100	0.49	337	165	2410	0	19	0	7.18	0	39.3	N
176	RAC3-60	100	0.3	600	180	2410	0	19	0	7.18	0	62.8	N
177	P1	50	0.42	380	159.6	2330	2590	20	20	6.1	1.16	41.6	O
178	P2	100	0.51	380	193.8	2330	0	20	0	6.1	0	31.4	O
179	P3	50	0.52	380	197.6	2330	2590	20	20	6.1	1.16	35.5	O
180	P4	100	0.61	380	231.8	2330	0	20	0	6.1	0	26	O
181	P5	50	0.44	380	167.2	2320	2590	20	20	5.8	1.16	46.6	O
182	P6	100	0.51	380	193.8	2320	0	20	0	5.8	0	36.7	O
183	P7	100	0.62	380	235.6	2320	0	20	0	5.8	0	29.5	O
184	P8	20	0.41	380	155.8	2360	2590	20	20	3.9	1.16	46.1	O
185	P9	50	0.42	380	159.6	2360	2590	20	20	3.9	1.16	45.1	O
186	P10	100	0.45	380	171	2360	0	20	0	3.9	0	42.9	O
187	P11	20	0.5	380	190	2360	2590	20	20	3.9	1.16	39.3	O
188	P12	50	0.52	380	197.6	2360	2590	20	20	3.9	1.16	39.5	O
189	P13	100	0.54	380	205.2	2360	0	20	0	3.9	0	37.7	O

190	P14	20	0.42	380	159.6	2350	2590	20	20	4.5	1.16	48.1	O
191	P15	50	0.43	380	163.4	2350	2590	20	20	4.5	1.16	41	O
192	P16	100	0.4	380	152	2350	0	20	0	4.5	0	38.7	O
193	P17	20	0.51	380	193.8	2350	2590	20	20	4.5	1.16	42.7	O
194	P18	50	0.52	380	197.6	2350	2590	20	20	4.5	1.16	35.4	O
195	P19	100	0.5	380	190	2350	0	20	0	4.5	0	31.4	O
196	P20	20	0.42	380	159.6	2350	2590	20	20	4.7	1.16	48.5	O
197	P21	50	0.42	380	159.6	2350	2590	20	20	4.7	1.16	45.4	O
198	P22	100	0.43	380	163.4	2350	0	20	0	4.7	0	37	O
199	P23	20	0.52	380	197.6	2350	2590	20	20	4.7	1.16	41.3	O
200	P24	50	0.52	380	197.6	2350	2590	20	20	4.7	1.16	36.8	O
201	P25	100	0.56	380	212.8	2350	0	20	0	4.7	0	31.2	O

APPENDIX D

PREDICTED AND EXPERIMENTAL COMPRESSIVE STRENGTH VALUES

Table D 1: Predicted versus Experimental Compressive Strength Values

Experimental Compressive Strength Values	Expected Compressive Strength Values
72.9	65.6443
67.4	61.1285
65.1	42.2573
63.5	54.5742
61.2	52.69197352
64.8	58.96036718
62	57.5199532
53.7	43.41287876
60.1	53.36585433
49.3	52.92231973
47.8	49.41295142
62	53.47242649
63.5	59.58737593
68.8	66.20784847
65.1	51.71143931
28.55	30.20219528
30.95	29.10143189
25.95	27.53026414
40.5	39.55919458
37.5	33.47987879
34.8	40.54947653
41.2	48.52556604
52.8	57.28542667
46.1	43.44148621
32.2	29.34556954
35.9	37.35628251
44	44.86122292
30.2	30.1998096
35	40.34179677
40.2	44.50313311
35.8	32.49365403
40	37.30155563
41.5	36.10519161
34.6	27.77151825

38.1	35.68430863
40.3	37.81745171
33.1	27.71225861
35.8	34.92220352
38.2	35.08124053
35.5	34.76079048
38.8	39.21080247
78.7	65.23938859
69.9	63.82928219
63.8	60.71312627
62.8	51.27029325
59.7	57.85789493
64.7	59.90421849
55	56.62055132
53.9	47.79280528
65.4	59.77564129
61.6	55.37055966
60	53.10248171
53.7	48.59989453
53.2	47.26869671
48.3	44.04759708
47.6	38.63630041
42	39.19028424
42.9	38.79666365
34.5	37.61783676
31.4	38.58285071
35.5	40.97671538
26	27.9747152
46.6	45.32979648
36.7	38.18311269
29.5	27.38104832
48.5	50.42201988
41.3	44.33196332
56.5	53.67345715
50.3	39.39657569
57.3	48.76053397
54.9	53.01529983
51.5	46.19980358
48.9	49.31320822
53.7	19.31995835

47.5	48.547773
43.1	37.91186843
33.2	35.60870014
39.4	43.70880364
50.4	52.73325745
32.1	33.89397848
37.2	41.77291738
47.2	46.48482783
29.3	30.0555794
35.3	42.20983143
42.8	52.6942944
34	35.68658941
41	42.35914209
47.4	46.92059156
33.5	30.26154513
38.9	38.70581503
30.2	31.5974278
33.2	38.33287643
34.6	34.82887644
36	39.38303157
35	36.37687871
33	42.90737101
70	71.07695805
68	63.31504518
60	62.77190921
25	24.34196722
24.79	27.16587919
23.76	23.90758456
23.14	21.5463661
22.3	23.32714903
51	54.83441667
49.36	48.28399063
49.8	46.63534661
50.5	53.69689632
48.1	49.56946024
45.2	39.92199039
41.3	51.85510911
51.4	46.5572887
44.7	44.21136667
41.9	45.58193199

45.6	45.58193199
48.8	59.4105767
35	42.90268938
29.2	37.78010155
27.7	36.35390142
46.7	47.71304194
46.9	46.20884376
46.4	51.77681224
48.6	41.9161851
33.4	41.86297345
38.9	41.70775613
48.8	59.93200969
46.1	50.06579209
45.1	45.57704249
42.9	41.75440874
39.3	44.30789402
39.5	40.4456139
37.7	37.74685896
45.4	46.79146749
47.1	46.81403046
45.1	46.30863738
44.54	43.49965496
25	24.34196722
24.6	25.00968375
23.9	22.40103412
23.7	21.25258712
23.1	22.49359059
50.78	54.83441667
49.66	54.02789236
47.93	49.31020062
46.9	45.77337801
46.2	46.9573585
70.2	68.66179759
69.8	71.95212058
70.7	69.84181159
67.5	68.40038366
67.1	65.84280665
60.3	60.94815
60	61.016416
60.9	58.96128833

57.4	57.21915171
57.1	59.08939585
57.5	56.98964519
57.1	56.00818508
57.7	53.54970905
54.1	51.08188578
53.8	54.79322099
49.6	52.49028151
49.3	52.85071621
50.2	50.32362045
46.7	47.72226924
46.3	48.8107553
40	39.81934268
41	42.04817959
42	42.75958572
42	40.9560752
38.3	39.93897786
39.4	41.3045847
48	53.50846368
47.7	46.54724638
47.2	44.54816471
37	54.85398381
33	48.13718355
39.5	45.02327793
39	46.82098602
80.8	74.13315935
78.2	67.96642279
71.2	61.28721278
61.9	60.64502726
30.7	51.78885593
38.6	41.21248553
48.2	50.47596827
60.1	59.73712159
31.1	39.86628734
49.4	57.96064544
39.3	41.27229125
62.8	64.50165712
41.6	48.27885323
48.1	49.97073021
41	45.57533087

38.7	44.45663087
42.7	44.39634734
35.4	40.67841231
31.4	39.79164626
37	43.59519064