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QUANTIFYING THE EFFECT OF CONSTRUCTION SITE FACTORS ON CONCRETE QUALITY, COSTS AND PRODUCTION RATES

Jorge L. Santamaria
University of New Mexico

Jorge L. Santamaria Carrera
Candidate

Civil Engineering
Department

This dissertation is approved, and it is acceptable in quality and form for publication:

Approved by the Dissertation Committee:

Dr. Vanessa Valentin, Chairperson

Dr. Susan Bogus

Dr. Timothy Ross

Dr. Gabriel Huerta

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BY

JORGE L. SANTAMARIA CARRERA

B.S., Civil Engineering, Central University of Ecuador, 1999
M.Sc., Civil and Environmental Engineering, Arizona State University, 2006

DISSERTATION

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DEDICATION

To my lovely family who supported me during all this journey.

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QUANTIFYING THE EFFECT OF CONSTRUCTION SITE FACTORS ON CONCRETE QUALITY, COSTS AND PRODUCTION RATES USING FUZZY INFERENCE SYSTEMS

by

Jorge L. Santamaria Carrera

B.S., Civil Engineering, Central University of Ecuador, 1999
M.Sc., Civil and Environmental Engineering, Arizona State University, 2006
Ph.D., Engineering, University of New Mexico, 2017

ABSTRACT

Factors affecting concrete can be categorized as structured factors or unstructured factors. The first group of factors consists of those related to the production process of concrete including water-cement ratio, properties of raw materials and mix proportions. Unstructured factors or construction site factors are related to labor skills and local conditions during the construction process of a project. Concrete compressive strength as a quality metric, costs and production rates may be affected significantly by such factors while performing concrete operations at the jobsite. Several prior studies have investigated the effect of structured factors on concrete. However literature is limited regarding the effects of unstructured factors during the construction phase of a facility.

This study proposes a systematic methodology to identify and quantify the effects of construction site factors including crew experience, compaction method, mixing time, curing humidity and curing temperature on concrete quality, costs and production rates using fuzzy inference systems. First, the perceived importance of construction-related

factors is identified and evaluated through literature review and a survey deployed to construction experts. Then, the theory of design of experiments (DOE) is used to conduct a full 2^5 factorial experiment consisting of 32 runs and 192 compressive strength tests to identify statistically significant unstructured factors. Fuzzy inference systems (FISs) are proposed for predicting concrete compressive strength, costs and production rate effects through the use of adapted network-based fuzzy inference system (ANFIS). Finally, an optimization model is formulated and tested for managing concrete during the construction process of a facility.

Literature review and survey results showed that curing humidity, crew experience, and compaction method are the top three factors perceived by construction experts to affect concrete compressive strength, whereas crew experience, mixing time and compaction method are the top three factors affecting concrete costs and production rates. Additionally, crew experience, compaction and mixing time were found to dominate global ranking of perceived affecting factors through the application of the relative importance index (RII). When conducting designed experiments and analysis of variance (ANOVA), compaction method, mixing time, curing humidity and curing temperature were identified to be statistically significant construction site factors for concrete compressive strength whereas crew experience, compaction method and mixing time were statistically significant factors for cost and production rates. A Sugeno type fuzzy inference system (FIS) for quantifying compressive strength, cost and production rate effects was created by using ANFIS, having correlation coefficients (R-squared values) greater than 93%, indicating that resulting models predict new observations well. Curing temperature (i.e., on-site curing temperature) was identified to be the most affecting condition for concrete compressive strength while mixing time had the biggest impact on concrete cost and production rates. The developed FISs can be used as a decision–support tool that allows for determining desired operating conditions, that ensures specified compressive strength, saves resources and maximizes profits when fabricating, placing and curing concrete.

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CHAPTER 1: INTRODUCTION

There are several affecting conditions that could impact concrete compressive strength, costs, and production rates when fabricating concrete at the jobsite. The impact is manifested by reducing strength, by reducing productivity, and by increasing costs. These potential impacts are usually unknown or ignored by construction laborers, foremen and project managers. Knowing such impacts in advance could prevent managers from wasting resources as well as help save time and money. The novel approach presented in this study assists in reducing uncertainty in order to manage concrete quality during the construction phase of a project through the use of novel fuzzy set theory.

One of the most popular construction materials is concrete (Neville and Brooks 2010), and it is the second most utilized product after water (Okasha and Aichouni 2015). Concrete as a construction material is actually present in almost every facility. This material is made of Portland cement, aggregates, admixtures and water and the characteristics and proportions of its components play an important role on its quality metrics. Compressive strength is the most common quality metric since concrete behaves very well under compression forces and it is commonly used to measure concrete quality (Kosmatka et al. 2002). Also, it is an important parameter for designers and concrete quality control (Mehta and Monteiro 2006). Therefore, concrete quality should be guaranteed not only during the production process of concrete but also during the construction phase of a project.

Ready-mixed concrete undergoes stringent quality controls during its fabrication and transportation processes. However, there are several uncertain factors or conditions that are not considered after concrete trucks arrive to a construction site, which can change final concrete product characteristics (Neville and Brooks 2010). In addition, when concrete should be fabricated in-situ, additional factors such as human or local aspects may affect not only concrete quality but also associated production costs and production, causing possible significant changes on its mechanical properties, project budget and duration. Thus, the quantification of the impact of the aforementioned constructions site factors could cause significant changes on concrete product metrics.

1.1 Problem Statement

Most of the quality control for concrete is done during its production process rather than during the construction phase of a project. Yuan et al. (2014) pointed out that the factors that affect concrete compressive strength may be classified into two categories: structured and unstructured factors. The first category is related to the factors affecting concrete during its production process such as the properties of raw materials, water– cement ratio, or mix proportions while the second category refers to the factors affecting concrete quality during the construction phase of a project such as manpower, weather and other local conditions. The influence of structured factors on concrete metrics are well understood; however, there is limited understanding of the effect of unstructured factors or construction site factors on concrete. The present research addresses the aforementioned limitations by developing a systematic procedure for quantifying the effect of such unstructured factors on concrete compressive strength as a quality metric, costs and productions rates by integrating survey results, design of experiments, and fuzzy inference systems.

1.2 Research background

Several prior studies have investigated the impact that structured factors have on concrete compressive strength as a quality metric such as the influence of water – cement ratio, entrained air, aggregate size, and age on compressive strength (Kosmatka et al. 2002; Mehta and Monteiro 2006; Neville and Brooks 2010) and the effects of admixtures on concrete compressive strength (Demirboğa et al. 2001; Jongpradist et al.2010). However, the literature is limited regarding construction site factors present when fabricating, placing or curing concrete and their impact on compressive strength, costs and production rates.

With respect to costs and production of concrete operations, studies of affecting factors are also scarce. O'Connor (2006) pointed out that factors affecting crew production rates are difficult to measure and quantify due to intrinsic construction processes' characteristics. Also, the author emphasizes that the lack of data for specific activities containing particular details prevents researchers from investigating accurate construction time estimation. Jarkas (2010; 2012) investigated the influence of buildability on labor productivity by employing experienced crews and argued other factors such as the level of crew skills and experience may influence concrete productivity and costs. Heravi and Eslamdoost (2015) studied labor productivity factors in the construction industry in order to lower costs and project duration.

Understanding the effect of construction site factors on concrete product is of special importance for project managers and concrete workers since project characteristics require the compliance of construction documents specifications, budget and time of execution. The present study intends to increase our understanding of the aforementioned factors on concrete product through experimentation and the use of fuzzy set theory.

1.3 Research Objectives

The main objective of this study is to develop a methodology that provides construction stakeholders, project managers, concrete technicians and workers with valuable information regarding the effect of construction site factors on concrete compressive strength, costs and production rates during the construction phase of a facility. The following are the research questions addressed in this dissertation:

1. What construction site factors (i.e., unstructured factors) may affect concrete quality (i.e., compressive strength), costs and production rates?

2. What experimentation strategy is effective for considering several disturbing conditions, and allowing the identification of construction site factors that affect concrete metrics significantly?

3. What method and criteria based on experimental data should be taken into consideration to develop membership functions and if–then rules in order to

develop a fuzzy inference system that predicts the effect of construction site factors on concrete?

4. How can project managers and contractors ensure concrete quality at the jobsite without increasing costs or decreasing productivity while considering identified construction site factors?

1.4 Methodology Overview

The proposed study is divided into four parts. The first part consists of identifying construction site factors (i.e., unstructured factors) by reviewing revelant literature and conducting an online suvey of construction experts. The relative importance of each factor is obtained through the calculation of relative importance indexes (RIIs), and the perceptions of construction experts on affecting conditions are discussed. Identified construction site factors are then utilized to be replicated in the laboratory for concrete sample fabrication. The second part of this dissertation focuses on applying the theory of Design of Experiments (DOE) by conducting a full factorial design. Five construction site factors are selected including crew experience, compaction method, mixing time, curing humidity and curing temperature, and a complete factorial analysis is conducted in order to identify statistically significant factors affecting concrete compressive strength, cost and production rates. The experimental design considers factors acting at two levels: low and high. Concrete samples are fabricated under affecting conditions replicated and controlled at a laboratory and tested for axial loading at the age of 28 days. Third, the resulting experimental input – output (I/O) data are collected and utilized to create a Sugeno type

FIS for predicting concrete compressive strength, cost and production rate effect by using subtractive clustering and ANFIS. Finally, optimal or desired compromised conditions that allow construction managers, concrete workers and technitians to find operating conditions tending to preserve concrete quality without increasing costs at high production rates are explored. The research methodology enables the development prediction fuzzy models for quantifying the effect of construction site factors on concrete metrics through the use of experimentation and fuzzy set theory, providing a decision–support tool for stakeholders.

1.5 Organization

This dissertation comprises six chapters. Chapter 1 introduces the problem statement and the research questions to be addressed. Chapter 2 identifies and evaluates the perceived importance of construction site factors that affect concrete in terms of compressive strength as a quality metric, costs and production rates, and measures how construction experts' characteristics influence significantly their perceptions on these factors. Chapter 3 describes the experimental program for conducting a full 2^5 factorial design and analyzes the results for identifying statistically significant construction site factors. In Chapter 4, fuzzy set theory is applied to develop fuzzy inference systems for quantifying concrete strength, cost and production effects using experimental input – output data. Also, the capabilities of each prediction model are discussed. Chapter 5 presents the formulation of a multi-objective optimization problem to find optimal operating conditions that meet or exceed the specified concrete compressive strength while minimizing costs and maximizing production rates. Lastly, Chapter 6 presents general inferences, contributions and limitations of this research as well as some suggestions for future reseach.

CHAPTER 2: PERCEPTIONS ON CONSTRUCTION-RELATED FACTORS THAT AFFECT CONCRETE QUALITY, COSTS AND PRODUCTION RATES

2.1 Introduction

Concrete is a construction material made of water, Portland cement, aggregates and admixtures, which are mixed together in specific proportions to meet construction specifications for such qualities as compressive, tensile or flexural strength. In addition to steel, concrete is one of the two most popular construction materials currently used in the construction industry (Neville and Brooks 2010), and it is the second most utilized product in the world after water (Okasha and Aichouni 2015). Moreover, concrete demand increases every day, due to increases in population around the world. In fact, in the United States, around 260 million cubic yards of concrete are used each year by the construction industry (PCA 2015).

Concrete compressive strength is commonly used to measure concrete quality (Kosmatka et al. 2002), and it is an important parameter for designers and for concrete quality control (Mehta and Monteiro 2006). Compressive strength is used for measuring concrete quality because concrete is mainly employed to withstand compression forces. Therefore, compressive strength is the quality metric used for judging concrete quality in this chapter.

Concrete quality should be ensured from its production to its final placement into the forms, finishing and curing on any construction site. Ready-mixed concrete undergoes stringent quality controls during its production and transportation. However, there are several uncertain factors or conditions that are not considered after concrete trucks arrive at a construction site that can change the characteristics of the final concrete product (Neville and Brooks, 2010). In addition, when concrete is fabricated in situ, additional factors may affect concrete quality and can cause possible significant changes in its mechanical properties.

Several prior studies have investigated the impact that factors related to the production of concrete – including raw material properties or mixture designs – have on concrete quality, such as the influence of water-cement ratio, entrained air, aggregate size and age on compressive strength (Kosmatka et al. 2002; Mehta and Monteiro 2006; Neville and Brooks 2010) and the effects of admixtures on concrete compressive strength (Demirboğa et al. 2001; Jongpradist et al. 2010). With respect to costs and production rates, studies of affecting factors are scarce. O'Connor (2006) pointed out that factors affecting crew production rates are difficult to measure and quantify due to intrinsic variables. Also, the author emphasized that the lack of existing actual data for specific activities containing particular details prevents researchers from accurately investigating construction time effects. Jarkas (2010; 2012) investigated the influence of buildability on labor productivity by employing experienced crews and argued other factors such as the level of crew skills and experience may influence concrete productivity and costs. Heravi and Eslamdoost (2015) studied labor productivity factors in the construction industry in order to lower costs and project duration. However, the literature is limited regarding factors present when fabricating concrete and their impact on compressive strength as a quality metric, as well as on costs and production rates.This chapter focuses on identifying and evaluating the perceived importance of factors that are inherent to concrete operations on a construction site during the construction phase of a facility, considering human conditions, machinery utilized, and environmental and/or curing conditions. Additionally, construction experts' characteristics, such as profession, that influence their perceptions on the impact of such factors on concrete are investigated by applying chi-square tests for equality of odds.

2.1.1 Factors Affecting Concrete Strength

Yuan et al. (2014) classified factors affecting concrete strength into two categories: structured and unstructured. Structured factors are factors related to the production of concrete (Yuan et al. 2014), such as raw materials quantities and quality and mix designs. As previously mentioned, these factors have already been studied deeply and, in fact, several correlations have already been proposed including the influence of water-cement ratio on compressive strength for non-air-entrained concretes (Kosmatka et al. 2002). Unstructured factors are those associated with the construction process of a facility such as workforce skills and local conditions on the construction site, and there is no clear understanding of their consequences on concrete strength (Yuan et al. 2014). Fig. 1 summarizes the factors that affect the concrete production and construction processes.

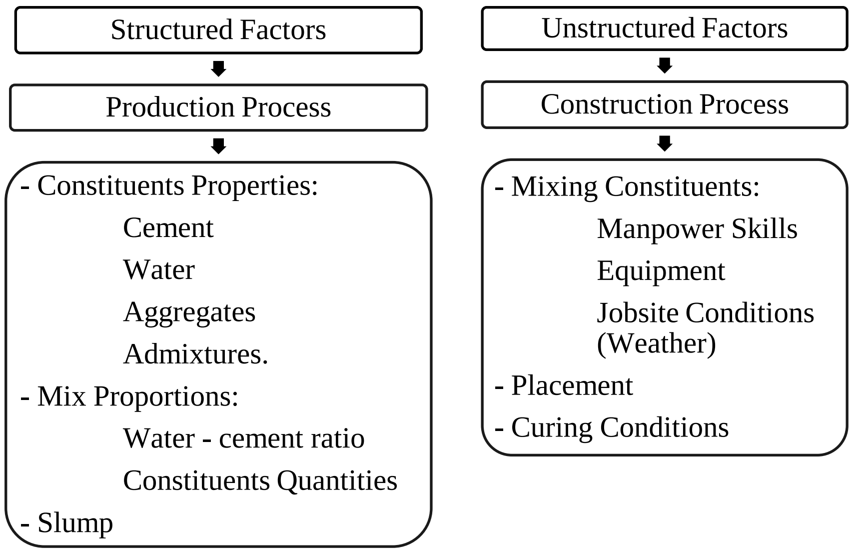


Fig. 1. Factors that affect concrete during its production and construction processes.

2.1.2 Impact of construction expert characteristics on perceptions

Understanding the impact of construction specialists' attributes on their perceptions about factors affecting concrete performance is crucial so that appropriate actions can be taken to improve construction processes and management. Even though perception studies are not common in engineering (Rodríguez-Garzón et al. 2016), several studies have analyzed how subjects' characteristics influence their perceptions on engineering and construction issues. Dai et al.(2009) studied the perceptions of construction workers regarding factors affecting their productivity by deploying a survey containing Likert-type questions. Lu and Yan (2013) pointed out that knowledge of construction groups or individuals is limited regarding risk perception. Zhang et al (2015) suggested that understanding the risk perceptions of different groups such as architects and engineers allows adequate construction management, implying that the attributes of different groups of professionals influence their perceptions. Rodríguez-Garzón et al. (2016), also using a questionnaire, studied the risk perception of construction workers in the context of uncertainty and occupational risk in the construction industry. Tymvios and Gambatese (2016) claimed that comparing the responses of different groups allows one to identify the group that is more likely to support a perception. All studies imply that perceptions depend on the characteristics of an individual or a group of people sharing the same background, meaning that different groups (e.g., architects and engineers) have different perceptions due to intrinsic characteristics of each group. Thus, it is important to evaluate the impact of construction experts' characteristics on their perceptions about construction-related factors to facilitate project management and preserve concrete properties.

2.2 Goals and Objectives

The main goal of this chapter is to increase our understanding about how unstructured factors affect concrete quality, costs and production rates. The objectives are: (1) identify and evaluate the perceived importance of construction-related factors that affect concrete compressive strength as a quality metric, as well as costs and production rates, and (2) measure how construction experts' characteristics influence their perceptions of these factors. These objectives will be accomplished by performing a comprehensive literature review, deploying a survey to construction experts and using RII and odds ratios to estimate their perceived importance. The results will inform project managers, superintendents and technicians, to prevent concrete quality from being influenced by affecting factors on the jobsite. In addition, current practices and mitigation actions are discussed for future research.

2.3 Methodology

The proposed methodology investigates unstructured factors affecting concrete quality during the construction process, since these factors can cause important concrete quality variability and should be taken into consideration on the job site (Yuan et al. 2014). To identify such unstructured factors, the research methodology shown in Fig. 2 was used.

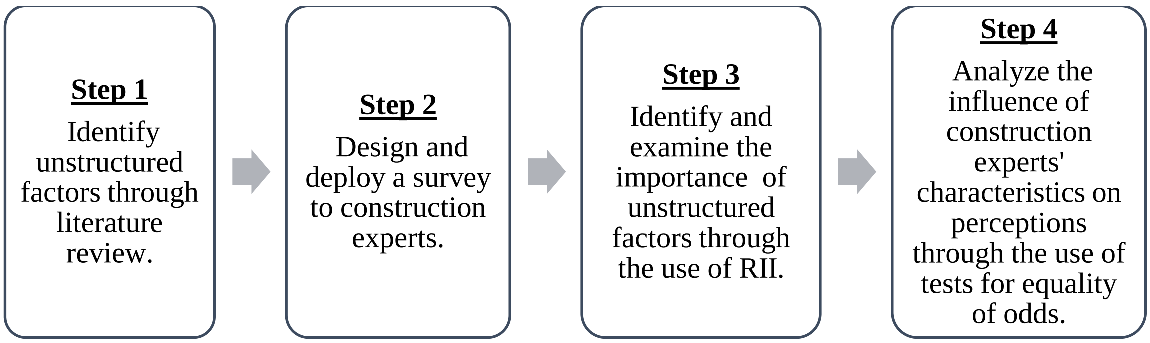


Fig. 2. Research methodology

The first step consisted of performing a review of relevant literature, to identify unstructured factors that affect concrete quality. Next, a survey was designed and deployed to construction experts (i.e., individuals with experience in the construction industry, such as contractors, architects, engineers and academics). This survey included questions about unstructured factors identified in the literature and asked for others that had been identified or recognized by the survey respondents throughout their careers. RII was then utilized to identify and evaluate the perceived importance of factors that highly affect concrete quality, costs and production rates. The quality metric for concrete was also determined from the literature and survey responses. Next, construction experts' characteristics, such as profession or experience, were analyzed through the use of Likert aggregation and 2x2 contingency tables (i.e., chi-square tests for equality of odds), to determine their influence on experts' responses. The techniques chosen for analysis responded to the study objectives and the properties of the survey data (Heeringa et al. 2010).

2.3.1 Identification of Unstructured Factors

Laungrungrong et al. (2010) argued that the increasing use of concrete creates the necessity of having methods or techniques to control its quality and that failing to identify strength problems may cause project delays and cost overruns. The variability in concrete compressive strength may be caused not only by mixing incorrect quantities of its components or utilizing poor quality materials but also by concrete transportation, placement and compaction (Wight et al. 2012), implying that compressive strength not only depends on its production process but also on uncertain conditions on the construction site.

Neville and Brooks (2010) pointed out that water-cement ratio, degree of compaction, age and ambient temperature (i.e., hot- and cold-weather concreting) should be taken into consideration in practice, in order to avoid compression strength reduction, implying that those factors should be monitored constantly. However, the study stated that there are other factors such as mixing time, curing temperature and humidity that should also be considered when making concrete. In addition, Li (2011) mentioned water-cement ratio, cement content, aggregates, admixtures, mixing procedures and curing conditions as factors that influence concrete properties, recognizing influencing factors inherent to construction processes.

Kosmatka et al. (2002) argued that special attention should be paid to mixing time, placement, consolidation (i.e., by hand or mechanically), rain protection (to avoid adding extra water to the concrete), finishing operations (e.g., flattening surfaces), curing and protection from extreme temperature changes (i.e., curing temperature and humidity) and hot and cold weather concreting (i.e., ambient temperature) in order to maintain concrete quality. Mehta and Monteiro (2006) argued that factors modifying concrete compressive strength include the proportions and materials of the concrete mixture and degree of consolidation and conditions of curing. The authors emphasized that concrete curing involves temperature, time and humidity conditions. Hassoun and Al-Manaseer (2012) highlighted that methods of mixing, compaction and curing affect the compressive strength. Proper mixing time, the use of appropriate concrete mixers and the right use of vibrators have a positive effect on concrete by increasing its compressive resistance, which is the consequence of having a uniform mixture and reducing voids. Curing moisture and temperature also play an important role in the strength of concrete, since the hydration of cement depends on them.

In recent studies about concrete strength variability, Unanwa and Mahan (2014) stated that strength variation is due to concrete placement, consolidation and curing methods (i.e., curing temperature and humidity), and Chen et al. (2014) suggested that special attention should be paid to temperature and humidity when producing, placing and curing concrete, implying that concrete strength may be affected after mixing its component materials until it is finally placed. Table 1 summarizes the preliminary construction site factors (unstructured factors) that affect concrete, as identified through the literature. However, relevant literature did not reveal the significance or effects of these unstructured factors on the concrete final product in terms of compressive strength, cost and production.

Table 1.Unstructured factors identified in the literature

Source	Factors
Kosmatka et al.(2002)	1. Mixing time 2. Segregation 3. Compaction 4. Adding extra water 5. Flattening surfaces (Finishing) 6. Curing temperature 7. Curing humidity 8. Ambient temperature
Mehta and Monteiro (2006)	1. Compaction 2. Curing temperature 3. Curing humidity
Neville and Brooks (2010)	1. Compaction 2. Ambient temperature 3. Mixing time 4. Curing temperature 5. Curing humidity
Li (2011)	1. Mixing time 2. Curing temperature 3. Curing humidity
Wight et al. (2012)	1. Segregation 2. Compaction
Hassoun and Al-Manaseer (2012)	1. Mixing time 2. Compaction 3. Curing humidity 4. Curing temperature
Unanwa and Mahan (2014)	1. Segregation 2. Compaction 3. Curing temperature 4. Curing humidity
Chen et al. (2014)	1. Segregation 2. Curing temperature 3. Curing humidity

Table 1 shows that researchers agreed on several factors that affect concrete compressive strength. These studies assumed that concrete was made by laborers with experience or expertise fabricating concrete; construction workers with appropriate skills must be hired in order to ensure the success of a project (Sears et al. 2015). Therefore, crew experience could be another unstructured factor that affects concrete quality variability. Table 2 shows a compiled list of preliminary unstrutured factors considered in this study. The factors are listed in no particular order.

Table 2. Preliminary unstructured factors

Number	Identified Factor
1	Mixing time
2	Compaction
3	Ambient Temperature
4	Curing Temperature
5	Curing Humidity
6	Adding extra water when mixing
7	Crew Experience

Regarding the number of factors that may affect concrete, Day (1999) appealed to Pareto's principle to say that 70% to 80% of the total variability in concrete strength is caused by two or three factors. The author suggested that strength variability is caused by less than ten factors, which is in agreement with what has been found elsewhere in the literature.

Finally, literature regarding factors that affect concrete compressive strength during its production until its final placement is limited. Most of the literature focuses on well known structured factors regarding concrete component properties and material proportions (e.g., water-cement ratio), and while the literature identifies unstructured factors, their impact on quality, cost and production has not been quantified.

2.3.2 Survey

Surveys are well-recognized tools that allow us to infer valuable knowledge about a population through the collection of quantitative and qualitative data, as long as the sample size chosen is representative of the actual population. The main purpose of any survey is to build quantitative descriptors (statistics) to summarize the observations (Groves et al.

2004); however, survey variables will always contain bias due to nonresponses or measurements errors (Chambers and Skinner, 2003).

Groves et al. (2004) stated that a survey should meet the following criteria to minimize errors: (1) respondents must describe their characteristics accurately, and; (2) respondents must be representative of the larger population. Meeting these criteria does not imply that survey statistics are error-free; errors of observation and non-observation will still be present in the results (Groves et al. 2004).

Thus, a survey was designed considering such criteria, and it was deployed online to a large group of construction experts in Ecuador who had at least one year of experience with concrete in the construction industry or academia. Survey respondents included members from professional associations of civil engineers and architects and from educational organizations such the School of Civil Engineering and Architecture of the Central University of Ecuador. This ensured that the respondents met the “expert” criteria. The study was granted an exemption through the pertinent Institutional Review Board (IRB) prior to conducting the investigation. The survey included a set of questions for identifying and ranking unstructured construction site factors that could affect concrete quality, costs and production rates during the construction process, as well as questions regarding concrete quality metrics and respondents’ characteristics such as profession and construction experience.

The survey was deployed online using the Qualtrics platform, and it was distributed to a group of approximately 5,000 active construction experts through their own organizational mailing list manager. The sample size of 297 valid responses ensured a confidence level of 95%. In addition, validation questions were included in the survey, to prevent respondents from answering survey questions randomly.

The questionnaire, IRB exemption letter, and detailed data analysis using Relative Importance Indexes are presented in Appendix A.

2.3.2.1 Sample Description

A total of 333 responses were collected during June and July of 2016 after deploying the online survey to construction experts. Out of the 333 total responses, 297 were valid. The sample exceeded the required sample size by 200 since only 97 valid responses were required to obtain a confidence level of 95% and a confidence interval of 10%, implying that the actual confidence interval was as low as 6%. Most of the respondents (more than 75%) were between 26 and 55 years old, and almost all of them (95.4%) had completed their college education. Since the survey was deployed to "construction experts" from professional organizations and academia, laborers were not included. Superintendents and foremen were included because it is necessary to have a college degree (in architecture or engineering) to work as a superintendent or foreman in Ecuador. The great majority of the respondents (80.1%) had a degree in engineering, while architects and contractors accounted for 17.5% of the respondents. Around 81% of the respondents had more than 5 years of experience in the construction industry and 69.8% of all the construction experts had their main field of expertise focused on construction. Also, 65.4% of all respondents worked on constructing buildings and houses. As can be inferred from the descriptors of the sample, the respondents had important expertise regarding the use of concrete as a construction material in building and housing projects, and transportation and hydraulic facilities.

For each of the factors in Table 2, respondents provided their perception of the impacts of unstructured factors on compressive strength, cost and production rates, using the following Likert scale: (1) no impact, (2) very low impact, (3) low impact, (4) medium impact, (5) high impact and (6) very high impact.

2.3.3 Data Analysis

RII was used to identify and evaluate the importance of the unstructured factors. Tests for equality of odds were performed by using Likert response aggregation to understand the influence of the respondents' characteristics on their perceptions of the impact of unstructured factors on concrete. The data collected will provide additional information about current practices and mitigation actions for future studies.

2.3.3.1 Relative Importance Index (RII)

RII can be applied for ranking construction-related affecting factors when using a Likert-type scale (Kometa et al. 1994; Odusami 2002; Davies and Harty 2013; Gündüz et al. 2013; El-Gohary and Aziz 2014; Gunduz et al. 2015; Jin et al., 2017; Sambasivan and Soon 2007). A six-point scale ranging from 1 (None) to 6 (Very High) was adopted to determine the impact of unstructured factors on compressive strength, costs and production rates. RII ranges from 0 to 1 and is calculated as in Eq. 1, where W is the weighting given to each factor by the respondents (1 to 6), A is the highest weight (i.e., 6) and N is the total number of respondents. The higher the RII, the higher the ranking and the perceived importance of the affecting factor.

$$RII = \frac{\Sigma W}{A.N} \tag{1}$$

2.3.3.2 Likert response aggregation

Siegel and Castellan (1988) suggested a procedure for aggregating Likert-type responses into only two values, allowing us to build up data for comparing the responses of two groups of participants with different characteristics (Tymvios and Gambatese 2016). In this way, construction experts' agreement to a particular state (e.g., high and very high impact) could be separated from others. The Likert aggregation process is illustrated in Fig. 3. It consists of adding together the responses with very high (VH) and high (H) impacts as well as the responses with None (N), Very Low (VL), Low (L) and Medium (M) impacts in order to compile each Likert response into only two values: (VH+H) and (N+L+VL+M). This approach was used because the intent was only to study factors perceived to affect concrete highly (VH+H).

Likert type response						
Group	None (N)	Very Low (VL)	Low (L)	Medium (M)	High (H)	Very High (VH)
1	1N	1VL	1L	1M	1H	1VH
2	2N	2VL	2L	2M	2H	2VH

Likert aggregation (2 x 2 Tables)		
Group	Very High / High (VH/H)	Other
1	1H+1VH	1N+1VL+1L+1M
2	2H+2VH	2N+2VL+2L+2M

Fig. 3. Likert response aggregation process

2.3.3.3 Tests for equality of odds

Contingency tables (2x2 tables) containing the responses of two categorical variables are appropriate instruments to explore the relationship between two categorical variables with natural ordering (Lavrakas 2008) and are used for performing chi-square tests of association between variables (two way tables). This test for equality of odds allows us to compare two different groups and determine if a response differs regarding the same question.

The odds ratio is then used to compare the effect of each level of a categorical variable on the estimated probability. Ramsey and Schafer (2013) described shortcut methods for estimating the odds ratio in such a table and the corresponding confidence interval. The odds ratio is computed as the ratio of the products of the main diagonals of the 2x2 table as shown in Eq. 2, and the confidence interval (CI) is calculated by using a shortcut method for the standard error (SE) of the log odds ratio. SE is the square root of the summation of the four reciprocals of a 2x2 table (Eq. 3) and the 95% CI is obtained from the antilogarithm of the end points of the 95% CI for the log odds ratio (Eq. 4).

$$Odds\ ratio = \frac{(1H+1VH)(2N+2VL+2L+2M)}{(2H+2VH)(1N+1VL+1L+1M)} \tag{2}$$

$$\mathrm{SE} = \sqrt{\frac{1}{x_{12}} + \frac{1}{x_{12}} + \frac{1}{x_{21}} + \frac{1}{x_{22}}} \tag{3}$$

$$95\%\ CI\ for\ the \log\ odds\ ratio = \ln(Odds\ ratio) \pm 1.96(SE) \tag{4}$$

2.4 Results

2.4.1 Concrete Quality Metric

The results indicated that concrete compressive strength is the metric used by most of the respondents (89.6%) for measuring concrete quality (Fig. 4) regardless of the type of facility or application, which is an expected result, confirming findings from the literature search. Thus, compressive strength is an appropriate quality metric to use in this study.

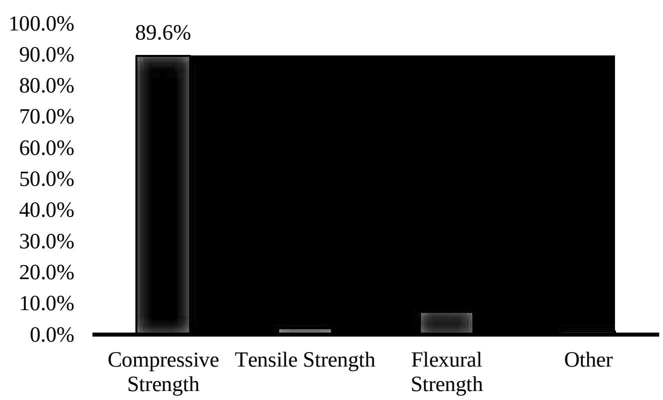


Fig. 4. Concrete quality metric

2.4.2 Perceived Importance of Unstructured Factors

As previously mentioned, survey respondents were asked to assess the importance of unstructured factors identified in Table 2 considering their perceived degree of impact on concrete compressive strength, costs and production rates through a Likert type scale. Importance indexes for each affecting factor, computed by using Eq. 1, were employed to evaluate the perceived importance of the unstructured factors and to establish the ranking of the unstructured factors.

Table 3 comprises RII values for each identified affecting factor, allowing us to establish lists of affecting factors in descending order. The numbers in parentheses represent the corresponding importance, with 1 being the most important. Thus, the higher the RII, the higher the importance.

Table 3. Impact of unstructured factors on concrete compressive strength, costs and production

Number	Identified Factor	RII		
		Compressive strength as a quality metric	Costs	Production
1	Mixing time	0.722 (6)	0.649 (3)	0.682 (2)
2	Compaction	0.753 (3)	0.654 (2)	0.649 (3)
3	Ambient temperature	0.686 (7)	0.534 (6)	0.616 (5)
4	Curing temperature	0.746 (4)	0.634 (5)	0.559 (7)
5	Curing humidity	0.792 (1)	0.635 (4)	0.612 (6)
6	Adding extra water	0.743 (5)	0.514 (7)	0.637 (4)
7	Crew experience	0.781 (2)	0.765 (1)	0.763 (1)

Curing humidity, crew experience and compaction are the top three factors affecting concrete compressive strength according to the respondents (Table 3). Regarding concrete costs and production rates, crew experience, mixing time and compaction lead the ranking list of the unstructured factors affecting concrete. Notice that crew experience and compaction are common perceived factors that greatly influence concrete, revealing that construction experts are aware that the use of qualified workers and appropriate equipment are crucial to concrete fabrication. Also, almost all respondents indicated that unstructured factors do affect concrete costs somehow. Only a very small percentage (1.9%) stated that unstructured factors do not have any effect on concrete cost. In addition, experts pointed out that curing conditions, mixing time and compaction should be paid special attention to ensure concrete quality and meet budget specifications (i.e., costs and production).

A global ranking of importance for the identified unstructured factors was calculated by compiling all responses (Table 4), giving the same weight for compressive strength, costs and production rates. Crew experience, compaction and mixing time are found to be the top three affecting factors perceived to influence concrete during the construction process. On the other hand, adding extra water (via rain) and ambient temperature are perceived to be the least affecting conditions when performing concrete operations.

Table 4. Overall ranking importance of identified unstructured factors for concrete compressive strength, costs and production

Rank	Identified Factors	RII
1	Crew experience	0.7695
2	Compaction	0.6854
3	Mixing time	0.6846
4	Curing humidity	0.6798
5	Curing temperature	0.6465
6	Adding extra water	0.6315
7	Ambient temperature	0.6120

2.4.3 Comparison of Responses by Group

Architects and engineers accounted for 94.6% of the respondents. Chi-square tests of association between variables using 2x2 tables (Fig. 3) and Ramsey and Schafer (2013) shortcut methods for estimating odds ratios and confidence intervals were utilized to analyze the data. A summary of the odd ratios, confidence intervals and p values for the perceptions of architects (Group 1) and engineers (Group 2) regarding the impact of identified unstructured factors on concrete strength, cost and production rates is presented in Table 5.

Table 5. Comparison of responses by architects and engineers regarding the impact of unstructured factors on concrete strength, costs and production

Impact	Odds Ratio	95% CI		p value
Mixing Time				
Strength	2.59	1.25	5.37	0.009
Cost	2.93	1.50	5.74	0.001
Production	3.60	1.78	7.25	0.000
Crew Experience				
Strength	2.60	1.19	5.66	0.014
Cost	3.14	1.44	6.83	0.003
Production	4.09	1.82	9.19	0.000
Compaction				
Strength	3.25	1.49	7.07	0.002
Cost	3.66	1.84	7.30	0.000
Production	4.83	2.38	9.77	0.000
Curing Temperature				
Strength	2.50	1.20	5.19	0.012
Cost	3.97	2.02	7.82	0.000
Production	0.80	0.36	1.77	0.587
Curing Humidity				
Strength	2.55	1.17	5.57	0.015
Cost	4.25	2.13	8.50	0.000
Production	0.59	0.27	1.29	0.179
Adding Extra Water				
Strength	2.98	1.41	6.33	0.003
Cost	0.72	0.33	1.58	0.412
Production	5.43	2.68	11.01	0.000
Ambient Temperature				
Strength	1.85	0.96	3.58	0.064
Cost	0.60	0.25	1.43	0.247
Production	2.60	1.34	5.03	0.004

As shown in Table 5 , with respect to mixing time, architects were 2.59, 2.93 and 3.60 times more likely than engineers to perceive a very high or high impact of mixing time on concrete strength, cost and production rates. In all cases the p values (0.009, 0.001 and 0.000) are less than 0.05. For ambient temperature, for example, p values for the impact on concrete strength and costs are greater than 0.05, indicating that there is not enough evidence that the odds ratio differs from 1, and thus no conclusion can be inferred from such comparisons in this case. Therefore, for all odds ratios that are greater than 1 and p values less than 0.05, it can be inferred that architects are more likely to perceive high or very high impacts of such unstructured factors on concrete than engineers do.

2.4.4 Identification of Additional Unstructured Factors

In addition to the unstructured factors identified in the literature and shown in Table 2, construction experts were asked to identify additional unstructured factors recognized throughout their careers. Only 23% of the respondents provided additional factors. They are listed in Table 6 and categorized into workforce, machinery and equipment, jobsite environment and concrete fabrication process.

Table 6. Additional unstructured factors identified by the respondents

<table>
<tr><th>Workforce</th><th>Machinery and Equipment</th><th>Jobsite Environment</th><th>Concrete Fabrication Process</th></tr>
<tr>
<td>Deficient formwork
Mixing wrong material quantities
Excess of admixtures
Height of concrete pouring (segregation)
Concrete volume to be made
Type of concrete element to be fabricated</td>
<td>The use of proper tools when dealing with concrete
Means of concrete transportation</td>
<td>Contaminated concrete materials (water and aggregates)
Wind (fast dry of concrete)
Vibrations after concrete setting
Nighttime construction
Aggressive environment (soil - foundations)</td>
<td>Time of concrete fabrication
Time of concrete placement</td>
</tr>
</table>

2.4.5 Current Practices and Mitigation Actions

Research results show that a significant percentage of construction experts (57.6%) are aware of the presence of unstructured factors during concrete operations, and some preventive actions are carried out to minimize their effects on concrete. When comparing the responses of the two major groups – architects and engineers – regarding the awareness of the existence of unstructured factors by using 2x2 tables, it can be concluded that there is not enough evidence that the odds ratio differs from 1 regarding previous knowledge of such factors. Also, construction experts who are aware of unstructured factors tend to take some mitigation actions during concrete operations.

For example, to prevent the addition of extra water to fresh concrete, the concrete is protected from rain by either avoiding concrete fabrication on rainy days or by using plastic protection. In addition, the use of experienced crews is preferred for concrete production. Survey results suggest that the use of experienced crews when fabricating concrete is preferred to reach concrete compressive strength. A very high percentage of construction experts (91.3%) have utilized experienced crews when dealing with concrete. Regarding curing conditions, 80.9% of respondents did not consider temperature when curing concrete. The only concern was keeping concrete wet (i.e., preserving humidity) due to the difficulty of providing such a controlled environment on the jobsite, and the costs associated with this activity.

Moreover, 28 days is thought to be the period of time necessary for concrete to reach its design capacity by the majority of construction experts (79.1%), which is in agreement with standard acceptance tests; namely, ASTM standards C31 (ASTM International, 2015e) and C39 (ASTM International, 2016a) and the requirements established by The American Concrete Institute (ACI Committee 318, 2014).

Even though concrete should not be fabricated in situ due to quality control aspects (Neville and Brooks 2010), the results indicate that significant amounts of concrete are actually made on the jobsite. Seventy-six percent of the respondents believed that more than 10% of concrete required for a facility is fabricated in situ; they recommended the use of concrete mixers to ensure all ingredients are mixed uniformly. The high percentage of concrete made on the jobsite could be explained due to the perception that ready-mixed concrete is more expensive than concrete fabricated in situ, even though the difference is not that large.

Although construction experts accepted that significant amounts of concrete are made on the jobsite, they were aware that concrete quality may be compromised. Most respondents (89.0%) believed that concrete fabricated in a plant (i.e., ready-mixed) and on the jobsite (either mixed by hand or using a concrete mixer) do not have the same quality.

2.5 Conclusions

In this chapter, unstructured factors affecting quality (as measured by compressive strength), costs and production rates have been identified in the literature and through the perceptions of construction experts, using a survey instrument. With respect to concrete compressive strength, curing humidity (RII=0.792), crew experience (RII=0.781) and compaction (RII=0.753) are the top three affecting construction site factors, followed by curing temperature (RII=0.746), adding extra water (e.g., rain) (RII=0.743), mixing time (RII=0.722) and ambient temperature (RII=0.686). Even though the majority of construction experts were aware of the existence of such factors, most of them did not report taking preventive actions to minimize the effects of the factors on concrete. For instance, 80.9% of respondents did not consider curing temperature when curing concrete. However, concreting when raining (which could add extra water to fresh concrete mixtures) was considered during concrete operations by protecting fresh concrete from rain.

In terms of costs, the respondents believed that crew experience (RII=0.765), compaction (RII=0.654) and mixing time (RII=0.649) are the most important factors that affect concrete. Also, construction experts recognized that curing conditions have an important impact on costs, suggesting that taking no mitigation actions against such factors could be due to the significant increase in concrete costs. With respect to production rates, construction experts believed that crew experience (RII=0. 0.763), mixing time (RII=0.682) and compaction (RII=0.649) control concrete productivity, agreeing with the saying “time is money”. The more resources, the more expensive.

When considering an overall ranking of affecting factors for concrete compressive strength, costs and production, crew experience (RII=0.7695) comes first, followed by compaction (RII=0.6854) and mixing time (RII=0.6846). The least perceived affecting factors are adding extra water (RII=0.6315) and ambient temperature (RII=0.6120). These global rankings were computed by giving the same weight or importance to compressive strength, costs and production.

In addition to the previous unstructured factors, a small group of construction experts identified other important unstructured factors recognized throughout their careers that may also affect concrete compressive strength, costs and production rates. Such factors were classified according to their source and included deficient formwork, nighttime construction and the use of improper tools when dealing with concrete. These factors should be investigated in future research.

Moreover, the use of 2x2 contingency tables and tests for equality of odds allowed us to understand how profession (being an architect or engineer) can influence respondents' perceptions about the impact of unstructured factors on particular concrete characteristics. When comparing the two main groups of respondents – architects and engineers – regarding their perceptions of the effect of unstructured factors on concrete compressive strength, costs and production rates, the results indicate that architects are more likely to perceive high or very high impacts than engineers do when judging the effect of an unstructured factor.

Unstructured factors should be considered and monitored during the construction phase of a facility. This will help ensure that concrete complies with design specifications established in the construction documents. However, additional research is needed to quantify the impact of these factors on concrete.

CHAPTER 3: QUANTIFYING THE EFFECT OF CONSTRUCTION SITE FACTORS ON CONCRETE COMPRESSIVE STRENGTH USING DESIGNED EXPERIMENTS

3.1 Introduction

Factors affecting concrete strength can be classified into structured and unstructured factors (Yuan et al. 2014). Structured factors, such as raw materials quantities and quality and mixture designs, are related to the production process of concrete. Several correlations have been developed in the literature for quantifying the effect of such factors including, for example, Abrams' law, which looks at the relationship between water–cement ratio and compressive strength. Unstructured factors (i.e., construction site factors) are the factors associated with the construction process, including weather conditions on the construction site or worker expertise; there is limited understanding of their consequences on concrete quality.

Several studies have used design of experiments (DOE) techniques to find and identify factors affecting concrete strength. DOE involves not only planning and experimental testing, but also estimating models that predict new observations for new inputs (Allen 2005). Yeh (2006) studied the effect of fly ash replacements and different water-cement ratios on early concrete compressive strength and low and high compressive strength. Long et al. (2012) observed the impact of material properties and mixture parameters on self-consolidating concrete. Rahim et al. (2013) attempted to quantify the effect of fire-type temperatures on concrete compressive strength. Hassan and Abouhussien (2014) utilized

DOE for concrete mixture optimizations for high-strength self-consolidating concrete by changing binder, water and admixture content. In a recent study, Khan et al. (2017) investigated the effect of water-cement ratio, cement content, aggregate percentage and admixtures on high-strength self-compacting concrete. DOE has also been utilized in asphalt pavement design. Anting et al. (2015) studied the effect of using wasted tile aggregates for reducing pavement surface temperature. All the aforementioned research argues that DOE leads to the development of prediction models that provide reliable information on the effect of considered factors on concrete compressive strength.

In this chapter, five construction site factors (i.e., unstructured factors), including mixing time, compaction method, crew experience, curing humidity and curing temperature, were selected from the literature (Kosmatka et al. 2002; Mehta and Monteiro 2006; Neville and Brooks 2010; Li 2011; Hassoun and Al-Manaseer 2012; Wight et al. 2012; Chen et al. 2014; Unanwa and Mahan 2014) to evaluate their effect on concrete compressive strength as a quality metric. DOE was utilized to conduct the experimental runs, for both evaluating the significance and quantifying the effect of these factors on concrete strength. DOE has several advantages over other methods of experimentation. DOE allows estimating interactions between two variables (Montgomery and Runger 2003; Piratelli-Filho and Shimabukuro 2008). It provides protection against bias or nuisance factors through randomization (Cox and Reid 2000; Gunst and Mason 2009; Montgomery 2013), meaning that the order of the runs matters when undertaking the experiment. Orthogonal coding (± 1 coding) is applied to represent extreme low and high levels of unstructured factors, to observe and quantify the relative size of factor effects as well as for easy interpretation of results (Allen 2005, Montgomery 2013). The use of uncoded units (e.g., engineering units) in a factorial design is not recommended because it may lead to erroneous conclusions due to different factor units (Montgomery 2013). The use of two-level factorial design within DOE is suitable when the study involves several factors or conditions acting at low and high levels of intensity (Montgomery 2013). A full factorial design is expressed as 2^k factorial design, where "k" is the number of factors and "2" is the number of levels (e.g., low and high) of each factor. The statistical tool employed to identify significant variables as well as their effects on the system is the analysis of variance (ANOVA).

3.2 Goal and Objectives

The main purpose of this chapter is to quantify the effect of construction site factors, including mixing time, compaction method, crew experience, curing humidity and curing temperature, on concrete compressive strength as a quality metric, by performing a full factorial design. The research objectives are to: (1) identify statistically significant unstructured factors affecting concrete strength, (2) develop a regression model for predicting the magnitude of their impact on concrete compressive strength, and (3) find operating conditions that preserve or improve concrete compressive strength during the construction process.

3.3 Methodology

The systematic procedures shown in Fig. 5 were followed to accomplish the research objectives.

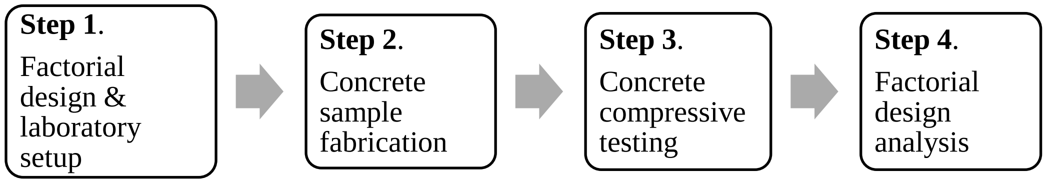


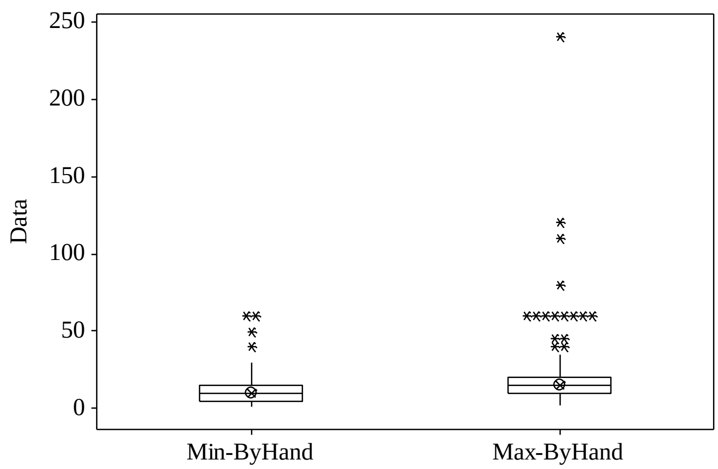
Fig. 5. Research methodology

3.3.1 Factorial Design and Laboratory Setup

Crew experience, compaction method, mixing time, curing humidity and curing temperature were the variables studied to quantify their effect on concrete compressive strength. These factors were used as independent variables to measure the concrete compressive strength response.

1. *Crew experience:* This was considered as a categorical variable having two levels: -1 for “not experienced” crews and 1 for experienced crews. Construction laborers with at least five years of experience in fabricating concrete by hand were recruited as experienced crews for fabricating the concrete samples while workers with no experience at all in concrete fabrication, including students, were categorized as “not experienced” crews.
2. *Compaction method*: Typical methods for on-site concrete compaction include hand rodding by a tamping rod and mechanical methods, such as internal and external vibration (Kosmatka et al. 2002; Neville and Brooks 2010; Li 2011). This study used a tamping rod (-1) and internal vibration (1) as the compaction method choices.
3. *Mixing time:* This refers to the time spent in mixing all concrete constituents by hand and comprises the time from adding mixing water to material constituents until fresh concrete is ready to be poured into forms. A survey instrument was utilized to estimate

low and high mixing-time levels for 0.15 m^3 of concrete. The survey sample size consisted of 173 civil engineers and architects (drawn from professional Ecuadorian organizations and academia) with at least one year of experience with concrete, to ensure a confidence level of 95% and a confidence interval of as low as 8%. Responses were collected between June and July of 2016. Fig.6 illustrates the boxplot and mixing time statistics for concrete fabricated by hand, where asterisks (*) represent outliers. In this study, mean mixing time values of 11.3 and 20.4 minutes were considered as low and high factor levels respectively.



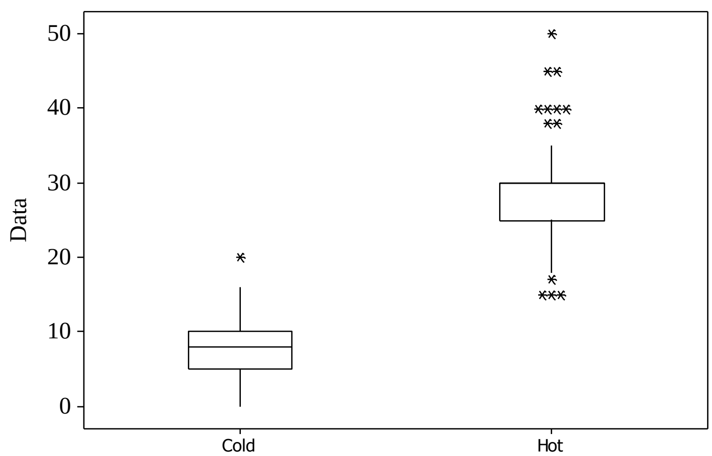
Statistics	Mixing Time (minutes)	
	Min	Max
Minimum	1.0	2.5
Q1	5.0	10.0
Median	10.0	15.0
Q3	15.0	20.0
Maximum	60.0	240.0
Mean	11.3	20.4

Fig.6. Boxplot of mixing time by hand

4. *Curing humidity:* This refers to the relative humidity (i.e., air moisture content) present at a jobsite during concrete hardening until the concrete reaches its designed compressive strength. In common practice, concrete is cured in the air under non-saturated environments (Kwon et al. 2014). Dry environments are considered to have a low relative humidity of less than 50% (Newman and Choo 2003) while wet

environments have a 100% relative humidity (ASTM International 2015a). Relative humidity ranges from 20% to 100% were investigated.

5. *Curing temperature*: This refers to the ambient temperature at the jobsite until concrete reaches its designed compressive strength. The aforementioned survey instrument was also utilized to estimate low and high curing-temperature levels. From the survey results (Fig.7), mean values of 7.9 °C and 28.5 °C were selected as the low and high levels for curing temperature.



Statistics	Curing Temperature (°C)	
	Cold	Hot
Minimum	0	15
Q1	5	25
Median	8	30
Q3	10	30
Maximum	20	50
Mean	7.9	28.5

Fig.7. Boxplot of curing temperature

Laboratory setup is crucial for ensuring proper site conditions and subsequent accurate determination of factor influences or significant factor effects. The experiment was conducted in the Laboratory for Testing and Construction Materials (LTCM) of the School of Civil Engineering in the Central University of Ecuador. LTCM is furnished with all the necessary equipment to perform concrete sample fabrication and compressive strength testing. Table 7 summarizes the experimental independent variables and their corresponding ranges that were used to conduct a full 2^5 factorial design. The statistical software Minitab 16 was utilized for designing the experiment and the factorial analysis.

Table 7. 2^5 Factorial Design Variables and Levels

Variables		Levels	
		Low (-1)	High (+1)
(A)	Crew Experience	Not Experienced	Experienced
(B)	Compaction Method	Manual	Vibrator
(C)	Mixing Time (min)	11.3	20.4
(D)	Curing Hum. (%)	20	100
(E)	Curing Temp. (°C)	7.9	28.5

3.3.2 Sample Fabrication

Six cylindrical concrete samples were fabricated under the selected variable conditions for each of the 32 runs to complete a full 2^5 factorial design, for a total of 192 samples. Setup conditions were controlled from sample fabrication to testing. In addition to the 192 samples, six additional concrete samples were made under standard conditions following ASTM C192 (ASTM International 2015a), to have a baseline compressive strength for computing strength effects. Table 8 summarizes the physical characteristics of concrete constituents. The following materials proportions by weight ensured having a concrete compressive strength of 28 MPa (4000 psi) on day 28: water-cement ratio = 0.5; cement = 1; fine aggregate = 1.5; coarse aggregate = 2.3. Mixture proportions and a slump of 10 cm (4 inches) (ASTM International 2015b) were kept constant for all experimental runs.

Table 8. Physical Properties of Concrete Materials

Material	Specific Gravity	Absorption	Fineness Modulus
Cement Type IP[a]	3.00[b]	---	---
Fine Aggregate	2.63[c]	1.3%[c]	2.68[e]
Coarse Aggregate	2.65[d]	1.4%[d]	6.80[e]

[a] Complying with ASTM C595 (ASTM International 2016c)
[b] Determined by ASTM C188 (ASTM International 2016b)
[c] Determined in saturated-surface-dry condition by ASTM C128 (ASTM International 2015d)
[d] Determined in saturated-surface-dry condition by ASTM C127 (ASTM International 2015c)
[e] Determined by ASTM C136 (ASTM International 2014)

3.3.3 Concrete Compressive Testing

All concrete samples were tested on day 28, since at this age the compressive strength is expected to be an index of concrete strength (Mehta and Monteiro 2006). The tests followed ASTM C39 (ASTM International 2016a), which consists of applying an axial compression force to a concrete cylinder until failure. Even though the American Concrete Institute (ACI 2014) points out that satisfactory concrete compressive strength is calculated by averaging the strength of three cylindrical specimens on day 28, six samples were fabricated and tested for each run, to minimize errors. Concrete compressive strength was measured for each experimental run; however, strength effect expressed as a percentage was used as the response for the experiment to see positive or negative effects caused by the selected variable conditions with respect to the baseline strength. This percentage was calculated by comparing the compressive strength average of each run to the baseline compressive strength, which was the average of the compressive strengths of six standard samples and was equivalent to 28.1 MPa. Then this ratio was subtracted from 1 and multiplied by 100. As previously mentioned, the standard samples were fabricated according to standard ASTM C192 (ASTM International 2015a). Table 9 summarizes all experimental runs, their corresponding strength average and strength effects. Positive strength effects indicate that there is an increment in concrete compressive strength when comparing run results against standard samples. Conversely, negative strength effects indicate that there is a decrease in concrete strength.

Table 9. Factorial Design and Response

Run[a]	Crew Experience	Compaction	Mixing Time (min)	Curing Hum. (%)	Curing Temp. (°C)	Strength Average[b] (MPa)	Strength Effect (%)
1	Experienced	Manual	20.4	100	28.5	36.8	31.0
2	Experienced	Manual	11.3	100	28.5	36.5	30.2
3	Not Experienced	Vibrator	11.3	20	7.9	22.9	-18.5
4	Not Experienced	Manual	11.3	20	7.9	24.6	-12.5
5	Not Experienced	Manual	11.3	100	7.9	27.4	-2.4
6	Not Experienced	Vibrator	20.4	20	7.9	23.7	-15.7
7	Experienced	Vibrator	20.4	100	28.5	35.5	26.3
8	Not Experienced	Vibrator	20.4	100	28.5	37.2	32.4
9	Experienced	Vibrator	11.3	100	7.9	25.3	-10.0
10	Experienced	Manual	11.3	20	28.5	28.3	0.8
11	Experienced	Vibrator	20.4	20	7.9	22.4	-20.2
12	Not Experienced	Manual	20.4	20	28.5	29.7	5.9
13	Not Experienced	Vibrator	11.3	100	28.5	31.6	12.6
14	Not Experienced	Vibrator	20.4	20	28.5	26.4	-5.9
15	Experienced	Vibrator	11.3	20	28.5	27.6	-1.6
16	Experienced	Vibrator	11.3	100	28.5	32.8	16.9
17	Experienced	Manual	20.4	20	7.9	21.6	-23.2
18	Not Experienced	Vibrator	11.3	20	28.5	23.2	-17.2
19	Experienced	Manual	11.3	100	7.9	25.4	-9.5
20	Experienced	Vibrator	20.4	20	28.5	29.0	3.2
21	Not Experienced	Manual	20.4	20	7.9	22.5	-19.9
22	Not Experienced	Manual	11.3	20	28.5	25.4	-9.6
23	Not Experienced	Vibrator	11.3	100	7.9	22.9	-18.5
24	Experienced	Manual	20.4	20	28.5	28.8	2.5
25	Not Experienced	Vibrator	20.4	100	7.9	25.9	-7.9
26	Experienced	Vibrator	20.4	100	7.9	25.6	-8.6
27	Experienced	Vibrator	11.3	20	7.9	22.8	-18.6
28	Not Experienced	Manual	20.4	100	7.9	27.0	-3.7
29	Not Experienced	Manual	20.4	100	28.5	33.7	20.0
30	Experienced	Manual	11.3	20	7.9	23.0	-18.2
31	Not Experienced	Manual	11.3	100	28.5	36.0	28.1
32	Experienced	Manual	20.4	100	7.9	28.2	0.4

[a]Each run consists of 6 concrete samples.
[b]The average concrete strength for the 6 samples in the run.

For raw material properties, complete experimental data as well as laboratory setup see Appendix B.

3.3.4 Factorial Design Analysis

3.3.4.1 Quantifying the Effects of Unstructured Factors on Concrete Strength

The effect of each factor is defined as the variation in the response due to the change in the factor levels. To compute a factor effect it is necessary to first obtain the contrast of that effect according to Eq. 5, where the sign is negative unless the factor is not considered. Factor effects can be positive or negative and they provide a general idea of the effect of main factors and their interactions. The values of $a, b, \dots, e$ represent the treatment combinations (i.e., factor combinations) where the corresponding factors are at high levels. In other words, $a, b, \dots, e$ are treatment combinations where the factors crew experience (A), compaction method (B), mixing time (C), curing humidity (D) and curing temperature (E) are acting at high levels and the others at low levels respectively.

$$Contrast_{AB\dots E} = (a \pm 1)(b \pm 1) \dots (e \pm 1) \tag{5}$$

After a contrast is determined, a factor effect and its corresponding sum of squares are computed by using Eq. 6 and Eq. 7 respectively, where n is the number of replicates of each run ($n = 1$ in this case, since the experiment was not replicated, i.e., there was only one run for each factor combination).

$$Effect_{AB\dots E} = \frac{2}{n2^k} \left(Contrast_{AB\dots E}\right) \tag{6}$$

$$SS_{AB\ldots E} = \frac{1}{n2^k}\ (Contrast_{AB\ldots E})^2 \quad (7)$$

3.3.4.2 Regression Model

A regression model is estimated by considering all main factors and their corresponding interactions (i.e., main factors A, B, C, D and E and their interactions: AB, AC, BC, ABC, AD, BD, ABD, CD, ACD, BCD, ABCD, AE, BE, ABE, CE, ACE, BCE, ABCE, DE, ADE, BDE, ABDE, CDE, ACDE, BCDE, ABCDE). For a 2^5 factorial design, the regression model is expressed by Eq. 8, where y is the predicted response (i.e., concrete strength effect), β_0 is the average of all observations, $\beta's$ are the regression coefficients which are equal to one half of the corresponding factor effects, and $x's$ are the coded variables (low level: -1; high level: 1) that represent each affecting factor: crew experience (A), compaction method (B), mixing time (C), curing humidity (D) and curing temperature (E).

$$y = \beta_0 + \beta_A x_A + \ldots + \beta_E x_E + \beta_{AB} x_A x_B + \cdots + \beta_{DE} x_D x_E + \beta_{ABC} x_A x_B x_C + \cdots + \beta_{CDE} x_C x_D x_E + $$
$$+ \beta_{ABCD} x_A x_B x_C x_D + \cdots + \beta_{BCDE} x_B x_C x_D x_E + \beta_{ABCDE} x_A x_B x_C x_D x_E \quad (8)$$

Using the calculated strength effect (Table 9) as the response of the experiment, a complete full 2^5 factorial design analysis was performed to investigate the significant construction site factors (i.e., unstructured factors) that affect concrete compressive strength. Table 10 gives a summary of all factor effect estimates and regression coefficients. The percent contribution column provides an indication of the percentage of participation of each model term and it is calculated in relation to the total sum of squares, showing the importance of each term in the model. The results pointed out that four of the main affecting factors—compaction method (B), mixing time (C), curing humidity (D), curing temperature (E)—and the term indicating interaction between curing humidity (D) and curing temperature (E) have a percentage of participation greater than 1%, implying that such terms are very important in the estimated model since they could become significant terms.

Table 10. Effect Estimate and Coefficients Summary for Concrete Strength Effect (Coded Units)

Terms	Effect	Coefficient	Sum of Squares	Percent Contribution
Constant (β_0)		-0.994		
Main Effects				
Crew Experience (A)	2.128	1.064	36.23	0.4
Compaction (B)	-4.443	-2.222	157.93	1.7
Mixing Time (C)	4.035	2.018	130.26	1.4
Curing Humidity (D)	19.124	9.562	2925.94	32.0
Curing Temperature (E)	23.910	11.955	4573.56	50.0
2-Way Interactions				
Crew Experience (A) * Compaction (B)	1.123	0.562	10.09	0.1
Crew Experience (A) * Mixing Time (C)	-1.356	-0.678	14.71	0.2
Crew Experience (A) * Curing Humidity (D)	-0.146	-0.073	0.17	0.0
Crew Experience (A) *Curing Temperature (E)	3.245	1.623	84.26	0.9
Compaction (B) * Mixing Time (C)	3.279	1.640	86.02	0.9
Compaction (B) * Curing Humidity (D)	-1.908	-0.954	29.13	0.3
Compaction (B) * Curing Temperature (E)	-0.833	-0.417	5.55	0.1
Mixing Time(C) * Curing Humidity (D)	1.279	0.639	13.08	0.1
Mixing Time (C) * Curing Temperature (E)	2.858	1.429	65.35	0.7
Curing Humidity (D) * Curing Temperature (E)	8.311	4.155	552.53	6.0
3-Way Interactions				
Crew Experience (A) * Compaction (B) * Mixing Time (C)	-2.447	-1.223	47.89	0.5
Crew Experience (A) * Compaction (B) * Curing Humidity (D)	-1.647	-0.824	21.70	0.2
Crew Experience (A) * Compaction (B) * Curing Temperature (E)	-0.755	-0.377	4.56	0.0
Crew Experience (A) * Mixing Time (C) * Curing Humidity (D)	1.432	0.716	16.41	0.2
Crew Experience (A) * Mixing Time(C) * Curing Temperature (E)	-1.358	-0.679	14.74	0.2
Crew Experience (A) * Curing Humidity (D) * Curing Temperature (E)	-2.419	-1.210	46.83	0.5

Compaction (B) * Mixing Time (C) * Curing Humidity (D)	1.697	0.849	23.04	0.3
Compaction (B) * Mixing Time (C) * Curing Temperature (E)	1.127	0.564	10.16	0.1
Compaction (B) * Curing Humidity (D) * Curing Temperature (E)	1.899	0.950	28.86	0.3
Mixing Time (C) * Curing Humidity (D) * Curing Temperature (E)	-2.689	-1.344	57.84	0.6
4-Way Interactions				
Crew Experience (A) * Compaction (B) * Mixing Time (C) * Curing Humidity (D)	-2.502	-1.251	50.07	0.5
Crew Experience (A) * Compaction (B) * Mixing Time (C) * Curing Temperature (E)	0.950	0.475	7.23	0.1
Crew Experience (A) * Compaction (B) * Curing Humidity (D) * Curing Temperature (E)	-2.435	-1.217	47.43	0.5
Crew Experience (A) * Mixing Time (C) * Curing Humidity (D) * Curing Temperature (E)	0.919	0.460	6.76	0.1
Compaction (B) * Mixing Time (C) * Curing Humidity (D) * Curing Temperature (E)	3.004	1.502	72.20	0.8
5-Way Interactions				
Crew Experience (A) * Compaction (B) * Mixing Time (C) * Curing Humidity (D) * Curing Temperature (E)	-0.793	-0.397	5.03	0.1

3.3.4.3 Statistical Testing for the Significance of Affecting Factors

An analysis of variance (ANOVA) is done to perform a statistical testing for the significance of unstructured factor effects and their interactions. ANOVA is computed for the factorial design to estimate the variance within and between treatments. F statistics are computed for each source of variation (e.g., main factors and factor combinations) by dividing the mean square error by the residual mean square error and are used for testing the following hypothesis: (1) $\beta's = 0$ and (2) $\beta's \neq 0$. Only significant factors with p values that are less than or equal to 0.05 are utilized for refining the full regression model estimated. Table 11 presents the results for the ANOVA, where the main effects—Compaction method (B), Mixing Time (C), Curing Humidity (D) and Curing Temperature

(E)—and the interaction between Curing Humidity (D) and Curing Temperature (E) were found to be significant.

Table 11. ANOVA Table for Compressive Strength Effect (Coded Units)

Source	Degrees of Freedom	Sum of Squares	Mean Square	F Value	P Value
Main Effects	4	7787.7	1946.92	62.85	0.00
Compaction (B)	1	157.9	157.93	5.10	0.03
Mixing Time (C)	1	130.3	130.26	4.21	0.05
Curing Humidity (D)	1	2925.9	2925.94	94.46	0.00
Curing Temperature (E)	1	4573.6	4573.56	147.64	0.00
2-Way Interactions	1	552.5	552.53	17.84	0.00
Curing Humidity (D) * Curing Temperature (E)	1	552.5	552.53	17.84	0.00
Residual Error	26	805.4	30.98		
Total	31	9145.6			

3.3.4.4 Final Regression Model

The final model contains only the significant affecting factors identified by ANOVA. Montgomery (2013) pointed out that when at least two factors are quantitative, it is feasible to analyze the results by creating a response surface or contour lines. Table 12 summarizes the final model coefficients including only significant terms for coded and uncoded units, while Eq. 9 and Eq. 10 represent the final equations in terms of coded (-1 and 1) and uncoded units (real units) respectively derived from Eq. 8.

Table 12. Final Estimated Coefficients for Strength Effect (%)

Term	Model Coefficient	
	Coded Units	Uncoded Units
Constant	-0.994	-32.4761
Compaction (B)	-2.222	-2.2216
Mixing Time (C)	2.018	0.4434
Curing Humidity (D)	9.562	0.0555
Curing Temperature (E)	11.955	0.5555
Curing Humidity (D) * Curing Temperature (E)	4.155	0.0101

$$\boldsymbol{Strength\ Effect}\ (\%) = -0.994 - 2.222 * Compaction + 2.018 * Mixing\ Time + 9.562 * Curing\ Humidity + 11.955 * Curing\ Temperature + 4.155 * Curing\ Humidity * Curing\ Temperature \quad \text{(Variables must be entered in coded units)} \tag{9}$$

$$\boldsymbol{Strength\ Effect}\ (\%) = -32.4761 - 2.2216 * Compaction + 0.4434 * Mixing\ Time + 0.0555 * Curing\ Humidity + 0.5555 * Curing\ Temperature + 0.0101 * Curing\ Humidity * Curing\ Temperature \quad \text{(Variables must be entered in real units)} \tag{10}$$

3.3.4.5 Analysis of Residuals

Residuals were obtained by computing the difference between experimental and predicted responses and they were used for checking model adequacy. Montgomery (2013) argued that residuals should not follow obvious patterns (i.e., they should be structureless) when the model is adequate, and suggested that many assumption violations can be detected by plotting graphs of the residuals. The presence of obvious residual patterns would reveal any assumption violations. A normal probability plot for the residuals was utilized to check the normality assumption. Fig. 8 does not reveal a violation for the normality assumption since all residuals are close to the line of the normal distribution, centered at zero. Montgomery (2013) claimed that ANOVA is robust to the normality assumption and moderate deviations from normality do not necessarily imply a serious violation of the assumption. A graph of residuals versus run order or time can detect if there is a violation of the independence assumption between runs, which is produced when there is a tendency to have runs of positive and negative residuals. Appropriate randomization of the experiment ensures independence. The plots of residuals versus observation order (Fig.9) and residuals versus fitted values (Fig.10) do not indicate any violation of the independence assumption and equality of variances since the residuals do not follow obvious patterns. Plots of the residuals versus the predicted yields for each significant affecting factor are shown to find if there is any violation of inequality of variance (Fig.11). Resulting plots indicate no violation of this assumption, even though some graphs show a very slight inequality of variance. Thus, the analysis of residuals does not indicate any problem with assumptions or model adequacy, validating the conclusions.

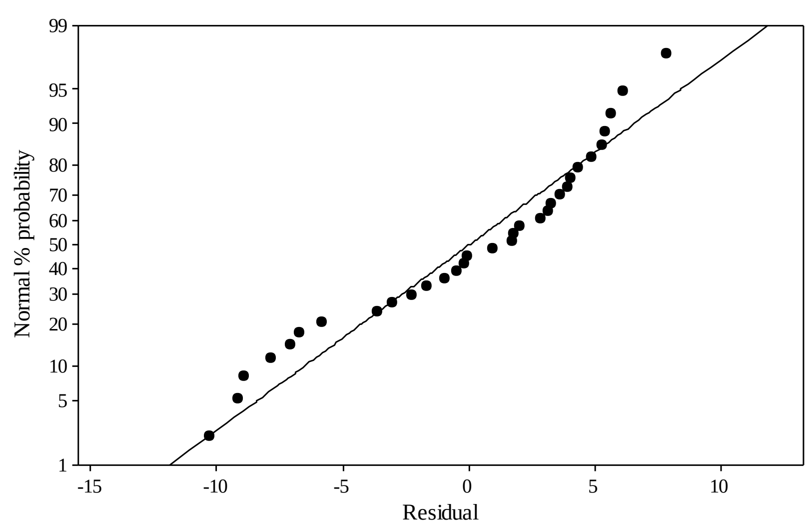


Fig. 8. Normal plot of residuals for strength effect

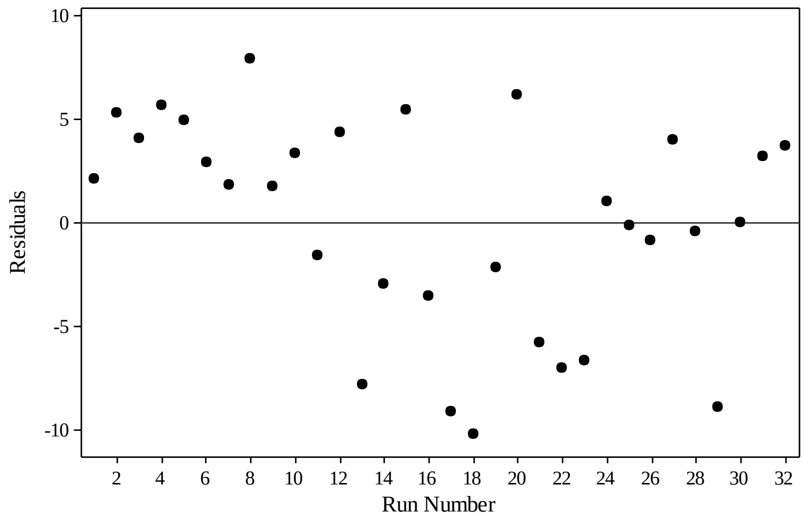


Fig.9. Residuals vs. observation order for strength effect

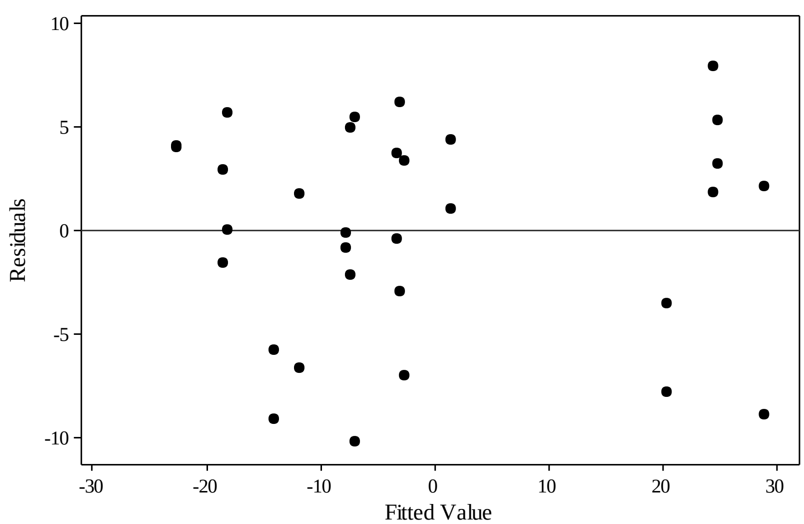


Fig.10. Residuals vs. fitted values for strength effect

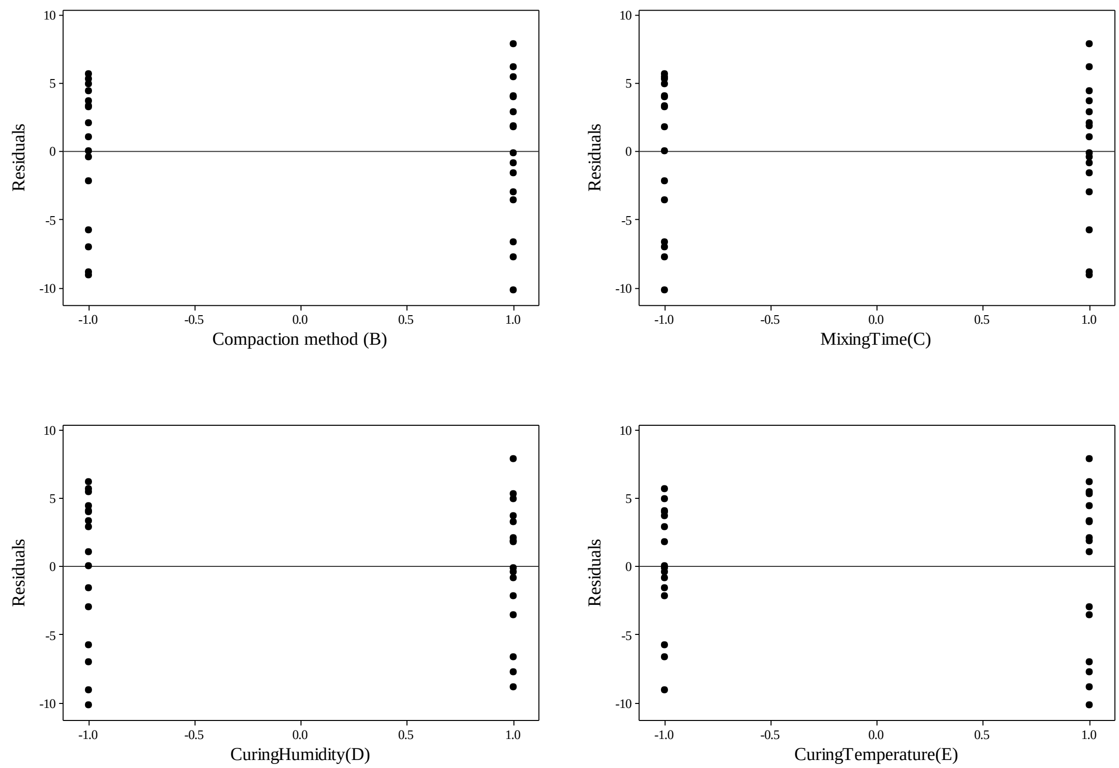


Fig.11. Residuals vs. predicted yields for each affecting factor for strength effect

3.3.4.6 Model Validation

A plot depicting predicted versus experimental data was developed to evaluate how well the final model predicts concrete strength effect (Fig. 12). The result of R-squared is 91.2%, which indicates that the model is able to accurately predict more than 90% of the data. The standard error (S) represents the standard distance between the experimental and the predicted data. The smaller the S value, the better the model performs.

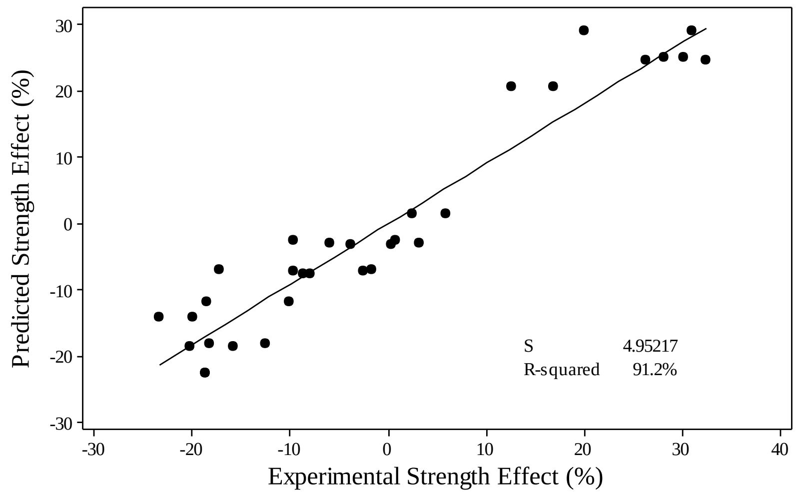


Fig. 12. Predicted data vs. experimental data for strength effect

3.4 Operating Conditions to Preserve Concrete Quality

The final regression model for estimating concrete compressive strength effect (Eq. 10) can be used as a decision-support tool for construction workers that enables them to find operating conditions to preserve concrete quality through the use of contour lines. Contour plots of strength effect (%) that consider curing temperature and mixing time as variables (Fig.13) point out that high curing temperatures are needed to preserve concrete strength when curing concrete in a dry environment. Keeping concrete saturated with water (100% relative humidity) when curing avoids losing compressive strength; in fact, it increases strength by around 25%. Curing temperature does not have the same impact when curing humidity changes, due to their corresponding interaction effect. Also, the impact of the method of compaction (i.e., -1 for manual or 1 for vibrated) and mixing time on strength is not as severe as curing temperature. The contour lines in Fig.13 have negative slopes, indicating the more the mixing time, the less the curing temperature needed to maintain a desired strength effect.

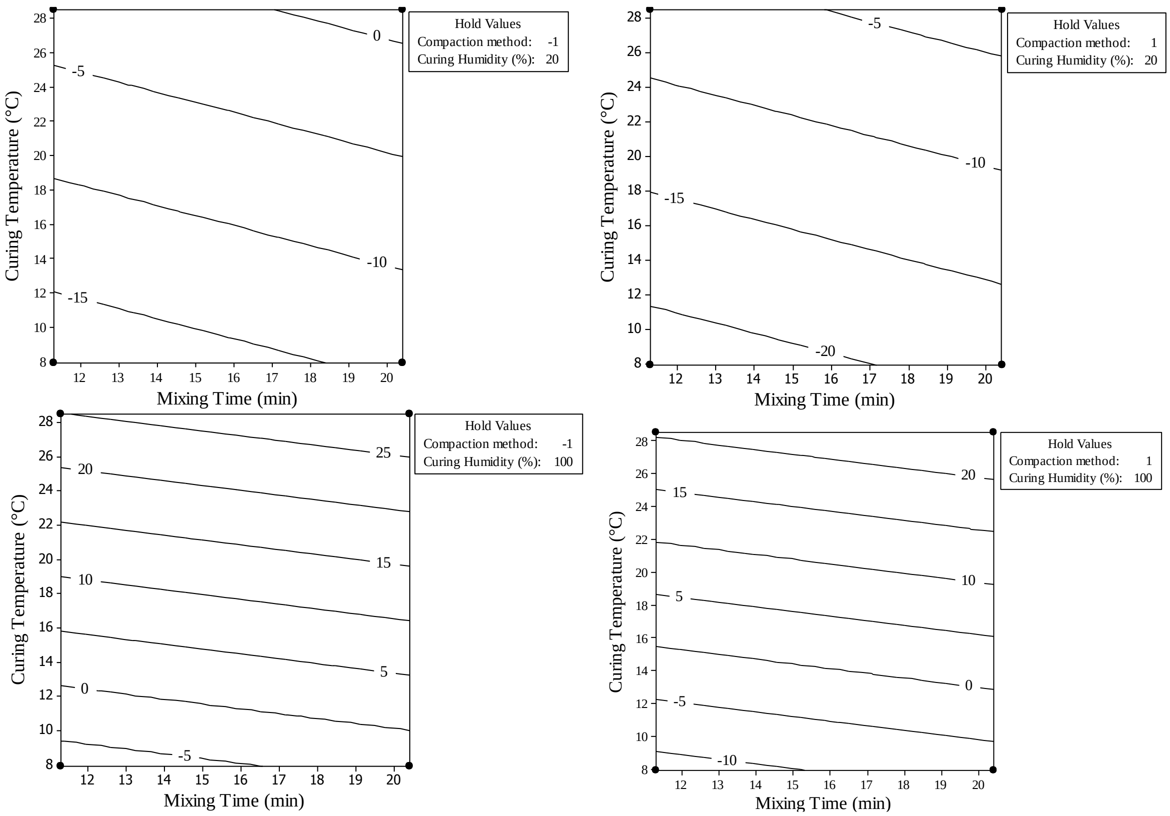


Fig.13. Contour plots of strength effect (%) considering curing temperature and mixing time as variables

Also, contour plots of strength effect (%) that consider curing humidity and mixing time as variables (Fig.14) illustrate that high values of curing humidity and mixing times reduce the impact of affecting factors at low curing temperatures, even though they cannot mitigate strength reduction completely. A contour line of zero strength effect does not appear in the contour plots. At high curing temperatures, low curing humidity (20%) could be accepted to preserve compressive strength (i.e., zero contour line). In contrast, significant positive strength effect (20-25%) can be gained by curing concrete at high temperatures and humidity (100% relative humidity). In the same manner as stated before, the impact of curing humidity varies greatly when curing temperature changes because of two-way factor interaction. The impact of the method of compaction (i.e., -1 for manual or 1 for vibrated) and mixing time on strength is not as severe as curing temperature. Also, high mixing times promote concrete compressive strength.

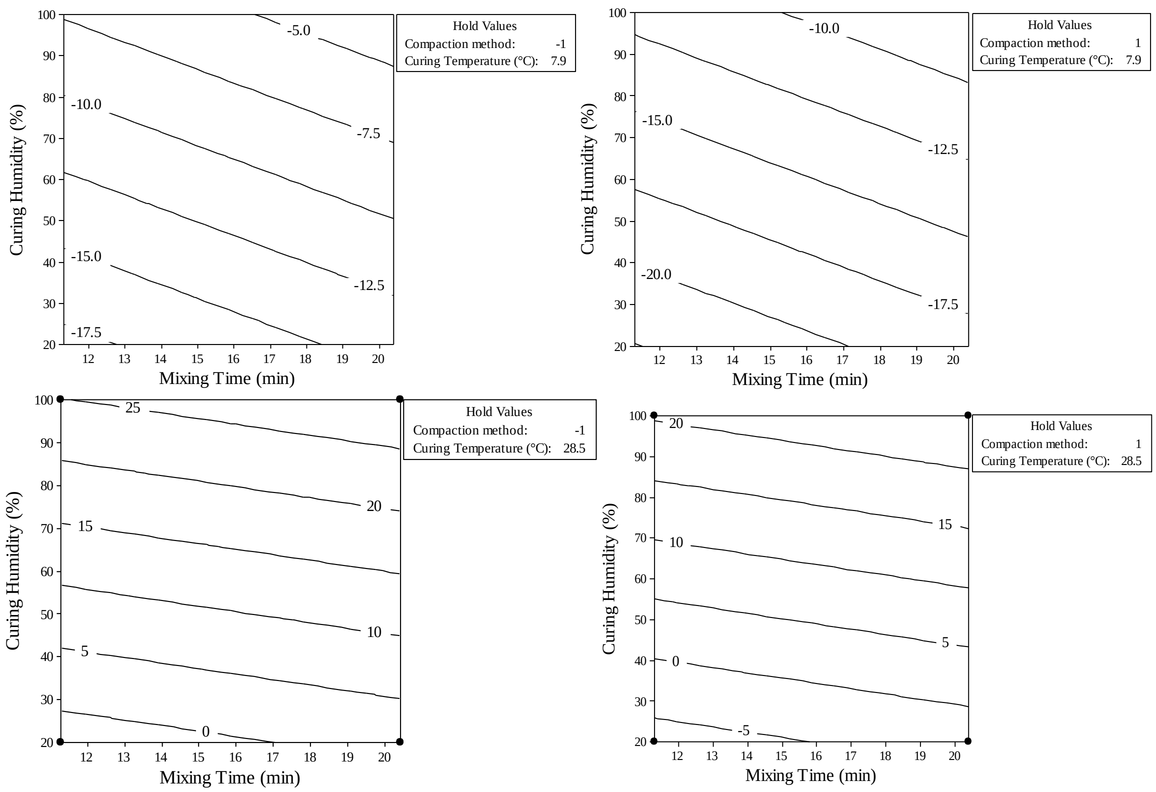


Fig.14. Contour plots of strength effect (%) considering curing humidity and mixing time as variables

Moreover, contour plots of strength effect (%) that consider curing humidity and curing temperature as variables (Fig.15) reveal that high values of curing humidity and curing temperature cause a positive effect on concrete compressive strength, causing an increment of more than 20% in compressive strength regardless of crew experience and mixing time. To maintain compressive strength, curing temperature should increase while curing humidity decreases and vice versa. In addition, vibrating the concrete seems to decrease concrete compressive strength rather than increasing it. This could be due to possible concrete segregation during sample fabrication in all cases. In contrast, consolidating the concrete by utilizing a tamping rod (i.e., -1 for manual compaction) yields better compressive strengths.

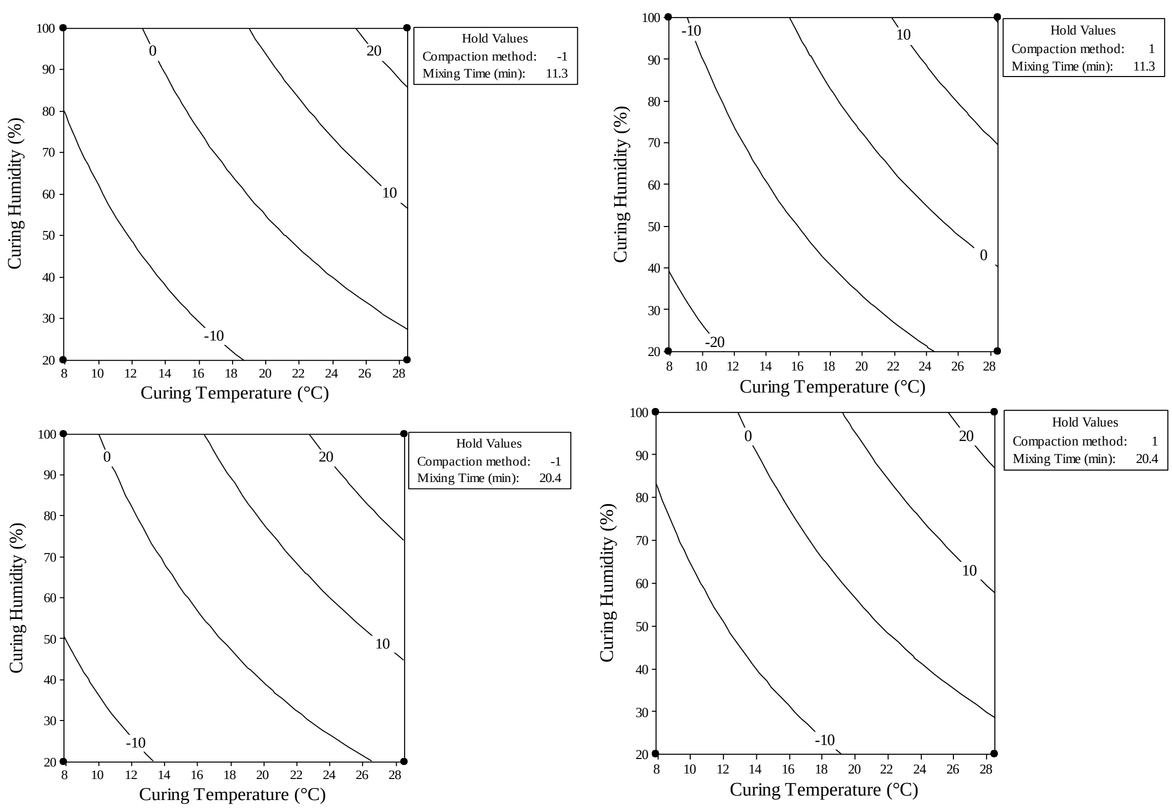


Fig.15. Contour plots of strength effect (%) considering curing humidity and curing temperature as variables

3.5 Conclusions

This chapter presents a comprehensive systematic framework to identify significant construction site factors (i.e., unstructured factors) that affect concrete compressive strength, including crew experience, compaction method, mixing time, curing humidity and curing temperature, by conducting a full 2^5 factorial design. The experimental design assisted in the concrete sample fabrication process while the factorial design analysis quantified main factor effects with corresponding interactions. It also exposed statistically significant affecting factors for developing a prediction model for new observations, with the final regression model consisting of a supporting tool for decision making.

Compaction method, mixing time, curing humidity and curing temperature are construction site factors that affect concrete compressive strength significantly. These factors were identified by performing an ANOVA at 0.05 level of significance with a 95% confidence level. The percentage of participation of each model term (Table 10) indicates that curing temperature has the highest percent contribution on concrete compressive strength, with 50.0% of the total effect caused by main factor effects and their corresponding interactions. Curing humidity accounts for 32.0% of the total effect, the second highest percent contribution, while mixing time and compaction method together only have a contribution of 3.1% to the model. Also, only one two-factor interaction—curing humidity and curing temperature—has important participation in the model. It accounts for 6.0% of the total percent contribution, implying that curing humidity does not produce the same effect when curing temperature changes and vice versa. One factor effect depends on the other.

The final regression model (Eq. 10), containing only significant affecting factors for predicting the impact of construction site factors (i.e., unstructured factors) on concrete compressive strength, became a decision-support tool that not only enables construction workers to find operating conditions but also to explore other factors tending to preserve concrete quality while building a facility. A high value of the coefficient of determination (R squared) of 91.2% indicates that the model can predict new observations well. Fig.13, Fig.14 and Fig.15, for instance, depict different contour plots to identify desirable values or operating conditions that allow construction workers such as supervisors or construction managers to be aware of possible concrete compressive strength impacts under certain conditions. Such impacts can be either positive or negative. Positive contour lines represent desired conditions since they represent operating conditions where concrete undergoes an increment in its compressive strength. Contour lines with a zero value indicate that concrete compressive strength is not being affected by existing onsite conditions and could be considered the desired jobsite condition. On the other hand, negative contour lines are meant to be warning zones, indicating the present combination of factors is reducing compressive strength. Knowing the effect of construction site factors on concrete compressive strength in advance will help workers comply with the concrete specification stated in the construction documents by taking corrective measures.

3.6 Recommendations for Operating Conditions

The impact of unstructured factors should be considered in concrete operations, even though some significant affecting factors can be controlled while others cannot. Compaction method and mixing time can be chosen by technicians in charge of preparing concrete. Compacting concrete by using a vibrator or a tamping rod is up to a supervisor, while setting the curing humidity and temperature of a concrete element of a structure is not possible to control most of the time, due to project location or curing limitations. The experimental results indicate that curing concrete in an environment with high surrounding humidity and temperature is ideal to stimulate concrete compressive strength; however, such conditions are difficult to simulate and control during the construction process. Thus, appropriate concrete fabrication conditions in situ should be taken into consideration to ensure that the concrete complies with material specifications contained in any project construction documents.

Furthermore, appropriate resources should be utilized when fabricating concrete. Construction workers having appropriate skills must be hired to ensure the success of a project (Sears et al. 2015). During the construction process, there could be concrete elements for which it would be difficult to perform concrete compaction well or where compaction is not adequate. Some structural elements can be compacted by using a concrete vibrator while others can only be compacted manually by using tamping rods, depending on concrete consistency (i.e., slump) and placing conditions such as rebar spacing and geometry of formwork (Kosmatka et al. 2002; Mehta and Monteiro 2006; Li 2011). Despite the method of concrete compaction selected, the formation of internal voids should be avoided. Hassoun and Al-Manaseer (2012) emphasized that correct concrete compaction guarantees a positive effect on concrete compressive strength. Mixing time should be enough to obtain homogeneous concrete mixtures. Standard common practices for mixing times vary, but the time applied to mix concrete should guarantee a uniform mixture with a reduction of voids. Thorough mixing ensures concrete quality (ACI 2000). Mixing time of around 15 minutes, which corresponds to the average of minimum and maximum mixing times, is recommended for manual concrete fabrication. Curing conditions cannot be controlled easily at a jobsite since they include the local relative humidity and temperature. Fig. 16 illustrates an overlay contour plot of compressive strength effect that considers curing temperature and curing humidity while utilizing experienced crews, concrete vibrators and 15 minutes of mixing time. The white region on the plot represents the feasible region where concrete compressive strength is affected slightly (± 5%). Other overlay plots could also be constructed by specifying different parameters of affecting factors. Decreasing curing temperature and curing humidity would decrease concrete compressive strength effect. To preserve compressive strength (i.e., strength effect equals 0%), concrete construction personnel should pay special attention to weather or ambient conditions.

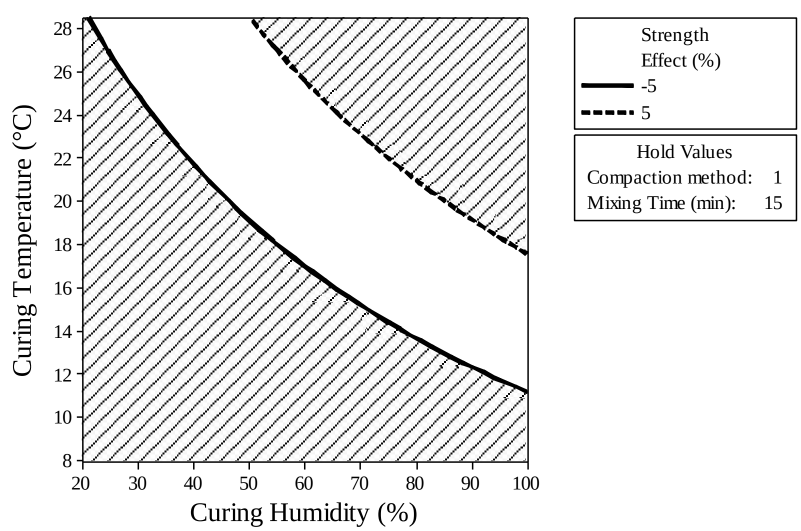


Fig. 16.Recommended operating conditions for concrete compressive strength

CHAPTER 4: IMPACT OF UNSTRUCTURED FACTORS ON CONCRETE THROUGH FUZZY MODELS

4.1 Introduction

There are several affecting conditions that could impact concrete compressive strength, costs, and production rates when fabricating concrete at the jobsite. The impact is manifested by reducing strength, by reducing productivity, and by increasing costs. These potential impacts are usually unknown or ignored by construction laborers, foremen and project managers. Knowing such impacts in advance could prevent managers from wasting resources as well as help save time and money. The novel approach presented in this chapter assists in reducing uncertainty in order to manage concrete quality during the construction phase of a project through the use of novel fuzzy set theory.

4.1.1 Fuzzy Set Theory Overview

Several theories or approaches are available to deal with uncertainties including probability, belief and plausibility, possibility, and fuzzy set theory (Klir 2006; Ross 2017). Fuzzy set theory, introduced by Zadeh (1965), is a very efficient tool to understand complex systems where there are unknown mathematical functions (Ross 2017). Usually, the more complex the system is, the less knowledge about the system is available and vice versa. Fuzzy rule-based systems are known as fuzzy inference systems (FISs), and they are suitable mechanisms to manage problems where uncertainties are caused by lack of knowledge and vagueness (Zadeh, 1973), recalling that a FIS can provide researchers with information, increasing their understanding about how a system works. Also, a FIS could be thought of as an approximation of a mathematical function, being very useful when modeling complex systems that are described by humans through the use of linguistic variables (Ross 2017). On the contrary, it would not be necessary to use fuzzy set theory if the function governing the system were known or defined.

4.1.2 Fuzzy Inference Systems (FISs)

Two main components can be distinguished for a FIS: (1) a fuzzy knowledge base and (2) an inference mechanism, as depicted in Fig. 17. The knowledge base component consists of input–output (I/O) data coming from the observed system and if–then rules. This information is used by the inference mechanism to predict or map outputs for any input. The knowledge base describes I/O relationships, while the inference mechanism uses such knowledge for estimating outputs (Fig. 17). The most common inference mechanism methods are Mamdani (Mamdani and Assilian 1975; Mamdani 1977), Sugeno, also known as Takagi, Sugeno and Kang (TSK) (Takagi and Sugeno 1985) and Tsukamoto models (Tsukamoto 1979), all based on if–then rules. Mamdani's inference mechanism differs from the others in that the output is a fuzzy set while the other procedures produce crisp outputs for each rule by using mathematical functions.

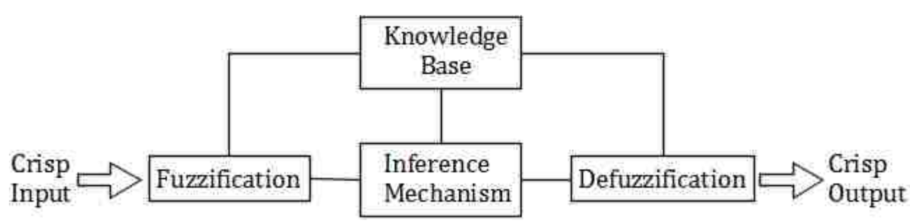


Fig. 17. FIS structure

The use of fuzzy inference systems is an appropriate approach for understanting and quantifying the impact of construction site factors (i.e., unstructured factors) affecting concrete compressive strength, costs, and production rates through experimental I/O data. Influencing factors affect such concrete characteristics nonlinearly, and fuzzy systems perform well when dealing with such models. FISs perform well when having I/O data, and the rules derived from that data provide knowledge of the system (Ross 2017). An experimenter or analyst uses experimental data obtained through testing in order to model or predict results when dealing with complex systems, and thus FISs may be applied in these cases (Ross 2017). Furthermore,several investigations have attempted to develop prediction models for concrete strength from experimental I/O data. Tesfamariam and Najjaran (2007) utilized adaptive neuro-fuzzy inference systems (ANFIS) for predicting concrete compressive strength by testing different mix proportions. They concluded that this technique has significant advantages in estimating concrete strength from experimental data; i.e., in-situ quality controls. Also, the authors emphasized that the use of past experience (experimental data) should be utilized to gain knowledge of a system. Madandoust et al. (2012) attempted to predict concrete compressive strength by developing ANFIS based on concrete core testing data. Tayfur et al. (2014) fabricated concrete samples with varying binder contents and tested them at different ages, concluding that fuzzy logic is a very useful technique to predict concrete compressive strength. In a recent study, Khademi et al. (2017) evaluated concrete compressive strength made with different mix designs by means of sample fabrication and testing in the laboratory. The authors concluded that adaptive neural networks (ANN) and ANFIS models are preferred due to the nonlinear relationship between variables. Fuzzy set theory is thus an effective technique for mapping I/O data in concrete-related studies because of its ability to deal with nonlinearity and to provide information for understanding system behaviors.

4.1.3 Membership Functions (MFs) and If–Then Rules

A membership function (MF) of a fuzzy set maps each element of the universe of elements to a membership value or degree of membership between 0 and 1 (Jang et al. 1997), being 1 for full degree of membership. A MF can have many shapes, such as triangular, trapezoidal, and Gaussian, and the precision of the shape that comprises a membership function is not important as long as the functions represent each input. Overlap MFs is an important characteristic to be considered when partitioning the universe of discourse, allowing each element to have different degrees of membership in different MFs.

Several methods such as intuition, inference, inductive reasoning, and automated methods may be utilized to develop MFs, depending on data availability and the degree of knowledge of the system (Ross 2017). Automated methods are alternatives to creating not only MFs but also if–then rules. Passino & Yurkovich (1998) mentioned several automated techniques that are available for fuzzy identification and estimation including a clustering method (CM), which creates rules based on grouping or partitioning data into similar groups. Jang (1993) proposed a method called Adapted-Network-based Fuzzy Inference System (ANFIS) for constructing a FIS by developing if–then rules and MFs based on I/O data tuples through a hybrid learning algorithm that combines the gradient method and least squares estimates.

4.2 Goal and Objectives

The goal of this chapter is to provide construction workers and technicians with decision-support prediction models for quantifying the impact of construction site factors on concrete compressive strength, costs, and production rates by using experimental data and fuzzy set theory. The research objectives are to (1) develop a fuzzy inference system for quantifying concrete strength, cost, and production rate effects, (2) identify affecting conditions that dominate the output of each fuzzy model, and (3) create a decision tool for identifying desired operating conditions that will meet required concrete compressive strength as well as costs and production rates.

Even though concrete strength depends mostly on mixture constituents, proportions, and fabrication, it also depends on other factors affecting testing results, including boundary conditions (Kim et al. 2004). Yuan et al. (2014) pointed out that the factors that affect concrete compressive strength may be classified into structured and unstructured factors. The first category is related to the factors affecting concrete during its production process while the second category refers to construction site factors that influence concrete during the construction phase. The literature indicates there is limited understanding of the effect of such factors on concrete. The present chapter addresses this limitation by developing fuzzy models for quantifying their effect, assisting concrete laborers and technicians when performing concrete operations.

4.3 Methodology

Adapted-Network-based Fuzzy Inference System (ANFIS) utilizes data tuples for constructing a Sugeno-type FIS by developing if–then rules and MFs based on data clustering when having experimental I/O data. ANFIS is a neuro-fuzzy model that utilizes the advantages of adaptive neural networks (ANNs) by allowing fuzzy systems to learn through a hybrid learning algorithm (Jang et al. 1997). An ANFIS model was used to investigate the effects of construction site factors on concrete compressive strength, on costs and on production rates in this study. Fig.18 illustrates the systematic procedure that will be followed to accomplish the chapter objectives.

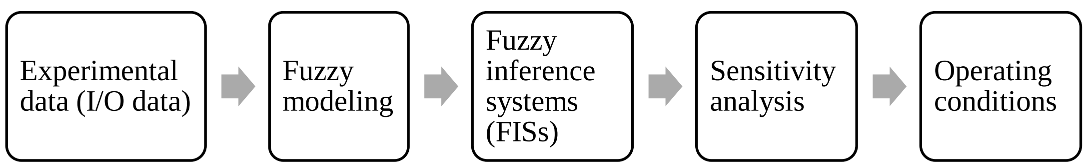


Fig.18. Research framework

4.3.1 Experimental Data (I/O data)

For this chapter, five construction site factors—crew experience, compaction method, mixing time, curing humidity, and curing temperature—were selected from the literature (Kosmatka et al. 2002; Mehta and Monteiro 2006; Neville and Brooks 2010; Li 2011; Hassoun and Al-Manaseer 2012; Wight et al. 2012; Chen et al. 2014; Unanwa and Mahan 2014). These factors refer to construction site conditions (i.e., unstructured factors) that are present during manual concrete fabrication, placement, and curing until the concrete is 28 days old at the jobsite. For developing a Sugeno FIS for quantifying compressive strength effect, four factors—compaction method, mixing time, curing humidity, and curing temperature—were utilized, since they were found to be significant after performing an analysis of variance (ANOVA) at 0.05 level of significance with a 95% confidence level.

Six cylindrical concrete samples of 150mm by 300 mm (6 by 12 inches) were fabricated and cured for each factor combination, simulating affecting conditions, and were tested for a compression axial load, as per ASTM C39 (ASTM International 2016a) at the laboratory for Testing and Construction Materials of the School of Civil Engineering of the Central University of Ecuador. A total of 192 samples were fabricated, keeping constant concrete mix proportions and slump, as per ASTM C143 (ASTM International 2015b). Additionally, six standard concrete samples, as per ASTM C192 (ASTM International 2015a) were fabricated to ensure a compression strength of 28 MPa (4000 psi) and used as a baseline for computing concrete strength effects by comparing affected samples and standard samples subtracted from unity and expressed as a percentage.

Input data comprised all four construction site factors while the output was the compressive strength effect. Half of the data (i.e., 96 strength responses) were used as training data and the other half as checking data for the ANFIS model. Training and checking datasets for ANFIS models were selected randomly, resulting in 32 data tuples made of the average of three compressive strengths of samples corresponding to the same experiment for each dataset. Training data were the data tuples used to generate the ANFIS model while checking data were used for verifying the performance of the model. Table 13 summarizes affecting conditions and strength effects for training and checking data. Negative values of strength effect indicate a reduction in strength, suggesting that affecting conditions had an adverse impact on concrete strength. Positive values indicate that affecting conditions increased concrete strength.

Table 13. Training and checking data for concrete strength effect

No.	Inputs				Output
	Compaction Method	Mixing Time (min)	Curing Humidity (%)	Curing Temperature (°C)	Strength Effect (%)
Training data					
1	Manual (-1)	20.4	100	28.5	31.5
2	Manual (-1)	11.3	100	28.5	28.0
3	Vibrator (1)	11.3	20	7.9	-20.6
4	Manual (-1)	11.3	20	7.9	-13.5
5	Manual (-1)	11.3	100	7.9	-1.0
6	Vibrator (1)	20.4	20	7.9	-15.5
7	Vibrator (1)	20.4	100	28.5	29.4
8	Vibrator (1)	20.4	100	28.5	33.9
9	Vibrator (1)	11.3	100	7.9	-11.1
10	Manual (-1)	11.3	20	28.5	0.0
11	Vibrator (1)	20.4	20	7.9	-20.6
12	Manual (-1)	20.4	20	28.5	4.0
13	Vibrator (1)	11.3	100	28.5	16.0
14	Vibrator (1)	20.4	20	28.5	-4.5
15	Vibrator (1)	11.3	20	28.5	-0.2
16	Vibrator (1)	11.3	100	28.5	15.8
17	Manual (-1)	20.4	20	7.9	-25.7
18	Vibrator (1)	11.3	20	28.5	-16.4
19	Manual (-1)	11.3	100	7.9	-11.6
20	Vibrator (1)	20.4	20	28.5	2.9
21	Manual (-1)	20.4	20	7.9	-21.4
22	Manual (-1)	11.3	20	28.5	-10.5
23	Vibrator (1)	11.3	100	7.9	-20.2
24	Manual (-1)	20.4	20	28.5	1.9
25	Vibrator (1)	20.4	100	7.9	-9.0
26	Vibrator (1)	20.4	100	7.9	-8.5
27	Vibrator (1)	11.3	20	7.9	-19.4
28	Manual (-1)	20.4	100	7.9	-3.4
29	Manual (-1)	20.4	100	28.5	18.8
30	Manual (-1)	11.3	20	7.9	-18.4
31	Manual (-1)	11.3	100	28.5	27.8
32	Manual (-1)	20.4	100	7.9	0.0
Checking data					

1	Manual (-1)	20.4	100	28.5	30.5
2	Manual (-1)	11.3	100	28.5	32.3
3	Vibrator (1)	11.3	20	7.9	-16.5
4	Manual (-1)	11.3	20	7.9	-11.5
5	Manual (-1)	11.3	100	7.9	-3.8
6	Vibrator (1)	20.4	20	7.9	-15.8
7	Vibrator (1)	20.4	100	28.5	23.2
8	Vibrator (1)	20.4	100	28.5	30.8
9	Vibrator (1)	11.3	100	7.9	-9.0
10	Manual (-1)	11.3	20	28.5	1.6
11	Vibrator (1)	20.4	20	7.9	-19.8
12	Manual (-1)	20.4	20	28.5	7.7
13	Vibrator (1)	11.3	100	28.5	9.2
14	Vibrator (1)	20.4	20	28.5	-7.4
15	Vibrator (1)	11.3	20	28.5	-3.0
16	Vibrator (1)	11.3	100	28.5	17.9
17	Manual (-1)	20.4	20	7.9	-20.8
18	Vibrator (1)	11.3	20	28.5	-18.0
19	Manual (-1)	11.3	100	7.9	-7.5
20	Vibrator (1)	20.4	20	28.5	3.5
21	Manual (-1)	20.4	20	7.9	-18.5
22	Manual (-1)	11.3	20	28.5	-8.7
23	Vibrator (1)	11.3	100	7.9	-16.7
24	Manual (-1)	20.4	20	28.5	3.1
25	Vibrator (1)	20.4	100	7.9	-6.7
26	Vibrator (1)	20.4	100	7.9	-8.8
27	Vibrator (1)	11.3	20	7.9	-17.8
28	Manual (-1)	20.4	100	7.9	-4.0
29	Manual (-1)	20.4	100	28.5	21.3
30	Manual (-1)	11.3	20	7.9	-17.9
31	Manual (-1)	11.3	100	28.5	28.3
32	Manual (-1)	20.4	100	7.9	0.8

Regarding concrete costs, three unstructured factors; namely, crew experience, compaction method, and mixing time, were considered for developing a Sugeno FIS. The costs of curing humidity and curing temperature were not considered in this study since they correspond to environmental conditions existing at the jobsite. Concrete cost effects were computed by taking into consideration the costs of labor and equipment utilized for fabricating a batch of concrete for six samples under each factor combination, and were then compared to the costs of the standard sample fabrication. Affecting conditions (inputs) and the corresponding effect on concrete cost (output) are shown in Table 14. The data for training and checking ANFIS consisted of 16 data tuples respectively since 32 experiments were conducted. Positive values indicate that concrete costs increased while negative values indicate a reduction in concrete costs due to the presence of construction site factors.

Table 14. Training and checking data for concrete cost effect

No.	Inputs			Output
	Crew Experience	Compaction Method	Mixing Time (min)	Cost Effect (%)
		Training data		
1	Experienced (1)	Manual (-1)	20.4	36.0
2	Experienced (1)	Manual (-1)	11.3	-8.0
3	Not Experienced (-1)	Manual (-1)	11.3	-1.2
4	Experienced (1)	Vibrator (1)	20.4	39.4
5	Not Experienced (-1)	Vibrator (1)	11.3	-12.3
6	Not Experienced (-1)	Vibrator (1)	20.4	34.3
7	Experienced (1)	Vibrator (1)	11.3	-15.5
8	Not Experienced (-1)	Vibrator (1)	11.3	0.2
9	Experienced (1)	Vibrator (1)	20.4	26.8
10	Not Experienced (-1)	Manual (-1)	20.4	46.2
11	Not Experienced (-1)	Vibrator (1)	20.4	37.8
12	Experienced (1)	Vibrator (1)	11.3	-11.3
13	Not Experienced (-1)	Manual (-1)	20.4	50.2
14	Experienced (1)	Manual (-1)	11.3	-16.0
15	Not Experienced (-1)	Manual (-1)	11.3	2.7
16	Experienced (1)	Manual (-1)	20.4	32.0
		Checking data		
1	Not Experienced (-1)	Vibrator (1)	11.3	-3.9
2	Not Experienced (-1)	Manual (-1)	11.3	6.7
3	Not Experienced (-1)	Vibrator (1)	20.4	42.0
4	Experienced (1)	Vibrator (1)	20.4	35.2
5	Not Experienced (-1)	Vibrator (1)	20.4	29.5
6	Experienced (1)	Vibrator (1)	11.3	-18.8
7	Experienced (1)	Manual (-1)	11.3	-20.0
8	Not Experienced (-1)	Manual (-1)	20.4	54.1
9	Experienced (1)	Vibrator (1)	11.3	-7.0
10	Experienced (1)	Manual (-1)	20.4	28.0
11	Experienced (1)	Manual (-1)	11.3	-12.0
12	Not Experienced (-1)	Manual (-1)	11.3	-5.2
13	Not Experienced (-1)	Vibrator (1)	11.3	-8.1
14	Experienced (1)	Manual (-1)	20.4	40.0
15	Experienced (1)	Vibrator (1)	20.4	31.0
16	Not Experienced (-1)	Manual (-1)	20.4	42.3

Regarding production rate effect, the same three unstructured factors—crew experience, compaction, and mixing time—were selected for developing the Sugeno FIS, just as for concrete costs. Concrete production rate effects were computed by considering production rates for fabricating a batch of concrete for six samples made under affecting conditions and compared to a standard sample fabrication rate. Training and checking data for the ANFIS model are illustrated in Table 15 and consisted of 16 data tuples for each dataset. Construction site factors were the inputs and the corresponding effect on concrete production rates was the output. Positive numbers imply that production rates increased due to affecting conditions and vice versa for negative output.

Table 15. Training and checking data for production rate effect

No.	Inputs			Output
	Crew Experience	Compaction	Mixing Time (min)	Production Rate Effect (%)
		Training data		
1	Experienced (1)	Manual (-1)	20.4	-26.5
2	Experienced (1)	Manual (-1)	11.3	8.7
3	Not Experienced (-1)	Manual (-1)	11.3	0.0
4	Experienced (1)	Vibrator (1)	20.4	-24.2
5	Not Experienced (-1)	Vibrator (1)	11.3	19.0
6	Not Experienced (-1)	Vibrator (1)	20.4	-21.9
7	Experienced (1)	Vibrator (1)	11.3	25.0
8	Not Experienced (-1)	Vibrator (1)	11.3	4.2
9	Experienced (1)	Vibrator (1)	20.4	-16.7
10	Not Experienced (-1)	Manual (-1)	20.4	-32.4
11	Not Experienced (-1)	Vibrator (1)	20.4	-24.2
12	Experienced (1)	Vibrator (1)	11.3	19.0
13	Not Experienced (-1)	Manual (-1)	20.4	-34.2
14	Experienced (1)	Manual (-1)	11.3	19.0
15	Not Experienced (-1)	Manual (-1)	11.3	-3.8
16	Experienced (1)	Manual (-1)	20.4	-24.2
		Checking data		
1	Not Experienced (-1)	Vibrator (1)	11.3	8.7
2	Not Experienced (-1)	Manual (-1)	11.3	-7.4
3	Not Experienced (-1)	Vibrator (1)	20.4	-26.5
4	Experienced (1)	Vibrator (1)	20.4	-21.9

5	Not Experienced (-1)	Vibrator (1)	20.4	-19.4
6	Experienced (1)	Vibrator (1)	11.3	31.6
7	Experienced (1)	Manual (-1)	11.3	25.0
8	Not Experienced (-1)	Manual (-1)	20.4	-35.9
9	Experienced (1)	Vibrator (1)	11.3	13.6
10	Experienced (1)	Manual (-1)	20.4	-21.9
11	Experienced (1)	Manual (-1)	11.3	13.6
12	Not Experienced (-1)	Manual (-1)	11.3	4.2
13	Not Experienced (-1)	Vibrator (1)	11.3	13.6
14	Experienced (1)	Manual (-1)	20.4	-28.6
15	Experienced (1)	Vibrator (1)	20.4	-19.4
16	Not Experienced (-1)	Manual (-1)	20.4	-30.6

4.3.2 Fuzzy Modeling

Yager and Filev (1994a) pointed out that there are two approaches for developing fuzzy models; namely, a direct approach and system identification. The first one consists of creating a fuzzy inference system based on expert knowledge. An expert oversees partitioning the data, creating if–then rules, choosing an appropriate inference mechanism, and evaluating the model. On the other hand, system identification is a method for developing a FIS based exclusively on I/O data (e.g., experimental data). This approach was used in this research to develop a Sugeno-type FIS.

4.3.2.1 System Identification

System identification can be divided into (1) structure identification and (2) parameter identification (Sugeno and Yasukawa 1993). The main goal of structure identification is to determine the partitions of the I/O data points, if–then rules, and the number of rules, while parameter identification involves adjusting the parameters of the model to minimize output errors. All cluster centers identified by a clustering method determine the number of if–then rules and antecedent membership functions (i.e., the MFs for the inputs) that are utilized by ANFIS during the parameter identification process. The subtractive clustering method (Chiu 1994) and ANFIS are used for structure and parameter identification respectively.

4.3.2.1.1 Structure Identification

There are several methods for clustering data (i.e., classifying data). Fuzzy c-means is a very popular method proposed by Bezdek (1981) and is based on iterative optimization. The objective function is intended to minimize Euclidean distances between a data point and its cluster center, and to maximize the Euclidean distance between cluster centers (Ross 2017). The mountain method, a simple and effective clustering algorithm, is another procedure used for grouping data and was proposed by Yager and Filev (1994b). This method is based on gridding the data space of each input and output variable. A grid point with many surrounding points has a high potential value and is chosen as a cluster center. The main drawback is that it is very computationally intensive when the number of inputs increases. Subtractive clustering, introduced by Chiu (1994) is a variation of the mountain method. In this method, any data point is considered as a potential cluster center instead of a grid point. The number of grid points is equal to the number of data points, reducing computational load significantly, even for a large number of input variables. This method is fast, since it does not involve iterative nonlinear optimization. Also, it is recommended for use when the possible number of clusters is unknown (MathWorks 2017). Thus, the subtractive clustering method was used in this research for the structure identification process to determine the number of if–then rules and membership functions.

4.3.2.1.1.1 Subtractive Clustering

As mentioned before, each data point is consider as a potential cluster center and the potential value (Pi) of a data point x_i is defined by Eq. 11. The value α is defined by Eq. 12, where r_a, a positive constant, is the radius of influence of a cluster center. This parameter is specified by the user and a large value of r_a produces fewer clusters and vice versa. The radius r_a is adjusted based on the results of the model accordingly, meaning that it can be modified according to the number of cluster centers identified.

$$Pi = \sum_{j=1}^{n} e^{-\alpha \|x_i - x_j\|^2} \quad (11)$$

$$\alpha = \frac{4}{{r_a}^2} \quad (12)$$

It is inferred from Eq. 11 that a data point with many neighbors has a high potential value. After computing the potential of each point (Pi), the point with the highest potential value is assigned to be the first cluster center (P_1). Then the potential values of all remaining data points are updated with respect to the first cluster according to Eq. 13. The value β is defined by Eq.14 and it is inversely proportional to r_b which is a positive constant defined as the radius of the neighborhood having measurable reductions. x_1^* is the first cluster center, and P_1^* is its corresponding potential value. r_b can be computed by using Eq. 15, where η is called the squash factor. Typically a good choice for r_b is when $\eta = 1.5$ to ensure that cluster centers are not too close to each other; however, trial and error processes determine ideal subtractive clustering parameters.

$$P_i \Leftarrow P_i - P_1^* \, e^{-\beta \|x_i - x_1^*\|^2} \quad (13)$$

$$\beta = \frac{4}{{r_b}^2} \tag{14}$$

$$r_b = \eta * r_a \tag{15}$$

Once all potential values of the remaining data points are calculated using Eq. 13, the data point with the highest potential value becomes the second cluster center. Then the potential of the remaining data points are reduced with respect to the second cluster center and so forth as indicated in Eq. 16, where x_k^* is the kth cluster center and P_k^* is its corresponding potential value.

$$P_i \Leftarrow P_i - P_k^* \, e^{-\beta \|x_i - x_k^*\|^2} \tag{16}$$

The procedure described using Eq. 16 is repeated until meeting the criteria according to Chiu (1994) as follows, using an if – then – else rule:

if $P_k^* > \bar{\varepsilon} P_1^*$, accept x_k^* as a cluster center and continue.

else if $P_k^* < \underline{\varepsilon} P_1^*$, reject x_k^* and end the clustering process.

else Let $d_{min} =$ shortest of the distances between x_k^* and all previously found cluster center.

if $\frac{d_{min}}{r_a} + \frac{P_k^*}{P_1^*} \geq 1$, accept x_k^* as a cluster center and continue.

else Reject x_k^* and set the potential at x_k^* to 0. Then select the data point with the next highest potential as the new x_k^* and re-test.

end if

end if

In this procedure, $\bar{\varepsilon}$ is a threshold above which a data point is accepted to be a cluster center and $\underline{\varepsilon}$ is a threshold below which a data point will be rejected as a cluster center. The values that are commonly used for these thresholds are 0.5 and 0.15 respectively.

After clusters have been identified, they are used to create the MFs that are going to be utilized by the ANFIS model. First, the number of clusters identified determine both the number of MFs for each input and the total number of if – then rules for the FIS. The parameters needed for creating a Gaussian MF become each cluster center (c_i) with its corresponding sigma (σ_i) as shown in Fig.19. Sigma is computed by using Eq. 17 for each cluster by subtracting the maximum and the minimum values of the X data matrix (i.e., each input data).

$$\sigma = \frac{r_a * (\max(X) - \min(X))}{\sqrt{8}} \tag{17}$$

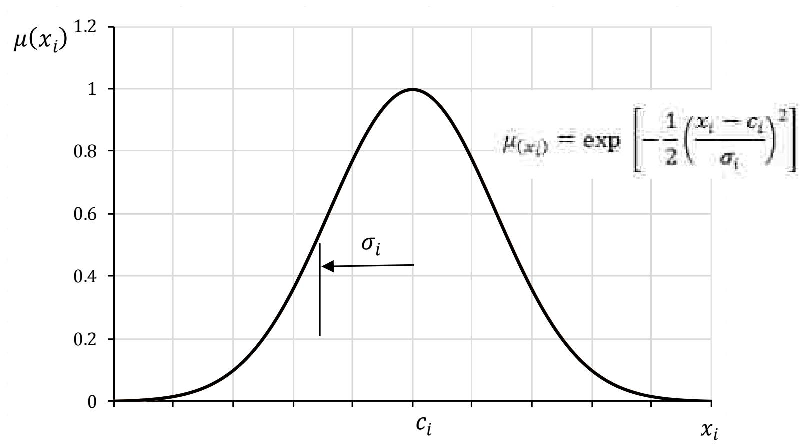


Fig.19. Gaussian membership function parameters.

4.3.2.1.2 Parameter Identification

When using the subtractive clustering method for parameter identification with adaptive ANFIS and under a MATLAB platform, the resulting FIS structure has the following characteristics: first or zero order Sugeno-type FIS; single output using weighted average defuzzification method; Gaussian MFs only, all of the same type; equal number of MFs and if – then rules; and unity weight for each rule. A characteristic of this model is that it gives crisp outputs or functions for each rule.

4.3.2.1.2.1 Adaptive Neuro Fuzzy Inference Systems (ANFIS)

ANFIS, developed by Jang (1993), is a neuro-fuzzy model that makes use of the advantages of artificial neural networks by allowing fuzzy systems to learn through a hybrid learning algorithm.19 ANFIS uses experimental I/O data available from a system to tune MFs and create if–then rules for a Sugeno-type FIS. Fig.20 shows an example of a Sugeno system with four rules, two inputs (e.g., construction site factors F1 and F2), and one output (i.e., concrete compressive strength effect). In addition, Fig.21 illustrates ANFIS architecture with its 5 layers. It can be inferred from both figures that a characteristic of this model is that it gives crisp outputs or functions for each rule and an aggregated total output of the system. The number and shapes of MFs for ANFIS are set first through the structure identification process.

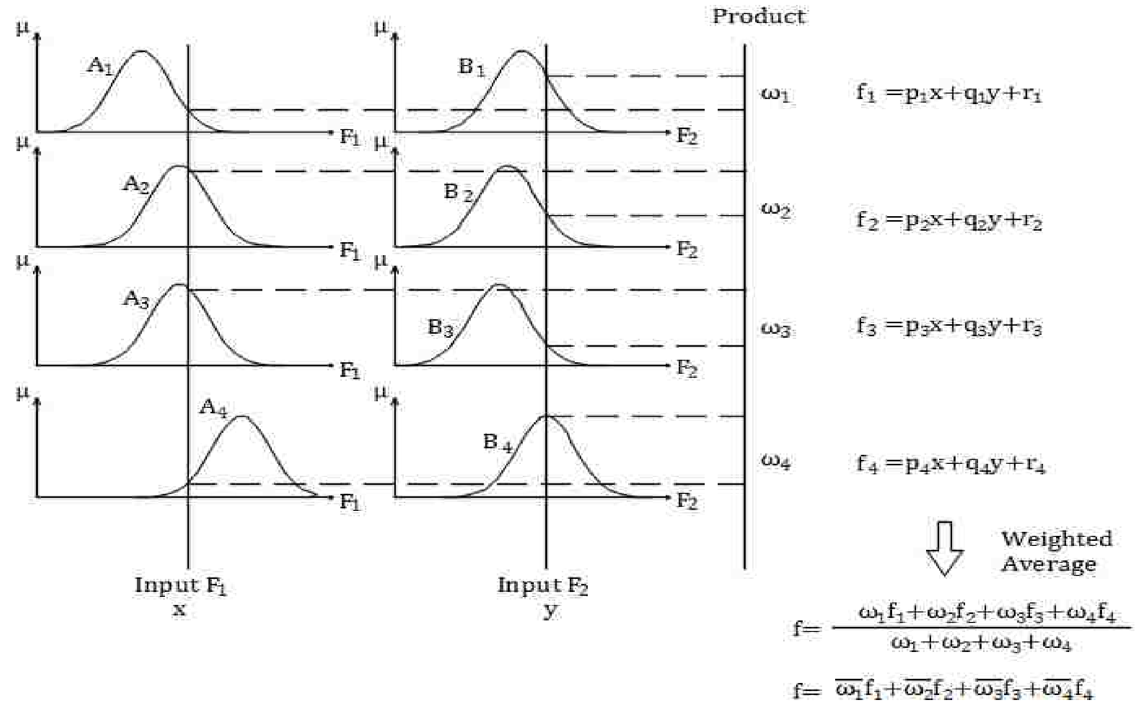


Fig.20. Sugeno fuzzy inference system (*Adapted from Jang et al. (1997)*)

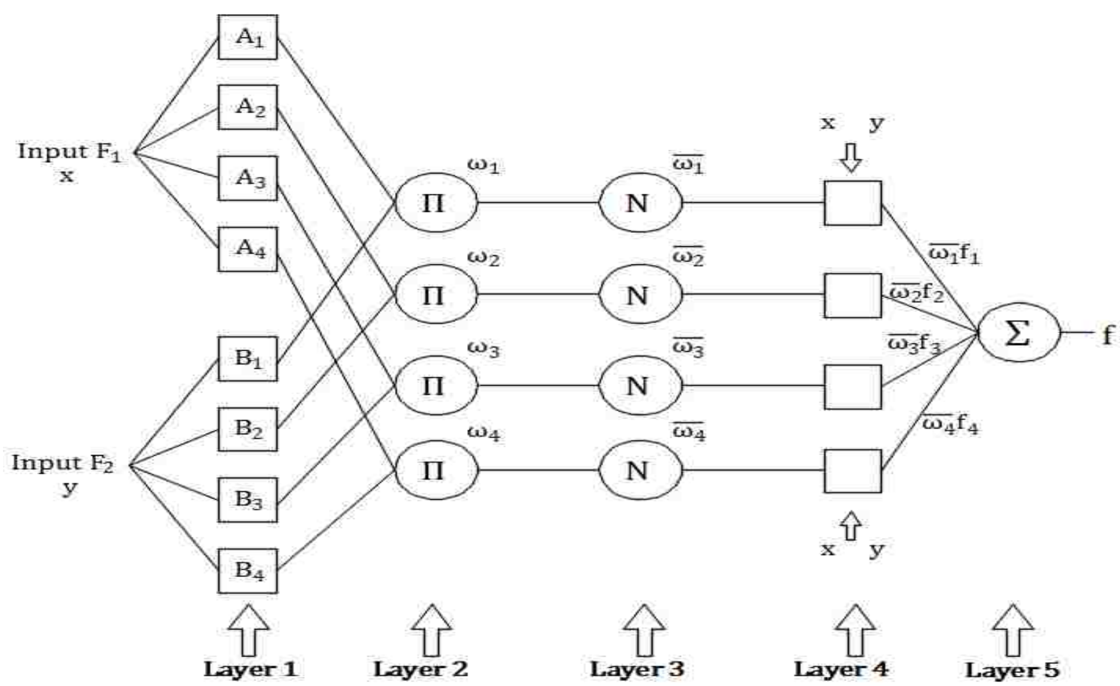


Fig.21. ANFIS architecture (*Adapted from Jang et al. (1997)*)

Each layer (Fig.21) of ANFIS has a specific purpose, in order to process input data until a final output is obtained. Calculations performed in each layer are described as follows:

Layer 1: This layer is an input layer and it is where the degree of membership of each construction site factor is calculated from its corresponding Gaussian MF (i.e., $\mu A_{1_{(x)}}$, …, $\mu A_{4_{(x)}}$, $\mu B_{1_{(y)}}$, …, $\mu B_{4_{(y)}}$) by applying Eq. 18, where x_i corresponds to each input (i.e., a construction site factor), and c_i and σ_i are the subtractive clustering parameters resulting from the structure identification process.

$$\mu(x_i) = e^{-\frac{1}{2}(\frac{x_i - c_i}{\sigma_i})^2} \tag{18}$$

Layer 2: It is a product layer represented by Π where firing strengths (ω_i) are computed by multiplying (i.e., fuzzy operation t-norm) all membership values that arrive to each node.

$$\omega_1 = \mu A_{1_{(x)}}.\mu B_{1_{(y)}};\ \omega_2 = \mu A_{2_{(x)}}.\mu B_{2_{(y)}};\ \omega_3 = \mu A_{3_{(x)}}.\mu B_{3_{(y)}};\ \omega_4 = \mu A_{4_{(x)}}.\mu B_{4_{(y)}}$$

Layer 3: It is a normalization layer where each firing strength (ω_i) is normalized by dividing it to the summation of all firing strengths.

$$\overline{\omega_1} = \frac{\omega_1}{\omega_1+\omega_2+\omega_3+\omega_4};\ \overline{\omega_2} = \frac{\omega_2}{\omega_1+\omega_2+\omega_3+\omega_4};\ \overline{\omega_3} = \frac{\omega_3}{\omega_1+\omega_2+\omega_3+\omega_4};\ \overline{\omega_4} = \frac{\omega_4}{\omega_1+\omega_2+\omega_3+\omega_4}$$

Layer 4: This is a layer where the output of each rule is calculated. The consequent parameters, $p, q, and\ r$, are estimated by using linear least squares estimation.

$$\overline{\omega_1}f_1 = \overline{\omega_1}(p_1x + q_1y + r_1); \overline{\omega_2}f_2 = \overline{\omega_2}(p_2x + q_2y + r_2)$$

$$\overline{\omega_3}f_3 = \overline{\omega_3}(p_3x + q_3y + r_3); \overline{\omega_4}f_4 = \overline{\omega_4}(p_4x + q_4y + r_4)$$

Layer 5: The total output of the fuzzy inference system (f) is computed in this layer by using weighted average defuzzification method.

$$f = \overline{\omega_1}f_1 + \overline{\omega_2}f_2 + \overline{\omega_3}f_3 + \overline{\omega_4}f_4 \quad \Rightarrow \quad f = \Sigma\overline{\omega_i}f_i$$

Lastly, ANFIS model validation is recommended and it should be carried out to test the performance of the resulting Sugeno FIS by comparing predicted and experimental data. In this study, statistics including the correlation coefficient, R-squared value, and standard errors were used for interpreting model performance. One aspect to be taken into consideration is that training data should not be used for model validation; instead, checking or testing data should be applied (Tesfamariam and Najjaran 2007).

4.4 Results

4.4.1 FIS for Compressive Strength Effect

The Sugeno fuzzy inference system (FIS) for predicting the concrete compressive strength effect had four inputs—compaction method, mixing time, curing humidity, and curing temperature. The subtractive clustering parameters used to partition the input data were accept ratio ($\bar{\varepsilon}$) = 0.5, reject ratio ($\underline{\varepsilon}$) = 0.15, range of influence (r_a) = 0.95 and a squash factor (η) = 4.0, ensuring MF overlap and a small number of cluster centers (i.e., number of MFs and if–then rules). Table 16 summarizes the Gaussian parameters—cluster centers (c_i) and sigmas (σ_i) —obtained for each MF; i.e., (1) compaction method ($\mu_{compaction}$), (2) mixing time ($\mu_{mixing\ time}$), (3) curing humidity $\mu_{curing\ Humidity}$), and (4) curing temperature ($\mu_{curing\ temperature}$).

Table 16. Membership function parameters for compressive strength effect

Rules	$\mu_{compaction}$		$\mu_{mixing\ time}$		$\mu_{curing\ humidity}$		$\mu_{curing\ temperature}$	
	σ	c	σ	c	σ	c	σ	c
1	0.670	1.000	3.099	11.310	26.870	20.000	6.907	7.896
2	0.683	-0.996	3.101	20.380	26.870	100.000	6.908	28.500

In addition, two if–then rules determined by clustering were utilized:

1. If (compaction is $\mu_{compaction1}$) and (mixing time is $\mu_{mixing\ time1}$) and (curing humidity is $\mu_{curing\ humidity1}$) and (curing temperature is $\mu_{curing\ temperature1}$) then (strength effect is f_1)
2. If (compaction is $\mu_{compaction2}$) and (mixing time is $\mu_{mixing\ time2}$) and (curing humidity is $\mu_{curing\ humidity2}$) and (curing temperature is $\mu_{curing\ temperature2}$) then (strength effect is f_2)

The results for each ANFIS layer are indicated as follows:

Layer 1: The degrees of membership of each input were computed by using Eq. 18 and the parameters of Table 16: (1) compaction method (In_1):$\mu_{compaction1}(In_1)$ and $\mu_{Compaction2}(In_1)$; (2) mixing time (In_2): $\mu_{mixing\ time1}(In_2)$, $\mu_{mixing\ time2}(In_2)$; (3) curing humidity (In_3): $\mu_{curing\ humidity1}(In_3)$, $\mu_{curing\ \mathrm{humidity}\ 2}(In_3)$; and, (4) curing temperature (In_4): $\mu_{curing\ temperature1}(In_4)$, $\mu_{curing\ temperature2}(In_4)$.

Layer 2: Firing strengths

$$\omega_1 = \mu_{compaction1}(In_1).\mu_{mixing\ time1}(In_2).\mu_{curing\ humidity1}(In_3).\mu_{curing\ temperature1}(In_4)$$

$$\omega_2 = \mu_{compaction2}(In_1).\mu_{mixing\ time2}(In_2).\mu_{curing\ humidity2}(In_3).\mu_{curing\ \ temperature2}(In_4)$$

Layer 3: Normalized firing strengths:

$$\overline{\omega_1} = \omega_1/(\omega_1 + \omega_2);\ \text{and,}\ \overline{\omega_2} = \omega_2/(\omega_1 + \omega_2)$$

Layer 4: Consequent parameters:

$$\overline{\omega_1}f_1 = \overline{\omega_1}(-0.6458.In_1 - 0.0699.In_2 + 0.0330.In_3 + 0.4551.In_4 - 21.26)$$

$$\overline{\omega_2}f_2 = \overline{\omega_2}(2.2840.In_1 - 0.0543.In_2 + 0.3170.In_3 + 1.4120.In_4 - 41.80)$$

4.4.2 FIS for Cost Effect

The Sugeno FIS for predicting the cost effect has the three inputs: crew experience, compaction method, and mixing time. The same previous subtractive clustering constants were used for developing the FIS for cost effect, producing the Gaussian parameters shown in Table 17 for each construction site factor: (1) crew experience: $\mu_{crew\ experience}$, (2) compaction method: $\mu_{compaction}$, and (3) mixing time: $\mu_{mixing\ time}$.

Table 17. Membership function parameters for cost effect

Rules	$\mu_{crew\ experience}$		$\mu_{compaction}$		$\mu_{mixing\ time}$	
	σ	c	σ	c	σ	c
1	0.6836	-0.9960	0.6832	0.9962	3.0570	20.4000
2	0.6658	1.0020	0.6653	-1.0020	3.0540	11.3000

The Sugeno FIS also has two if–then rules, since only two clusters were identified:

1. If (crew experience is $\mu_{crew\ experience1}$) and (compaction is $\mu_{compaction1}$) and (mixing time is $\mu_{mixing\ time1}$) then (cost effect is f_1)
2. If (crew experience is $\mu_{crew\ experience2}$) and (compaction is $\mu_{compaction2}$) and (mixing time is $\mu_{mixing\ time2}$) then (cost effect is f_2)

The results for each ANFIS layer are indicated as follows:

Layer 1: (1) crew experience (In_1): $\mu_{crew\ experience\ 1}(In_1)$, $\mu_{crew\ experience\ 2}(In_1)$, (2) compaction method (In_2): $\mu_{compaction\ 1}(In_2)$, $\mu_{compaction\ 2}(In_2)$, (3) mixing time (In_3): $\mu_{mixing\ time\ 1}(In_3)$, $\mu_{mixing\ time\ 2}(In_3)$

Layer 2: $\omega_1 = \mu_{crew\ experience1}(In_1).\mu_{compaction1}(In_2).\mu_{mixing\ time1}(In_3);$ and,

$$\omega_2 = \mu_{crew\ experience2}(In_1).\mu_{compaction2}(In_2).\mu_{mixing\ time2}(In_3)$$

Layer 3: $\overline{\omega_1} = \omega_1/(\omega_1 + \omega_2)$; and, $\overline{\omega_2} = \omega_2/(\omega_1 + \omega_2)$

Layer 4: $\overline{\omega_1}f_1 = \overline{\omega_1}(-1.492.In_1 - 6.055.In_2 + 4.633.In_3 - 53.85)$; and,

$$\overline{\omega_2}f_2 = \overline{\omega_2}(-6.342.In_1 - 0.724.In_2 + 5.034.In_3 - 63.27)$$

4.4.3 FIS for Production Rate Effect

The Sugeno FIS for predicting the production rate effects has the same characteristics (i.e., inputs) as for the previous FIS for predicting cost effect. Table 18 summarizes the Gaussian parameters for each affecting factor: (1) crew experience: $\mu_{crew\ cxperience}$, (2) compaction method: $\mu_{compaction}$, and (3) mixing time: $\mu_{mixing\ time}$, using the same clustering constants as for strength and cost effects.

Table 18. Membership function parameters for production effect

Rules	$\mu_{crew\ experience}$		$\mu_{compaction}$		$\mu_{mixing\ time}$	
	σ	c	σ	c	σ	c
1	0.6622	-1.0030	0.6665	-1.0020	3.0530	20.4000
2	0.6801	0.9972	0.6843	0.9958	3.0570	11.3000

This Sugeno FIS also has two if–then rules determined by the clustering process:

1. If (crew experience is $\mu_{crew\ experience1}$) and (compaction is $\mu_{compaction1}$) and (mixing time is $\mu_{mixing\ time1}$) then (production rate effect is f_1)
2. If (crew experience is $\mu_{crew\ experience2}$) and (compaction is $\mu_{compaction2}$) and (mixing time is $\mu_{mixing\ time2}$) then (production rate effect is f_2)

The results for each ANFIS layer are indicated as follows:

Layer 1: (1) crew experience (In_1): $\mu_{crew\ experience\ 1}(In_1)$, $\mu_{crew\ experience\ 2}(In_1)$; (2) compaction method (In_2): $\mu_{compaction\ 1}(In_2)$, $\mu_{compaction\ 2}(In_2)$; and, (3) mixing time (In_3): $\mu_{mixing\ time\ 1}(In_3)$, $\mu_{mixing\ time\ 2}(In_3)$

Layer 2: $\omega_1 = \mu_{crew\ experience1}(In_1).\mu_{compaction1}(In_2).\mu_{mixing\ time1}(In_3)$; and,

$$\omega_2 = \mu_{crew\ experience2}(In_1).\mu_{compaction2}(In_2).\mu_{mixing\ time2}(In_3)$$

Layer 3: $\overline{\omega_1} = \omega_1/(\omega_1 + \omega_2)$; and, $\overline{\omega_2} = \omega_2/(\omega_1 + \omega_2)$

Layer 4: $\overline{\omega_1}f_1 = \overline{\omega_1}(4.009.In_1 + 5.187.In_2 - 3.440.In_3 + 46.06)$*;* and,

$$\overline{\omega_2}f_2 = \overline{\omega_2}(5.192.In_1 + 4.041.In_2 - 4.674.In_3 + 65.61)$$

All three fuzzy inference systems are valid as long as the input variables vary between the ranges shown in Table 19, since those were the limit values corresponding to the experimental data on which the ANFIS models were based. The crisp output of each FIS was computed by the weighted average defuzzification method as previously mentioned in layer 5 (Fig.21).

Table 19. Input data ranges for FISs

Construction Site Factors	Range	
	Low	High
Crew experience[a]	-1	1
Compaction method[b]	-1	1
Mixing time (min)	11.3	20.4
Curing humidity (%)	20	100
Curing temperature (°C)	7.9	28.5

[a] -1 for unexperienced crews and 1 for experienced crews
[b] -1 for manual and 1 for vibrator

4.4.4 Model Validation

Statistical parameters such as the correlation coefficient, R-squared (R2), root mean squared errors (RMSE), and standard errors (S) allow testing of model performance (Rantala and Koivisto 2002; Tesfamariam and Najjaran 2007; Topçu and Sarıdemir 2008; Sonebi and Cevik 2009; Tayfur et al. 2014; Kostić and Vasović 2015). Predicted versus experimental data plots were developed for each model by using checking data (Tesfamariam and Najjaran 2007) in order to see how well each final Sugeno FIS would perform. Statistical results are summarized in Table 20, indicating that all models had R2 values greater than 93%, which suggests that all FISs were able to fit data for new observations very well. Also, similar low error values for S and RMSE were obtained for each FIS.

Table 20. Statistical values of predicted vs. experimental data

Statistic	Compressive Strength Effect	Cost Effect	Production Rate Effect
R^2	93.6%	95.5%	94.2%
S	4.44	5.34	5.07
RMSE	4.34	5.26	5.19

4.4.5 Sensitivity Analysis

A sensitivity analysis of each model was performed to estimate the effect of construction site factors on concrete compressive strength, cost, and production rates. Monte Carlo simulation and Spearman's rank correlation were the procedures utilized to identify which factors impacted the outputs the most (Tesfamariam et al. 2006). Discrete probability distributions were used for categorical variables (i.e., crew experience and compaction method) and uniform probability distributions for numerical variables (i.e., mixing time, curing humidity, and temperature). Table 21 summarizes Spearman's correlation coefficients, where positive values indicate that the output increased as the input also increased, and negative coefficients point out that the output decreased as the inputs increased. The numbers in parentheses represent the rank of each construction site factor, where 1 is the rank for the factor that affected a specific output the most. The results of the sensitivity analyses are depicted in Table 22, where the contribution to variance indicates the percentage contribution of each construction site factor on compressive strength, cost, and production rate effects caused by switching a specific input parameter from low level to high level.

Table 21. Spearman's correlation coefficient

Construction Site Factor	Strength Effect	Cost Effect	Production Rate Effect
Crew experience	---	-0.304 (2)	0.347 (3)
Compaction method	-0.354 (3)	-0.162 (3)	0.354 (2)
Mixing time	0.143 (4)	0.922 (1)	-0.857 (1)
Curing humidity	0.511 (2)	---	---
Curing temperature	0.712 (1)	---	---

Table 22. Contribution to variance (%)

Construction Site Factor	Strength Effect	Cost Effect	Production Rate Effect
Crew experience	---	10.3	13.6
Compaction method	9.7	3.3	13.2
Mixing time	2.6	83.4	71.8
Curing humidity	28.2	---	---
Curing temperature	44.2	---	---

For comparison fuzzy inference systems versus regression models obtained through designed experiments, see Appendix C.

4.4.6 Operating Conditions

Desired operating conditions refer to those construction site factors existing during concrete fabrication, placement, and curing that tend to preserve concrete compressive strength while avoiding cost increments and reduction in production rates. Such conditions can be identified from each FIS by, for example, plotting response surfaces. Some affecting conditions, including crew experience, mixing time, and compaction method, can actually be controlled when performing concrete operations while others are difficult to manage on the jobsite, since they rely on surrounding conditions such as ambient temperature and relative humidity. Experienced crews are always preferred for concrete fabrication (Sears et al. 2015), mixing time should ensure uniform and homogeneous mixtures (ACI Committee 304 2000), and compaction method should avoid voids in concrete after placing (Hassoun and Al-Manaseer 2012). Several response surfaces could be explored by keeping constant the previous construction site conditions. For instance, Fig. 22(a) shows the influence of curing temperature and humidity on compressive strength, suggesting that the compressive strength effect is augmented as curing temperature and humidity increase; however, being aware of the consequences of existing conditions would be the real advantage of this supporting tool. A strength effect equaling zero indicates that concrete compressive strength was not affected by construction site factors, and it can be reached by changing controllable construction site conditions accordingly. Fig. 22(b) illustrates the impact of mixing time and compaction method on concrete cost. Compaction method has a slight impact on cost; however, mixing time greatly affects cost. Regarding concrete production, Fig. 22(c) points out that the compaction method does not have an important impact on concrete production; rather, mixing time is the factor that dominates production rates. As can be inferred, many other potential scenarios may be investigated to find desired operating conditions.

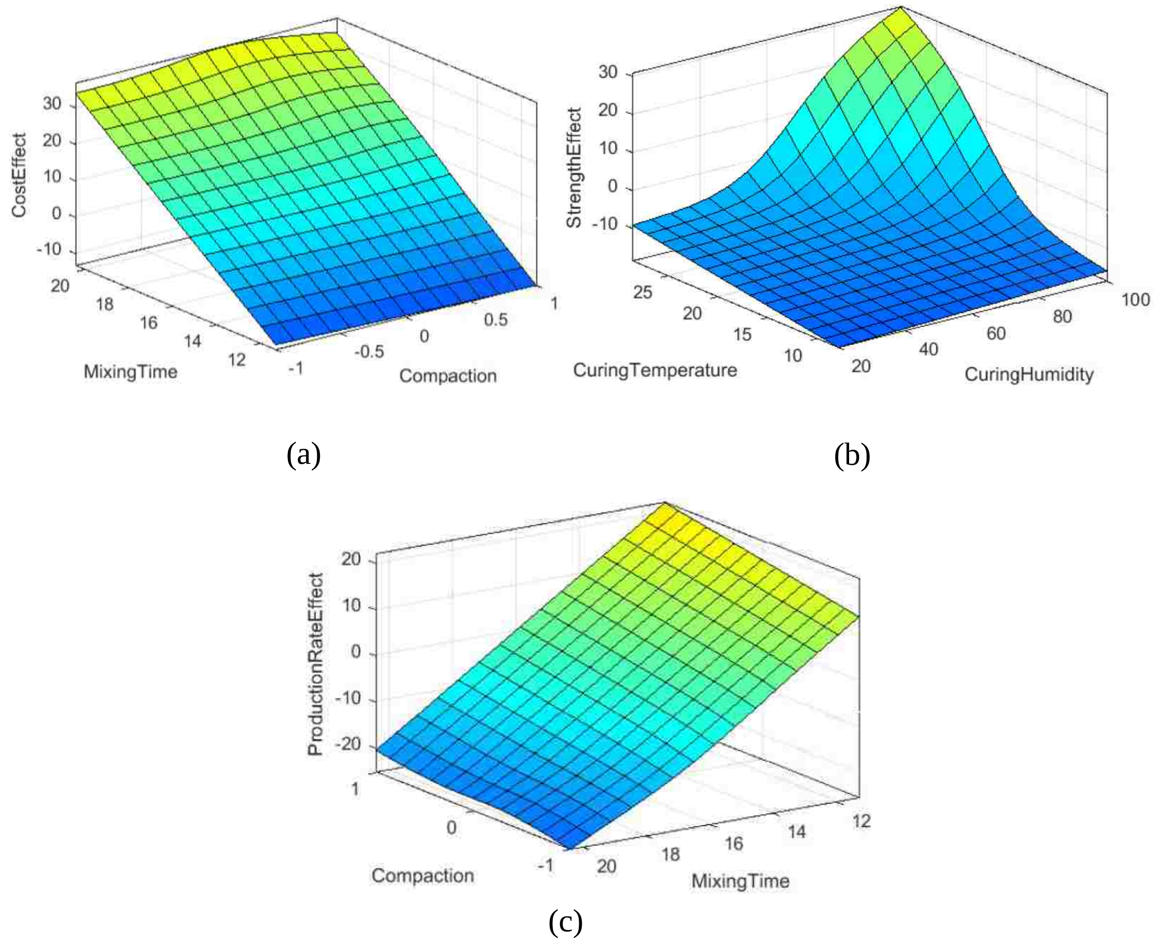


Fig.22. Response surface for: (a) strength effect (vibrator and 15 min of mixing time), (b) cost effect (experienced crews), and (c) production rate effect (experienced crews)

4.5 Conclusions

Sugeno-type fuzzy inference systems perform well when quantifying the effect of construction site factors on concrete compressive strength, cost, and production rates. Three FISs were created to accomplish this research goal based on experimental I/O data. A structure identification process was performed by using a subtractive clustering method, and a parameter identification process was completed through ANFIS, resulting in a Sugeno-type FIS. When using recommended values for subtractive clustering, 16, 8 and 8 membership functions (MFs) were identified for each FIS respectively at first; however, only two MFs for each FIS were found to be necessary to map input data, since MFs mapping low values and MFs mapping high values were similar to each other. In other words, there was no improvement in the errors when considering more than two MFs. For this reason, only two MFs were used in each FIS by using a radius of influence (r_a) of 0.95 and a squash factor (η) of 4. The lower the number of if–then rules, the lower the computational cost. Furthermore, all Sugeno-type FISs have correlation coefficients (R^2) greater than 93%, indicating that models can predict new observations very well. Errors (S and RMSE) range from approximately 4.3 to 5.3 for all fuzzy models, which are relatively low when using checking data.

To evaluate the effect of construction site factors (i.e., unstructured factors) on concrete compressive strength, cost, and production rates, sensitivity analyses were conducted by using a random sampling method (Monte Carlo simulation) combined with a rank correlation method (Spearman's rank coefficients). The sensitivity analyses indicated that curing temperature dominates concrete compressive strength effect while curing humidity is the second most influential factor. Strength effect increased by 44.2%, 28.2%, and 2.6% as curing temperature, curing humidity, and mixing time increased respectively from low level to high ranges (Table 19). In terms of concrete cost, mixing time is the most influential condition. Cost effect increased (83.4%) as mixing time increased from low level to high level, suggesting that the more mixing time, the more expensive concrete becomes. In contrast, concrete cost was reduced by 3.3% when switching from manual compaction to vibrator compaction and by 10.3% when switching from not experienced crews to experienced crews. Regarding concrete production rates, production rate effect decreased (71.8%) as mixing time increased from low to high values, which was expected, since production rates are reduced when production time increases. Concrete productivity improved by 13.6% when switching from not experienced crews to experienced crews and by 13.2% when selecting vibrators as a compaction method instead of manual tamping rods.

The FISs developed as part of this study are supporting tools that provide concrete laborers and technicians with information to make them aware of potential impacts on concrete compressive strength, cost, and production rates caused by the construction site factors studied: crew experience, compaction method, mixing time, curing humidity, and curing temperature. Developed FISs allow construction workers not only to identify desired operating conditions but also to explore other possible onsite conditions in advance, facilitating decision makers to take preventive actions in time. Several response surfaces (see Fig. 22) could be created, depending on each case and when required for each prediction model, by considering two input variables and keeping the others set at constant levels. Maximum and minimum zones can be inferred from response surfaces, helping find conditions that will stimulate compressive strength or increase concrete productivity at low cost. Fig. 22, for instance, allows us to recognize operating conditions where concrete strength, cost, and production are not being affected by construction site factors (i.e., effects equal to zero). Therefore, being aware of potential adverse conditions for concrete fabrication gives a tremendous advantage that can help a project be completed on time and under budget.

CHAPTER 5: OPTIMAL CONSTRUCTION SITE CONDITIONS FOR CONCRETE OPERATIONS

5.1 Introduction

Concrete as a building material is used widely in the construction industry. Yuan et al. (2014) recognized that factors affecting concrete strength may be classified in two categories: structured and unstructured factors. Structured factors are related to the production process of concrete such as properties of raw materials and mixture proportions. Prior studies indicated that several correlations have been developed to quantify the effect of structured factors on compressive strength as a quality metric such as the influence of water – cement ratio, entrained air, aggregate size, age and admixtures on compressive strength (Demirboğa et al. 2001; Kosmatka et al. 2002; Mehta and Monteiro 2006; Jongpradist et al. 2010; Neville and Brooks 2010).

Unstructured factors refer to on site affecting conditions or construction site factors associated to concrete fabrication during the construction process of a facility including manpower and local conditions present at a jobsite. Several of these affecting conditions have been identified in the literature (Kosmatka et al. 2002; Mehta and Monteiro 2006; Neville and Brooks 2010; Li 2011; Hassoun and Al-Manaseer 2012; Wight et al. 2012; Chen et al. 2014; Unanwa and Mahan 2014) including mixing time, compaction method, curing temperature, curing humidity, and crew experience; however, literature is limited with respect to the effects of such factors on concrete product when performing concrete operations.

The theory of design of experiments (DOE) was the technique chosen to conduct a full 2^5 factorial design in order to evaluate the significance of each affecting condition (i.e., an independent variable) as well as to quantify their effect on concrete compressive strength as a quality metric, costs and production rates by developing prediction regression models. DOE has several advantages over other methods of experimentation including estimating interactions between two variables (Montgomery and Runger 2003; Piratelli-Filho and Shimabukuro 2008), and providing protection against bias through randomization (Cox and Reid 2000; Gunst and Mason 2009; Montgomery 2013). Also, the use ± 1 coding for representing low and high factor levels allows to analyze the relative size of factor effects and interpret results easily (Allen 2005; Montgomery 2013).

Reduction in compressive strength, increment in costs of concrete fabrication and low productivity rates are among the consequences of adverse jobsite conditions. Almost all processes in industry require some sort of optimization since minimizing production costs and maximizing profits is the main goal in business. Generally, an optimization process consists of finding optimal solutions from a group of reasonable solutions complying with specific constraints and minimizing computational costs (Ross 2017), suggesting that there could be several solutions for a specific problem and compromised solutions should fulfill decision makers' expectations. Optimization processes may become very intricate. Diwekar (2008) argued that systems become very complex when there are several stakeholders and a number of constrain factors involved. The author also pointed out that those systems cannot be solved by using human experience only. Indeed, most of the time these systems require to follow intensive mathematical algorithms to find a potential compromised solutions satisfying each interested party.

The objectives of this chapter were to: (1) identify statistically significant construction site factors affecting concrete compressive strength, cost and production rates through the analysis of variance (ANOVA); (2) develop regression models for predicting each response, and (3) formulate a multi-objective optimization model for assisting project managers in finding optimal operating conditions by using goal programming optimization method.

5.2 Experimental Data

As aforementioned, the variables taken into consideration to perform a full 2^5 factorial design were compaction method, mixing time, curing humidity and curing temperature, giving a total of 32 experiments. Each run consisted of a unique factor combination where each variable was acting at low or high levels (Table 7). Moderate-strength concrete was selected for this study since it is commonly utilized for buildings and infrastructures (Li 2011). A concrete mixture design was prepared to have a compressive strength of 28 MPa (4000 psi) at the age of 28 days. Six cylindrical concrete samples of 15cm by 30cm were fabricated for each run giving a total of 192 samples. In addition, six extra samples were made-up under standard laboratory conditions in order to serve as a baseline for computing compressive strength, costs and production rates effects by comparing average responses of each run to the average baseline. Three responses were estimated: compressive strength, cost and production rates effects (Table 23). Positive effects indicate that the response was increased by the influence of unstructured factors while negative values indicate the opposite.

Table 23. 2^5 Factorial Design Data

Run No	Independent Variables					Responses		
	Crew Experience	Comp. Method	Mix. Time (min)	Curing Hum. (%)	Curing Temp. (°C)	Comp. Strength Effect (%)	Cost Effect (%)	Prod. Rates Effect (%)
1	Experienced	Manual	20.4	100	28.5	31.0	36.0	-26.5
2	Experienced	Manual	11.3	100	28.5	30.2	-8.0	8.7
3	Not Experienced	Vibrator	11.3	20	7.9	-18.5	-3.9	8.7
4	Not Experienced	Manual	11.3	20	7.9	-12.5	-1.2	0.0
5	Not Experienced	Manual	11.3	100	7.9	-2.4	6.7	-7.4
6	Not Experienced	Vibrator	20.4	20	7.9	-15.7	42.0	-26.5
7	Experienced	Vibrator	20.4	100	28.5	26.3	35.2	-21.9
8	Not Experienced	Vibrator	20.4	100	28.5	32.4	29.5	-19.4
9	Experienced	Vibrator	11.3	100	7.9	-10.0	-18.8	31.6
10	Experienced	Manual	11.3	20	28.5	0.8	-20.0	25.0
11	Experienced	Vibrator	20.4	20	7.9	-20.2	39.4	-24.2
12	Not Experienced	Manual	20.4	20	28.5	5.9	54.1	-35.9
13	Not Experienced	Vibrator	11.3	100	28.5	12.6	-12.3	19.0
14	Not Experienced	Vibrator	20.4	20	28.5	-5.9	34.3	-21.9
15	Experienced	Vibrator	11.3	20	28.5	-1.6	-7.0	13.6
16	Experienced	Vibrator	11.3	100	28.5	16.9	-15.5	25.0
17	Experienced	Manual	20.4	20	7.9	-23.2	28.0	-21.9
18	Not Experienced	Vibrator	11.3	20	28.5	-17.2	0.2	4.2
19	Experienced	Manual	11.3	100	7.9	-9.5	-12.0	13.6
20	Experienced	Vibrator	20.4	20	28.5	3.2	26.8	-16.7
21	Not Experienced	Manual	20.4	20	7.9	-19.9	46.2	-32.4
22	Not Experienced	Manual	11.3	20	28.5	-9.6	-5.2	4.2
23	Not Experienced	Vibrator	11.3	100	7.9	-18.5	-8.1	13.6
24	Experienced	Manual	20.4	20	28.5	2.5	40.0	-28.6
25	Not Experienced	Vibrator	20.4	100	7.9	-7.9	37.8	-24.2
26	Experienced	Vibrator	20.4	100	7.9	-8.6	31.0	-19.4
27	Experienced	Vibrator	11.3	20	7.9	-18.6	-11.3	19.0
28	Not Experienced	Manual	20.4	100	7.9	-3.7	42.3	-30.6
29	Not Experienced	Manual	20.4	100	28.5	20.0	50.2	-34.2
30	Experienced	Manual	11.3	20	7.9	-18.2	-16.0	19.0
31	Not Experienced	Manual	11.3	100	28.5	28.1	2.7	-3.8
32	Experienced	Manual	20.4	100	7.9	0.4	32.0	-24.2

5.3 Factorial Design Analysis

5.3.1 Statistical Testing for the Significance of Affecting Factors

Significant construction site conditions were identified by performing the analysis of variance (ANOVA) at 0.05 level of significance with 95% confidence level. Table 24 summarizes the results of ANOVA statistical tests for each response: compressive strength, cost and production rate effect. Low p-values of 0.05 or less indicate that all factors are significant and they were taken into consideration for developing final regression models.

Table 24. ANOVA Table for Construction Site Conditions

Source	Degrees of Freedom	Sum of Squares	Mean Square	F value	p value
Compressive Strength Effect					
Main Effects	4	7787.7	1946.92	62.85	0.00
Compaction (B)	1	157.9	157.93	5.10	0.03
Mixing Time (C)	1	130.3	130.26	4.21	0.05
Curing Humidity (D)	1	2925.9	2925.94	94.46	0.00
Curing Temperature (E)	1	4573.6	4573.56	147.65	0.00
2-Way Interactions	1	552.7	552.70	17.84	0.00
Curing Humidity (D) * Curing Temperature (E)	1	552.5	552.53	17.84	0.00
Residual Error	26	805.4	30.98		
Total	31	9145.6			
Cost Effect					
Main Effects	3	17795.40	5931.80	228.50	0.00
Crew Experience (A)	1	756.60	756.60	29.14	0.00
Compaction (B)	1	182.40	182.40	7.02	0.01
Mixing Time (C)	1	16856.50	16856.50	649.32	0.00
2-Way Interactions	1	180.40	180.40	6.95	0.01
Crew Experience (A) * Compaction (B)	1	180.40	180.40	6.95	0.01
Residual Error	27	700.90	26.00		
Total	31	18676.70			
Production Rate Effect					
Main Effects	3	12706.30	4235.40	159.15	0.00
Crew Experience (A)	1	789.30	789.30	29.66	0.00
Compaction (B)	1	575.40	575.40	21.62	0.00

Mixing Time (C)	1	11341.70	11341.70	426.18	0.00
2-Way Interactions	1	177.90	177.90	6.68	0.02
Crew Experience (A) * Mixing Time (C)	1	177.90	177.90	6.68	0.02
Residual Error	27	718.50	26.60		
Total	31	13602.70			

5.3.2 Regression Models

Final regression models were estimated by considering significant terms identified through ANOVA depicted in Table 24. Eq. 8 represents the general regression model for a 2^5 factorial design for predicting new observations, where Z is the fitted response, β_0 is the average of all observations, $\beta' s$ are the regression coefficients, and $x' s$ are the independent variables representing each construction site condition; namely, crew experience, compaction method, mixing time, curing humidity, and curing temperature. Table 25 compiles all final estimated regression coefficients for each regression model in engineering units (i.e., uncoded units).

Table 25. Regression Model Coefficients

Terms ($\boldsymbol{x's}$)	Model Coefficients ($\boldsymbol{\beta' s}$)		
	Compressive Strength Effect	Cost Effect	Production Effect
Constant (β_0)	-32.4761	-65.1022	58.8866
Crew Experience	-----	-4.8624	13.1790
Compaction Method	-2.2216	-2.3872	4.2403
Mixing Time	0.4434	5.0443	-4.1376
Curing Humidity	0.0555	-----	-----
Curing Temperature	0.5555	-----	-----
Crew Experience * Compaction	-----	2.3740	-----
Crew Experience * Mixing Time	-----	-----	-0.5182
Curing Humidity * Curing Temperature	0.0101	-----	-----

5.3.3 Analysis of Residuals

Model adequacy of each model was performed through the analysis of residuals in order to verify if there was not any assumption violation with respect to normality, independence and inequality of variance. Normal probability plots for the residuals indicate that the normality assumption was not violated since residuals remain reasonably close to the line of the normal distribution centered at zero in all three models. Moderate deviations from normality does not necessary imply a serious violation of the assumption (Montgomery 2013). Furthermore, the assumptions of independence and inequality of variance were checked by plotting residuals versus run order and residuals versus fitted values. No violation was found in any case because residuals did not follow obvious patterns (Montgomery 2013), meaning they are structureless. Even though some graphs showed a very slight inequality of variance, there is no strong evidence of that situation.

5.3.4 Model Validation

Model validation is always recommended to evaluate how well final prediction models performs when predicting new observations. A predicted versus experimental data plot was developed for each response; namely, compressive strength, cost and production rates effects in order to obtain correlation coefficients (i.e., R-squared values (R-Sq)) and standard errors (S). Table 26 summarizes R-Sq values and S for each regression model. All R-Sq values are greater than 91%, indicating that all models fit data for new observations very well. S represents the standard distance between experimental and predicted data. Smaller values of S are desired for model validation.

Table 26. Correlation Coefficients and Errors

Statistic	Effects		
	Compressive Strength	Cost	Production
R-Sq	91.20%	96.20%	94.70%
S	4.952	4.742	4.763

5.3.5 Sensitivity Analysis

Sensitivity analysis was accomplished through Monte Carlo simulation and Spearman's rank correlation (Tesfamariam et al. 2006) in order to identify the construction site conditions that affect concrete strength, cost and production rates the most. Discrete and uniform probability distributions were utilized for categorical and numerical variables respectively. Positive Spearman's correlation coefficients shown in Table 27 indicate that the output increases as the input also increases while negative values indicate the opposite. Also, the greater the Spearman's correlation coefficient in absolute value, the greater the factor effect on the response. Tornado diagrams were utilized to shows the results of the sensitivity analyses (Fig. 23, Fig. 24 and Fig. 25), illustrating the positive and negative percent contributions of each construction site condition on concrete compressive strength, cost and production rates effects as a consequence of increasing a specific input parameter from low to high level.

Table 27. Spearman's Rank Coefficients

Affecting factor	Spearman's correlation coefficient		
	Comp. Strength	Cost	Production
Crew experience	-	-0.322	0.368
Compaction method	-0.233	-0.151	0.319
Mixing time	0.124	0.919	-0.861
Curing humidity	0.580	-	-
Curing temperature	0.751	-	-

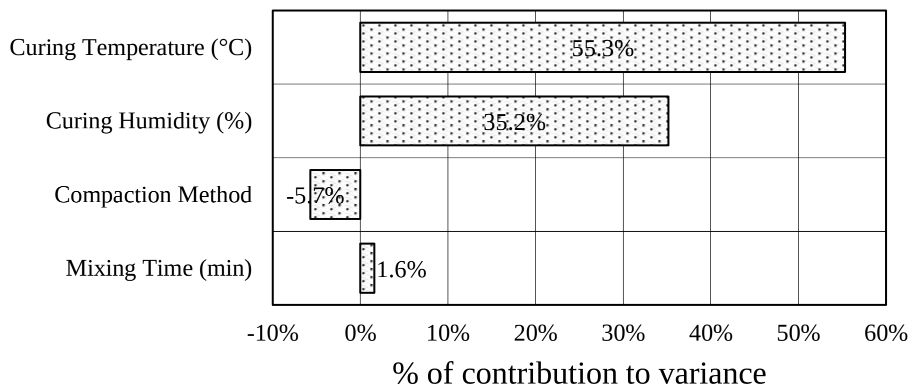


Fig. 23. Sensitivity of Compressive Strength Effect

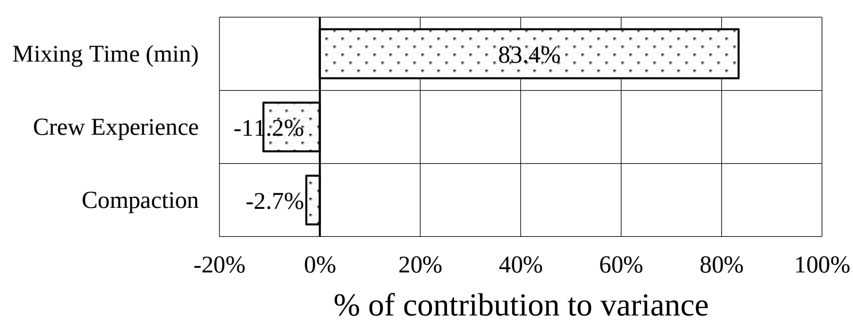


Fig. 24. Sensitivity of Cost Effect

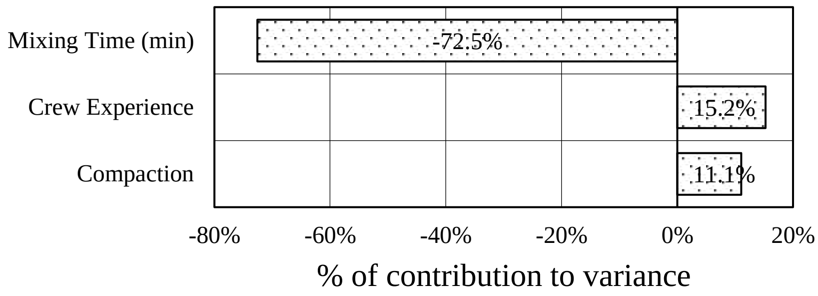


Fig. 25. Sensitivity of Production Rate Effect

5.4 Optimal Operating Conditions

Optimal operating conditions refer to those conditions desired during concrete fabrication at the jobsite tending to satisfy compromised goals in terms of concrete compressive strength, cost of fabrication and production rates. Finding optimal operating conditions that allow to minimize concrete costs and maximize production rates without affecting concrete compressive strength as a quality metric are usually preferred or desired by project managers when performing concrete operations. A multi-objective optimization problem (MOP) based on compromised solutions was formulated to maximize both concrete compressive strength and production rates, and reduce concrete fabrication cost. All this tending to serve as a decision tool for managing concrete made by hand at the construction site. Goal programming optimization method, a preference based method, was selected as a reasonable and fast procedure to handle with this type of MOP problem (Diwekar 2008).

5.5 Optimization Model

The problem formulation involves defining goals (G_i) for each function (Z_i) and the corresponding deviations ($\delta_i^+$and δ_i^-). G_i represents each goal established by decision makers (e.g., project managers and foremen) when fabricating concrete at the jobsite depending on their interests. The goals considered in this chapter were to: (1) preserve concrete compressive strength; i.e., $Compressive\ strength\ effect \geq 0$, (2) minimize concrete costs; i.e., $Cost\ effect \leq 0$, and (3) maximize production rates; i.e., $Production\ Rates\ effect \geq 0$. Regarding the mathematical functions (Z_i) representing compressive strength, cost and production rates effects, they are related to each regression model derived from Eq. 19 by using coefficients contained in Table 25, where the independent variables are crew experience, compaction method, mixing time, curing humidity and curing temperature constrained to the ranges shown in Table 7.

Positive and negative deviations (i.e., $\delta_i^+$and δ_i^-) need to be included into each function Z_i by subtracting δ_i^+ and by adding δ_i^-. They indicate the amount deviated above and below of each corresponding goal, being restricted to $\delta_1^+ \geq 0$; $\delta_1^- \geq 0$; $\delta_2^+ \geq 0$; $\delta_2^- \geq 0$; $\delta_3^+ \geq 0$; $\delta_3^- \geq 0$. For strength effect, the deviation δ_1^+ can be considered null since the expected compressive strength effect has to be equal to or greater than zero according to goal (1), meaning that it is not important for the model when the compressive strength effect is increased by unstructured factors. On the other hand, δ_1^- should be equal to one since the reduction of compressive strength is not part of the goal. In terms of concrete costs and production rates and in the same manner as for concrete compressive strength effect, the deviations δ_2^+ and δ_3^- should be equal to one and δ_2^- and δ_3^+ should be considered null in order to comply with pre-established goals. To implement this into the optimization model, penalty weights of zeros were assigned. The summation of all deviations becomes the objective function that needs to be minimized according to Eq. 19 and constrained to Eq. 20.

$$Minimize\ Z_{goal} = \sum_{i=1}^{3} \delta_i^+ + \delta_i^- \tag{19}$$

$$Z_i - G_i - \delta_i^+ + \delta_i^- = 0 \tag{20}$$

Goal programming formulation could be carried out once standard and deviation variables were defined. Table 28 contains the optimization model for finding optimal construction site conditions when making concrete at the jobsite manually. The Input Values row contains changing cells corresponding to standard and deviation variables. The Left Hand Side (LHS) column contains the results of each prediction model including their corresponding deviations for a specified input value whereas the Right Hand Side (RHS) column is the input column containing compromised goals. The objective function was minimized by using the generalized reduced gradient method (GRG) which is a nonlinear solving method for nonlinear optimization. A solution is found when both columns –LHD and RHS– are equal. For instance, Table 28 presents the results of the optimization model for the following goals entered into RHS column: (1) an increment of 10% in compressive strength effect, (2) 0% increase in concrete fabrication cost and (3) 10% increase in concrete production rates. The value of $\delta_3^+ = 1.72$ indicates that there is a deviation of 1.72% above the third goal set for production rates, meaning that the actual value of production rates effect is 11.72%. However, this does not mean that there are no other possible solutions since there could be more than one locally optimal solution.

Table 28. Optimization Model

Goals	Constant (βo)	Standard variables (Affecting Factors)					Deviation Variables						Left Hand Side (LHS)	Right Hand Side (RHS)
		Crew Exp.[1]	**Comp. Method**[2]	**Mixing Time (min)**	**Curing Hum. (%)**	**Curing Temp. (°C)**	δ_1^+	δ_1^-	δ_2^+	δ_2^-	δ_3^+	δ_3^-		
Compressive Strength Effect	-32.4761	0.0000	-2.2216	0.4434	0.0555	0.5555	-1	1					10.0	10.0
Cost Effect	-65.1022	-4.8623	-2.3872	5.0443	0.0000	0.0000			-1	1			0.0	0.0
Production Rates	58.8866	13.1790	4.2403	-4.1376	0.0000	0.0000					-1	1	10.0	10.0
		Changing Values												
Input Values		1	1	13.9	66.2	28.5	0.00	0.00	0.00	0.00	1.72	0.00		
Penalty Weights[3]							0	1	1	0	0	1		
$Minimize\ Z = 0 * \delta_1^+ + 1 * \delta_1^- + 1 * \delta_2^+ + 0 * \delta_2^- + 0 * \delta_3^+ + 1 * \delta_3^-$									0	Objective Function				

[1] -1 for unexperienced crews and 1 for experienced crews
[2] -1 for manual compaction and 1 for vibrator
[3] Zero values correspond to null deviations

5.6 Conclusions

Concrete as a construction material undergoes several affecting conditions at the jobsite during its fabrication by hand, placing into the forms, curing process until it finally hardens. DOE provided with a systematic experimental program to test the effect of such affecting conditions including crew experience, compaction method, mixing time, curing humidity and curing temperature on concrete compressive strength, cost and production rates while ANOVA allowed us to identify which of such conditions were statistically significant. Only crew experience was not found to be significant for compressive strength whereas crew experience, compaction method and mixing time were identified as significant for concrete fabrication costs and production rates. Also, ANOVA revealed several factor interactions (i.e., one factor effect depends on the level of the other) that are significant as shown in Table 24. For instance, curing humidity and curing temperature is a two-way factor interaction with respect to compressive strength effect.

The adequacy of developed prediction regression models for each response was performed through the analysis of residuals. The plots of residuals indicate that there is no evidence of violating the assumption of normality, independence and inequality of variance, which validated the conclusions. Furthermore, high R-squared values (Table 26) of all regression models indicate that they perform well when predicting new observations. To evaluate the effect of each construction site factor, a sensitivity analysis was conducted for each regression model through Monte Carlo simulation coupled with Spearman rank coefficients. For concrete compressive strength effect, the sensitivity analyses (Fig. 23) shows that curing temperature dominates the output while mixing time does for concrete cost and production rates (Fig. 24 and Fig. 25). Therefore, the results pointed out that curing humidity, temperature and mixing time are the independent variables driving optimal construction site conditions. High curing humidity and curing temperature have a positive effect on compressive strength while high mixing times increases concrete cost and reduces productivity.

The developed optimization model constitutes a decision support tool for concrete workers, technicians and project managers since it provides them with valuable information when fabricating concrete at the jobsite. The model is able to assist in finding specific construction site conditions according to pre-established compromised goals, facilitating the decision making process. For instance, managers are usually required to deliver a project to a certain cost and schedule complying with concrete specifications and thus such optimal construction site conditions could be identified through this tool. Furthermore, if existing on-site conditions influence concrete characteristics negatively, corrective actions could be made before fabricating the product. On the other hand, resources including time and money could be saved if present conditions are found to be favorable through the model. In other words, the proposed optimization model could also be utilized to predict possible effects on concrete compressive strength, costs and production rates caused by local surrounding ambient conditions and explore others. For instance, keeping some of the controllable variables constant such as crew experience, compaction method (i.e., concrete consolidation) and mixing time and entering ambient conditions including curing humidity and curing temperature.

Being aware in advance of potential effects of construction site conditions on concrete in terms of compressive strength, cost of fabrication and production rates is indeed an advantage in order to take preventive actions. The more information is available, the less undesired consequences are expected. Therefore, the proposed optimization model provides not only construction managers but also concrete workers and foremen with a valuable tool allowing to find on-site construction conditions in order to accomplish proposed goals.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

Construction site factors including crew experience, compaction method, mixing time, curing humidity and curing temperature, which are present at the jobsite, may cause significant variation of concrete compressive strength, concrete cost overruns and reduction in concrete productivity. Some of the aforementioned factors related to manpower expertise, equipment and mixing can usually be controlled while performing concrete operations whereas other factors including local environmental surroundings and curing environments are difficult to manage during the construction project. This dissertation presented a comprehensive framework to estimate the effect of construction site factors on concrete considering experimentation and the use of fuzzy set theory.

6.1 Summary of Research

The main porpose of this study was to quantify the effect of construction site factors on concrete compressive strength as a quality metric, cost and production rates by integrating the use of a survey, an experimetal design and fuzzy inference systems. The methodology was intended to identify such factors and create prediction models for estimating the impact of these factors on concrete characteristics, to assist project managers, foremen, technicians and concrete workers when performing concrete operations. The research framework involved four main parts: (1) identification of construction site factors and evaluation of their importance, (2) experimentation and recognition of statistically significant factors utilizing designed experiments, (3) quantification of the effect of construction site factors on concrete compressive strength, cost and production rates using fuzzy inference systems and, (4) finding optimal operating conditions for performing concrete operations.

The first part consisted of identifying construction site factors by performing a comprehensive literature review and through the use of a questionnarie. The literature revealed several construction site factors, named unstructured factors, that act during concrete fabrication process and that affect concrete quality (i.e., compressive strength), cost of fabrication and productivity. A survey instrument was then utilized to search for additional factors and to evaluate their importance based on construction experts' experience gained throughout their careers. Also, the questionnarie enabled understanding the influence of experts' characteristics (e.g., architects or engineers) on their perceptions regarding the degree of impact of a specific affecting factor. Results comprised not only ranking of construction site factors by category: concrete compressive strength, costs and production separately but also a global order of factors influencing concrete, which were then utilized for experimental designs.

In the second part of the research, a full 2^5 factorial design was conducted to investigate which factors are statistically significant. This type of designed experiment considers each factor acting at low and high levels and between specific ranges of action derived from the questionarie to construction experts.The top five factors identified during the previous stage were then taken into consireration for this component of the study. For the experimental program, 192 cylindrical concrete samples (i.e., 6 samples for each run) were fabricated under designed factor combinations in the laboratory and tested under axial loads in order to evaluate their effect on compressive strength. Costs were estimated and production rates were measured during the fabrication of each concrete batch for each one of the 32 experimental runs. Once the experimental responses were obtained for each run, a factorial analysis was executed and statistical testing for the significance of construction site factor effects and their interactions were performed using analysis of variance (ANOVA). Furthermore, design of experiments (DOE) allowed to generate prediction regression models that were used for further comparison against fuzzy inference systems. The significant factors identified in this part were then used as variables considered for developing fuzzy prediction models.

The third part involved the use of fuzzy set theory for developing fuzzy inference systems. The approach for fuzzy modeling was system identification consisting of structure and parameter identification, based on input – output experimenta data. Structure identification was performed using subtractive clustering to determine the partitions of data points, if – then rules and the number of rules. Parameter identification, was achieved through adaptive network- based fuzzy inference system (ANFIS) and involved adjusting the parameters of the model in order to minimize output errors. A fuzzy inference system (FIS) for quantifying the effect of construction site factors on concrete compressive strength, costs, and production rates was developed, being construction site factors (i.e., inputs) the independent variables of each prediction model.

The fourth part of the research consisted of developing a goal programming optimization model based on compromised solutions to find optimal operating conditions for performing concrete operations by using the regression models derived from factorial design analysis. The problem formulation involved defining goals for each function and its corresponding deviations. The goals considered in this study were to preserve concrete compressive strength, minimize concrete costs, and maximize production rates. The independent variables included the identified construction site factors; namely, crew experience, compaction method, mixing time, curing humidity and curing temperature. The developed optimization model constitutes a decision support – tool for concrete workers, technicians and project managers that allows not only to find optimal conditions but also to find other conditions for specific outputs.

6.2 Summary of Results

The proposed framework of this dissertation allowed to answer the research questions listed in section 1.3. The first research question was related to identifying construction site factors affecting concrete quality (i.e., compressive strength), costs and production rates. Several affecting conditions were identified through literature review and the use of a questionnaire to construction experts. The results included mixing time, compaction method, ambient temperature, curing temperature, curing humidity, adding extra water (i.e., rain when fabricating concrete) and crew experience. Their importance were evaluated through the use of relative importance index (RII) based on the perception of construction experts. Crew experience (RII=0.7695), compaction method (RII=0.6854) and mixing time (RII=0.6846), curing humidity (RII=0.6798) and curing temperature (RII=0.6465) were the top five affecting factors for concrete compressive strength, costs and production rates when considering an overall ranking. These were the factors considered into this research. In addition to the aforementioned factors, others related to workforce, machinery and equipment, jobsite environment, and concrete fabrication process were recognized by a small group of professionals throught their careers. A detailed procedure, results and analysis can be found in Chapter 2.

The theory of design of experiments (DOE) was used as the strategy of experimentation for identifying significant construction site factors. Since five factors were selected for the study, a full 2^5 factorial design was conducted. Analysis of variance (ANOVA) at 0.05 level of significance was used to identify statistical significant factors. Compaction method, mixing time, curing humidity and curing temperature were found to affect concrete compressive strength significantly. Their effect on compressive strength ranges from -25.7% to 33.9%. Regarding concrete costs and production rates, only fabrication costs (e.g., manpower, and equipment) and productivity (i.e., time) were taken into consideration for computing the response. Their effect on concrete costs ranges from -20% to 54.1% while their effect on production rates ranges from -35.9% to 31.6%. Curing humidity and curing temperature were not selected as variables since they are local jobsite conditions present until concrete reaches its designed capacity. Crew experience, compaction method and mixing time were the selected variables for developing fuzzy prediction models. A detailed experimental program, results (i.e., responses) and a factorial analys can be found in Chapter 3.

The results from the fuzzy modeling showed that all developed FISs have correlation coefficients (R-squared values) greater than 93%, indicating that models predict new observations well. Curing temperature was identified to be the most affecting condition for concrete compressive strength with the highest percentage of contribution to variance

(44.2%) while mixing time has the biggest impact on concrete cost (83.4%) and production rates (71.8%). A detailed fuzzy modeling process is described in Chapter 4.

This methodology could help stakeholders such as project managers, foremen, concrete technicians and workers to manage concrete at the jobsite maintaining quality, without increasing production costs and enhancing productivity. Developed fuzzy inference systems are supporting tools allowing to quantify factor effects and to discern desired operating conditions through the use, for example, of response surfaces. Furthermore, developed prediction models enable not only to find zero – effect zones where concrete metrics are not affected but also to explore many other potential jobsite conditions. The use of response surfaces is shown in Chapter 4.

As it can be inferred, prediction fuzzy models are supporting tools that provide with valuable information in order to be aware of potential impacts on concrete compressive strength, cost and production caused by construction site factors, facilitating decision makers to take preventive actions in advance tending to preserve project resources.

6.3 Research Contributions

The results of this doctoral dissertation have important contributions to the body of knowledge and practice in the field of project management, planning and project controls. The effects of construction site factors, known as unstructured factors, were estimated through the integration of different fields of study and prediction models were developed by utilizing a unique approach.

6.3.1 Contributions to the Body of Knowledge

A major contribution to the body of knowledge constitutes the comprehensive and systematic framework developed for identitying and quantifying the effect of construction site conditions (i.e., unstructured factors). The novel and flexible proposed framework enables to recognize factors existing at a jobsite and to quantify their effect on concrete compressive strength, costs and production rates by taking advantage of several techniques. The proposed methodology integrated previous knowledge, a survey instrument, theory of design of experiments and fuzzy set theory in a single framework. Literature review and the use of a questionnarie allowed to identify and evaluate the importance of each recognized construction site factor based on construction experts' expertise. The experimental design assisted in the concrete sample fabrication process while the factorial design analysis exposed statistically significant affecting factors, generating input – output data for fuzzy modelling. This methodology could be utilized by researchers to investigate other concrete affecting factors. In addition, this research provides a better understanding of specific construction site factors including crew experience, compaction method, mixing time, curing humidity and curing temperature that are present during the construction phase of a project.

6.3.2 Contribution to the Body of Practice

One of the main contributions of this research to body of practice was the development of fuzzy inference systems to quantify the effect of construction site factors (i.e., unstructured factors) on (1) concrete compressive strength as a quality metric, (2) costs, and (3) production rates. Several prior studies have investigated only the impact of factors related to concrete production process; namely, raw material properties, mixture proportions and admixtures; however, literature was limited regarding estimating the effect of construction site factors present when making, placing and curing concrete on the jobsite. No evidence including correlations or prediction models for assessing their effects on concrete metrics were found in this area. Resulting prediction fuzzy models are expected to be decision – support tools for project managers, foremen, concrete technitians and workers that could assist in finding operating conditions and explore other potential scenarios for decision making.

For instance, fuzzy inference systems can be utilized to find desired conditions existing during concrete fabrication tending to preserve concrete or enhance compressive strength while avoiding cost increments and reduction in production rates. Such operating conditions refer to zero – effect counter lines or compromised zones that can be easily identified either by plotting response surfaces or by trial and error feeding prediction models with independent variables (i.e., construction site factors). Also, the versatility of developed models allows to study or simulate potential scenarios tending to stimulate concrete compressive strength by avoiding adverse practices and taking advantage of available on-site environments. Indeed, appropriate concrete fabrication conditions should be taken into consideration when making concrete to ensure that it complies with material specifications stated in the project's construction documents.

6.4 Research Limitations

Data availability was a major limitation of this study for building fuzzy prediction models since fuzzy inference systems were developed based on input – output (I/O) experimental data. Fuzzy modelling was accomplished by using ANIFIS technique which utilizes I/O data for model learning process, thus the more data tuples, the more data can be considered for training and checking each model. Even though 192 concrete samples were fabricated for conducting a full 2^5 factorial design, only a total of 32 experiments (i.e., runs) were run considering each factor combination. Each response consisted of the average of six compressive strengths while costs and production rates responses were computed once for each run, implying that there was no replication of each run. Also, no center points were taken into consideration for quantitative variables for checking linearity between factor effects ; however, 2^k factorial designs perform well even when linearity is approximately. Nonetheless, all possible factor combinations were evaluated and taken into account during the factorial analysis. Besides, when a factor is found not to be a significant factor, the factorial design becomes a replicated design. For instance, crew experience was not a significant factor affecting concrete compressive strength. Only four out of five factors were significant. Therefore, the 2^5 factorial design becomes a 2^4 factorial design with two replicates.

The number of construction site factors considered for the study was a limitation due to the number of combinations when having many factors. Only the top five percieved factors were selected for the factorial design due to resources and experimental infrastructure availability. Costs implied for sample fabrication, simulating affecting conditions and testing were an obstacle when selecting the number of variables to be studied. Also, laboratory infrastructure prevented from considering great number of factors since full factorial design imply 2^k number of runs, with k number of factors. This may have caused the exclusion of a significant construction site condition.

In addition, extreme temperatures for concrete fabrication including hot and cold weather concreting were not considered. Low and high temperature levels for curing temperature were established by construction experts through a questionnarie for normal concreting according to their perception of the linguistic hot and cold terms. The majority of respondents belonged to Ecuador where ambient temperatures are not as extreme as they are in countries having four seasons.

Two major groups formed by architects and engineers accounted for almost all the sample population in the deployed survey for evaluating of the importance of the impact of construction site factors on concrete compressive strength, costs and production rates. Other groups such as contractors and owner representatives should be considered in future research. However, most of the respondents met the criteria of being a construction expert by having at least one year of experience with concrete in the construction industry and academia.

6.5 Recommendations for Future Research

Several recommendations for future research may be established based on the research limitations. With respect to construction site factors, other affecting conditions should be investigated by including the use of fractional factorial designs in order to reduce the number of experimental runs, saving time and resources. For instance, survey results showed that additional construction site factors such as deficient formwork and proper tool use could be factors affecting concrete, and they could be further explored in future research. In addition, a full factorial design with two or three replicates could then be performed by using only significant factors in order to minimize error. Experimental programs assisted by the theory of design of experiments (DOE) should also incorporate concrete made by a concrete mixer machine, broader levels of numerical variables (i.e., range of action) as well as the addition of center points to the factorial design. These recommendations will generate enough experimental data and strengthen prediction models.

This study utilizes only fuzzy inference systems (FISs) as prediction models for quantifying concrete compressive strength, costs and production effects; however, other techniques such as artifitial neural networks (ANN) should be not only explored but also compared with FISs for checking the performance of the estimated models.

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APPENDICES

Appendix A: Survey Instrument, Additional Data and Results for Chapter 2

Appendix A.1: IRB Exemption Letter

UNM | *Office of the Institutional Review Board*

DATE:	April 28, 2016
REFERENCE #:	07916
PROJECT TITLE:	[897000-1] Perceptions of construction experts on factors affecting concrete quality and costs
PI OF RECORD:	Vanessa Valentin, PhD
SUBMISSION TYPE:	New Project
BOARD DECISION:	DETERMINATION OF EXEMPT
EFFECTIVE DATE:	April 27, 2016
REVIEW CATEGORY:	Exempt category #2

DOCUMENTS:

- Advertisement - Recruitment script (UPDATED: 04/13/2016)
- Application Form - Project Information (UPDATED: 04/13/2016)
- Consent Form - Consent Form (UPDATED: 04/20/2016)
- CV/Resume - CV_Vanessa_Valentin (UPDATED: 04/14/2016)
- Other - Translation Certification Form (UPDATED: 04/13/2016)
- Other - Departmental Review (UPDATED: 04/13/2016)
- Other - Project Team (UPDATED: 04/13/2016)
- Protocol - Protocol (UPDATED: 04/20/2016)
- Questionnaire/Survey - Online survey (UPDATED: 04/20/2016)
- Training/Certification - CITI Santamaria (UPDATED: 04/13/2016)

Thank you for your submission of New Project materials for this project. The University of New Mexico (UNM) IRB Main Campus has determined that this project is EXEMPT from IRB oversight according to federal regulations. Because it has been granted exemption, this research project is not subject to continuing review. It is the responsibility of the researcher(s) to conduct this project in an ethical manner.

If Informed Consent is being obtained, use only approved consent document(s).

This determination applies only to the activities described in the submission and does not apply should any changes be made to this project. If changes are being considered, it is the responsibility of the Principal Investigator to submit an amendment to this project for IRB review and receive IRB approval prior to implementing the changes. A change in the research may disqualify this research from the current review category.

The Office of the IRB can be contacted through: mail at MSC02 1665, 1 University of New Mexico, Albuquerque, NM 87131-0001; phone at 505.277.2644; email at irbmaincampus@unm.edu; or in-person at 1805 Sigma Chi Rd. NE, Albuquerque, NM 87106. You can also visit the OIRB website at irb.unm.edu.

Sincerely,

J. Scott Tonigan, PhD
IRB Chair

Appendix A.2: Questionnaire

Perceptions of construction experts on factors affecting concrete quality and costs
Consent to Participate in Research
040716

Purpose of the study: You are being asked to participate in a research study that is being done by Dr. Vanessa Valentin and PhD student Jorge Santamaria, from the Department of Civil Engineering at the University of New Mexico (UNM). The purpose of this study is to identify the factors related to construction processes rather than concrete production that affect concrete quality and costs based on experts in the construction industry experience (i.e., owners, contractors, architects and engineers). You are being asked to take part in this study because of your position, experience and/or research background.

This form will explain what to expect when joining the research, as well as the possible risks and benefits of participation. If you have any questions, please ask one of the study researchers.

What you will do in the study: Your participation will involve responding to a set of questions about identifying and ranking factors that could affect concrete quality and costs during the construction process of a facility. Your involvement in the study is voluntary, and you may choose not to participate. The survey includes questions such as perception about concrete quality (e.g., compressive or tensile strength), the factors that may affect compressive strength according on experience (e.g., weather), and basic information regarding construction experience such as the number of years that you have been involved in this field of expertise. You can refuse to answer any of the questions at any time.

Participation in this study will take around 15 minutes to complete.

Risks: This research has minimal risk to participants. However, the risk for loss of confidentiality is possible with any study, and it will be minimized by not collecting any identifiable data. The survey is anonymous.

Benefits: There will be no immediate benefit to you from participating in this study. However, indirectly the information gained from this study will help understanding the impacts of unstructured factors on concrete quality and costs.

Confidentiality of your information: There are no names or identifying information associated with this survey. Your response will be anonymous. All questionnaires will be concealed, and no one other than the primary investigator and assistant researcher will have access to them. The data collected will be stored in the Qualtrics' secure database until the survey is completed. Once all the data is collected, a CD of the data will be kept locked in Dr. Valentín's office. Dr. Valentín will be the only one having access to this data. Your name will not be used in any published reports about this study.

Payment: You will not be paid for participating in this study.

Right to withdraw from the study: Your participation in this study is completely voluntary. You have the right to choose not to participate or to withdraw your participation at any point during the survey without penalty.

If you have any questions, concerns, or complaints about the research study, please contact:

Mr. Santamaria at jluis@unm.edu or call Dr. Valentin's office at (505) 277-0811.
If you would like to speak with someone other than the research team or have questions regarding your rights as a research participant, please contact the UNM Office of the IRB, (505) 277-2644, irbmaincampus@unm.edu. Website: http://irb.unm.edu/ .The IRB is a group of people from UNM and the community who provide independent oversight of safety and ethical issues related to research involving people:

CONSENT
By clicking "OK" you will be agreeing to participate in the above described research study.

- ❍ OK (1)
- ❍ Exit the survey (2)

I Subject's Information

1 Level of Education

- ❍ Less than High School (1)
- ❍ Bachelor's (2)
- ❍ Graduate (3)
- ❍ Other: (4) ____________________

2 Profession

- ❍ Architect (1)
- ❍ Engineer (2)
- ❍ Contractor (3)
- ❍ Owner (4)
- ❍ Other: (5) ____________________

3 Years of experience in the construction industry with concrete

- ❍ 1 to 5 (1)
- ❍ 6 to 10 (2)
- ❍ 10 to 15 (3)
- ❍ 16 to 20 (4)
- ❍ 21 to 25 (5)
- ❍ More than 25 (6)

4 Field of experience

- ❍ Design (1)
- ❍ Construction (2)
- ❍ Other: (3) ____________________

5 Specialty experience in construction (select only the main one)
- ❍ Buildings and houses (e.g. warehouses) (1)
- ❍ Transportation facilities (e.g. roads and bridges) (2)
- ❍ Hydraulic facilities (e.g. channels and dams) (3)
- ❍ Other: (4) ____________________

II Perception regarding concrete quality and costs

6 What metric do you consider is the most commonly used for measuring concrete quality regardless the type of facility?
- ❍ Compressive Strength (1)
- ❍ Tensile Strength (2)
- ❍ Flexural Strength (3)
- ❍ Other: (4) ____________________

7 Please choose "Yes"
- ❍ No (1)
- ❍ Maybe (2)
- ❍ Yes (3)

8 At what age do you consider concrete reaches its design capacity?
- ❍ 7 days (1)
- ❍ 14 days (2)
- ❍ 21 days (3)
- ❍ 28 days (4)
- ❍ Other: (5) ____________________

9 According to your experience, what percentage on average of the total volume of concrete used to build a facility do you consider is fabricated in situ (i.e., mixing water, cement and aggregates by using either a concrete machine or by hand in the construction site)?
- ❍ Less than 10% (1)
- ❍ 10 to 20 % (2)
- ❍ 21 to 30 % (3)
- ❍ 31 to 40 % (4)
- ❍ 41 to 50 % (5)
- ❍ More than 50 % (6)

10 Do you consider that concrete fabricated in situ (i.e., mixing water, cement and aggregates by using either a concrete machine or by hand in the construction site) and ready mixed concrete bought from a concrete supplier have the same quality (i.e., strength)?
- ❍ Yes (1)
- ❍ No (2)

11 Do you consider that making concrete in situ (i.e., mixing water, cement and aggregates by using either a concrete machine or by hand in the construction site) is cheaper than buying ready mixed concrete from a concrete supplier?

- ❍ Yes (1)
- ❍ No (2)

III Perceptions regarding unstructured factors that affect concrete compressive strength and costs

12 As mentioned before, there have been identified two main groups of factors that affect concrete quality; namely, structured factors and unstructured factors. The first ones are related to the process of fabrication of concrete such as water-cement ratio, materials' properties and mix proportions while unstructured factors are those related to the construction process of a facility such as weather while concreting. From the following unstructured factors identified in the literature; namely, (1) mixing time, (2) compaction, (3) ambient temperature, (4) curing temperature, (5) curing humidity, (6) adding extra water (i.e., rain) and (7) crew experience, can you mention others?Other Identified Unstructured Factors:

1.- (1) ____________________
2.- (2) ____________________
3.- (3) ____________________
4.- (4) ____________________
Note: Add more rows as needed. (5) ____________________

13 For all aforementioned factors (i.e., identified factors in the literature and others identified by you), please rate the impact (from none to very high) on concrete compressive strength, costs and production rates that these factors have. Unstructured Factors:

	Concrete Strength						Cost						Production Rates					
	None (1)	Very Low (2)	Low (3)	Medium (4)	High (5)	Very High (6)	None (1)	Very low (2)	Low (3)	Medium (4)	High (5)	Very high (6)	None (1)	Very low (2)	Low (3)	Medium (4)	High (5)	Very high (6)
1. Mixing time (1)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
2. Compaction (2)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
3. Ambient temperature (3)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
4. Curing temperature (4)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
5. Curing humidity (5)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
6. Adding extra water (i.e., rain) (6)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
7. Crew experience (7)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
8. (8)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
9. (9)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
10. (10)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
11. (11)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
12. (12)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
13. (13)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
14. (14)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
15. Add more rows as needed (15)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍

14 Have you ever considered the effect of such unstructured factors on concrete quality?

- ❍ Yes, If yes, how (1) ____________________
- ❍ No (2)

15 Please select "Yes"

- ❍ No (1)
- ❍ Yes (2)

16 In terms of costs, how significant do you think that unstructured factors can affect concrete? If you believe that such factors do not affect concrete costs at all, please mark 0%.

- ❍ 0 % (1)
- ❍ Less than 10% (2)
- ❍ 10 to 20 % (3)
- ❍ 21 to 30 % (4)
- ❍ 31 to 40 % (5)
- ❍ 41 to 50 % (6)
- ❍ More than 50 % (7)

17 What is the minimum and maximum mixing time in minutes for concrete that you generally apply when making concrete?

	Manually (e.g., By hand) (1)	Concrete machine (2)
Minimum (1)		
Maximum (2)		

18 In terms of labor, do you usually use experience crews (i.e., no carpenters or plumbers) when making concrete in situ (i.e., mixing water, cement and aggregates by using either a concrete machine or by hand in the construction site)?

- ❍ Yes (1)
- ❍ No, If no, how the crew is formed? (2) ____________________

19 What environment temperature (i.e., ambient temperature) do you consider cold, normal and hot in °C when dealing with concrete placement operations on a construction site?

	Temperature in °C (1)
Cold (1)	
Normal (2)	
Hot (3)	

20 In terms of curing concrete (i.e., keeping concrete wet), how long do you usually do it continuously?

	Days (1)
Curing time (1)	

21 In terms of curing concrete (i.e., keeping concrete wet), do you consider curing temperature?

- ❍ Yes, If yes, explain how? (1) ____________________
- ❍ No (2)

IV Additional subject's information

22 Age (years)

- 25 or Younger (1)
- 26 to 35 (2)
- 36 to 45 (3)
- 46 to 55 (4)
- 56 to 65 (5)
- 65 or older (6)

23 Gender

- Male (1)
- Female (2)

Thank you for your participation!!!!!

Appendix A3: Relative Importance Index (RII) Calculations

Table 29. Impact of Construction Site Factors on Concrete Compressive Strength

Factors	None	Very Low	Low	Medium	High	Very High	Weighting (W)	A	N	RII
	1	2	3	4	5	6				
Mixing Time	9	12	28	83	152	13	1287	6	297	0.722
Compaction Method	5	11	30	81	120	50	1341	6	297	0.753
Ambient Temperature	5	17	59	81	127	8	1223	6	297	0.686
Curing Temperature	1	9	32	87	141	27	1330	6	297	0.746
Curing Humidity	1	7	9	94	123	63	1411	6	297	0.792
Adding Extra Water	6	18	49	55	99	70	1324	6	297	0.743
Crew Experience	2	3	13	94	142	43	1391	6	297	0.781

Table 30. Impact of Construction Site Factors on Concrete Cost

Factors	None	Very Low	Low	Medium	High	Very High	Weighting (W)	A	N	RII
	1	2	3	4	5	6				
Mixing Time	23	20	46	86	120	2	1157	6	297	0.649
Compaction Method	19	15	59	85	114	5	1166	6	297	0.654
Ambient Temperature	45	47	79	56	68	2	952	6	297	0.534
Curing Temperature	16	22	71	86	99	3	1130	6	297	0.634
Curing Humidity	17	30	65	74	102	9	1132	6	297	0.635
Adding Extra Water	74	50	41	52	69	11	916	6	297	0.514
Crew Experience	1	4	19	100	141	32	1363	6	297	0.765

Table 31. Impact of Construction Site Factors on Concrete Production Rates

Factors	None	Very Low	Low	Medium	High	Very High	Weighting (W)	A	N	RII
	1	2	3	4	5	6				
Mixing Time	13	17	39	96	124	8	1216	6	297	0.682
Compaction Method	17	19	58	92	106	5	1157	6	297	0.649
Ambient Temperature	22	28	71	77	96	3	1097	6	297	0.616
Curing Temperature	29	52	76	69	67	4	996	6	297	0.559
Curing Humidity	24	26	70	89	79	9	1091	6	297	0.612
Adding Extra Water	22	23	66	79	88	19	1136	6	297	0.637
Crew Experience	3	2	24	101	125	42	1360	6	297	0.763

Table 32. Overall Ranking Importance of Identified Construction Site Factors for Concrete Compressive Strength, Costs and Production Rates

Factors	None	Very Low	Low	Medium	High	Very High	Weighting (W)	A	N	RII
	1	2	3	4	5	6				
Mixing Time	45	49	113	265	396	23	3660	6	891	0.6846
Compaction Method	41	45	147	258	340	60	3664	6	891	0.6854
Ambient Temperature	72	92	209	214	291	13	3272	6	891	0.6120
Curing Temperature	46	83	179	242	307	34	3456	6	891	0.6465
Curing Humidity	42	63	144	257	304	81	3634	6	891	0.6798
Adding Extra Water	102	91	156	186	256	100	3376	6	891	0.6315
Crew Experience	6	9	56	295	408	117	4114	6	891	0.7695

Appendix B: Properties of Raw Materials and Laboratory Setup for for Chapter 3

Appendix B.1: Specific Gravity of Cement

Method: ASTM C188 —Standard Test Method for Density of Hydraulic Cement

Specific Gravity		
Mt	Mass of the flask containing the liquid and the cement, g	238.67
Ma	Mass of the flask with the liquid to the first set of graduation, g	174.38
Mc	Mass of cement used, g (Mt-Ma)	64.29
Lo	Initial reading, cm^3	0.4
Lf	Final reading, cm^3	21.8
V	Volume of liquid displaced by the mass of cement, cm^3 (Lf-Lo)	21.4
	Specific gravity= Mc/V	3.00

Appendix B.2: Specific Gravity and Absorption of Fine Aggregate

Method: ASTM C128—Specific Gravity and Absorption of Fine Aggregate

Specific Gravity		
S	Mass of saturated surface-dry specimen, g	494.6
B	Mass of pycnometer filled with water, g	658.2
C	Mass of pycnometer filled with specimen and water to calibration mark, g	964.5
	Specific gravity (SSD) = S/(B+S-C)	2.63

Absorption		
A	Mass of oven-dry specimen in air, g	488.1
S	Mass of saturated surface-dry specimen, g	494.6
	Absorption, % = [(S-A)/A] x 100	1.3

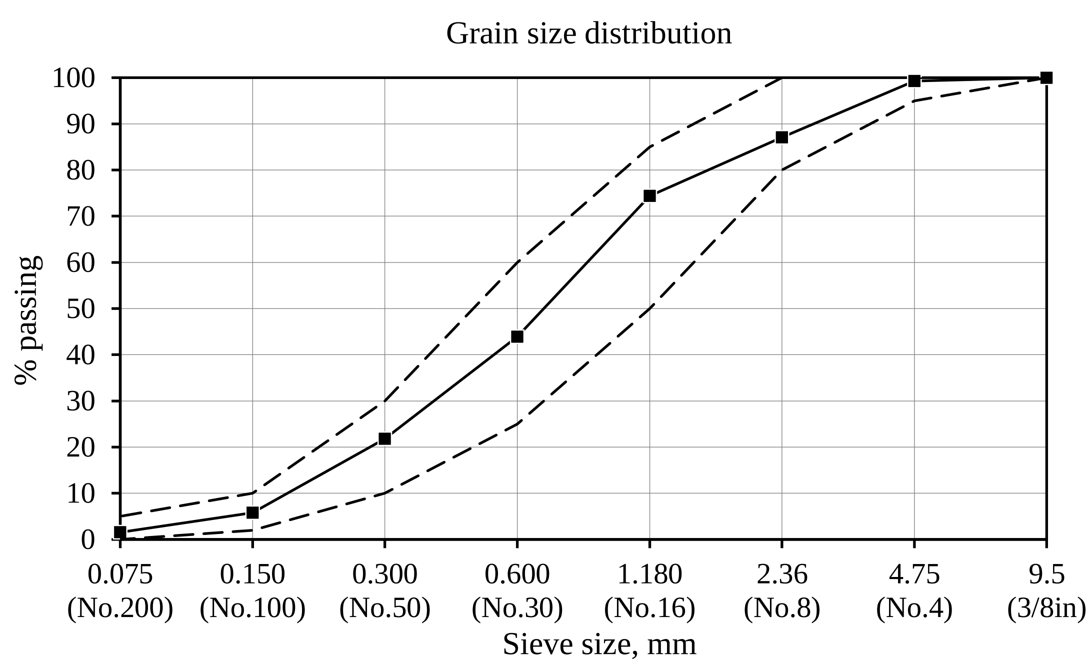
Appendix B.3: Sieve Analysis of Fine Aggregate

Method: ASTM C136—Sieve Analysis of Fine and Coarse Aggregates

Sample Mass (g) : 408.50

Sieve	Retained		%	%	Limits ASTM C33
	Partial (g)	Cumulative (g)	retained	passing	
9.5 (3/8 in)	0.00	0.00	0.0	100.0	100
4.75 (No. 4)	3.10	3.10	0.8	99.2	95 - 100
2.36 (No. 8)	49.60	52.70	12.9	87.1	80 - 100
1.180 (No. 16)	51.80	104.50	25.6	74.4	50 - 85
0.600 (No. 30)	124.60	229.10	56.1	43.9	25 - 60
0.300 (No. 50)	90.50	319.60	78.2	21.8	10 - 30
0.150 (No. 100)	65.20	384.80	94.2	5.8	2 - 10
0.075 (No. 200)	17.40	402.20	98.5	1.5	0 - 5
Tray	6.30	408.50	100.0	0.0	

Fineness Modulus: 2.68



Appendix B.4: Specific Gravity and Absorption of Coarse Aggregate

Method: ASTM C127—Specific Gravity and Absorption of Coarse Aggregate

Specific Gravity		
B	Mass of saturated-surface-dry test sample in air, g	3662
C	Apparent mass of saturated test sample in water, g	2281
	Specific gravity (SSD) = B/(B-C)	2.65

Absorption		
A	Mass of oven-dry test sample in air, g	3612
B	Mass of saturated-surface-dry test sample in air, g	3662
	Absorption, % = [(B-A)/A] x 100	1.4

Appendix B.5: Sieve Analysis of Coarse Aggregate

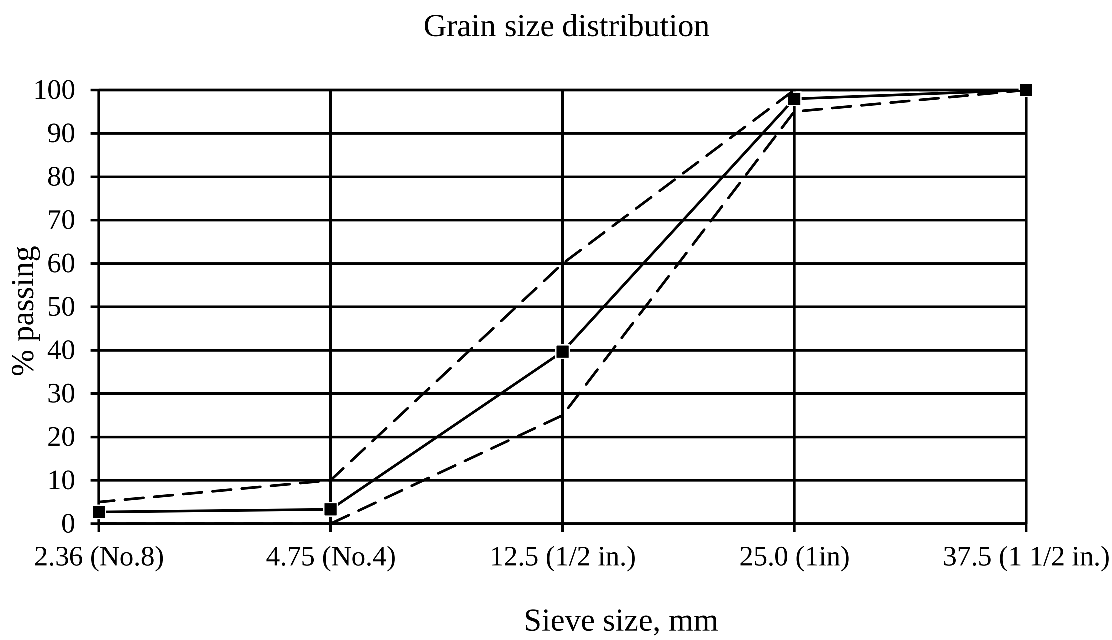
Method: ASTM C136—Sieve Analysis of Fine and Coarse Aggregates

Nominal Size: 25.0 to 4.75 mm (1 in. to No. 4)
Size Number: 57

Sample mass (g): 14542

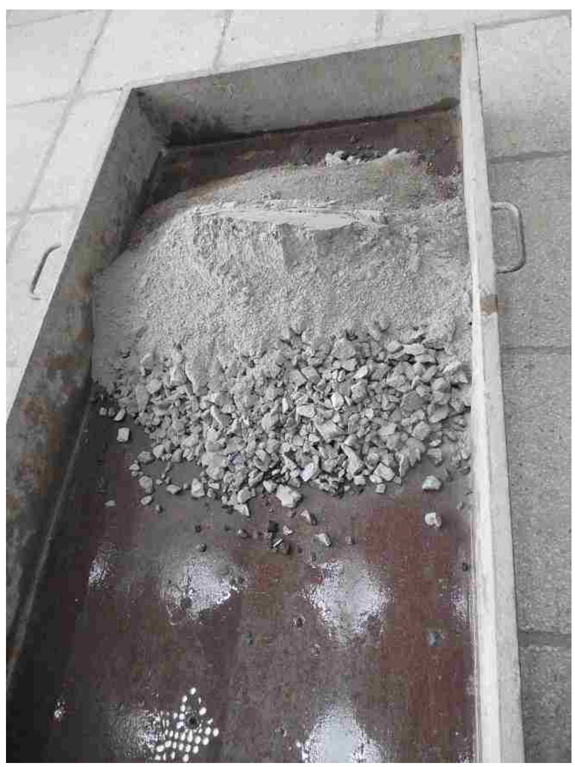
Sieve	Retained		%	%	Limits ASTM C33
	Partial (g)	Cumulative (g)	retained	passing	
37.5 (1 1/2 in.)	0	0	0.0	100.0	100
25.0 (1in)	1224	1224	8.4	91.6	95-100
19.0 (3/4 in.)	3227	4451	30.6	69.4	
12.5 (1/2 in.)	4603	9054	62.3	37.7	25-60
9.5 (3/8 in)	1972	11026	75.8	24.2	
4.75 (No. 4)	1886	12912	88.8	11.2	0-10
2.36 (No. 8)	597	13509	92.9	7.1	0-5
1.180 (No. 16)	315	13824	95.1	4.9	
Tray	718	14542	100.0	0.0	

Fineness Modulus: 6.83


Grain size distribution
100
90
80
70
60
50
40
30
20
10
0
% passing
2.36 (No.8)
4.75 (No.4)
12.5 (1/2 in.)
25.0 (1in)
37.5 (1 1/2 in.)
Sieve size, mm

Appendix B.6: Materials and Laboratory Setup

Scale (±0.1 Kg), wheelbarrows, metallic trays



Metallic tray for fabricating concrete

Abrams apparatus

Scale (±0.1 Kg)

Metallic cylindrical molds

Sulfur mortar for capping concrete samples

Cylinder capping equipment

Universal testing machine (2000 KN)

Appendix B.7: Compression Strength Responses

Table 33. Compression test results of each experimental run (192 samples)

No	Run	Sample	Construction Site Factors					Response
			Crew Experience	Compaction Method	Mixing Time, s	Curing Humidity %	Curing Temp. °C (°F)	Compressive Strength MPa (psi)
1	1	S-1-1	Experienced	Manual	20.4	100	28.5 (83)	35.6 (5158.7)
2		S-1-2	Experienced	Manual	20.4	100	28.5 (83)	36.8 (5334.2)
3		S-1-3	Experienced	Manual	20.4	100	28.5 (83)	37 (5372.6)
4		S-1-4	Experienced	Manual	20.4	100	28.5 (83)	35 (5077.2)
5		S-1-5	Experienced	Manual	20.4	100	28.5 (83)	38.2 (5533.2)
6		S-1-6	Experienced	Manual	20.4	100	28.5 (83)	38.1 (5526.1)
7	2	S-2-1	Experienced	Manual	11.3	100	28.5 (83)	36.7 (5324)
8		S-2-2	Experienced	Manual	11.3	100	28.5 (83)	37.1 (5377.5)
9		S-2-3	Experienced	Manual	11.3	100	28.5 (83)	35.5 (5146.9)
10		S-2-4	Experienced	Manual	11.3	100	28.5 (83)	36.7 (5318.9)
11		S-2-5	Experienced	Manual	11.3	100	28.5 (83)	35.6 (5169.5)
12		S-2-6	Experienced	Manual	11.3	100	28.5 (83)	37.7 (5468.3)
13	3	S-3-1	Not Experienced	Vibrator	11.3	20	7.9 (46)	21.9 (3171.4)
14		S-3-2	Not Experienced	Vibrator	11.3	20	7.9 (46)	23.4 (3391.3)
15		S-3-3	Not Experienced	Vibrator	11.3	20	7.9 (46)	21.3 (3091.5)
16		S-3-4	Not Experienced	Vibrator	11.3	20	7.9 (46)	22.8 (3306.6)
17		S-3-5	Not Experienced	Vibrator	11.3	20	7.9 (46)	23.7 (3442.2)
18		S-3-6	Not Experienced	Vibrator	11.3	20	7.9 (46)	24.1 (3498.9)
19	4	S-4-1	Not Experienced	Manual	11.3	20	7.9 (46)	24.3 (3520.1)
20		S-4-2	Not Experienced	Manual	11.3	20	7.9 (46)	24.8 (3592.7)
21		S-4-3	Not Experienced	Manual	11.3	20	7.9 (46)	25.1 (3639.9)
22		S-4-4	Not Experienced	Manual	11.3	20	7.9 (46)	24.3 (3526.6)

23		S-4-5	Not Experienced	Manual	11.3	20	7.9 (46)	23.5 (3408.9)
24		S-4-6	Not Experienced	Manual	11.3	20	7.9 (46)	25.4 (3689.5)
25	5	S-5-1	Not Experienced	Manual	11.3	100	7.9 (46)	27.6 (3998.5)
26		S-5-2	Not Experienced	Manual	11.3	100	7.9 (46)	26.2 (3805.2)
27		S-5-3	Not Experienced	Manual	11.3	100	7.9 (46)	27.2 (3950.6)
28		S-5-4	Not Experienced	Manual	11.3	100	7.9 (46)	27.6 (4005.5)
29		S-5-5	Not Experienced	Manual	11.3	100	7.9 (46)	28.6 (4146)
30		S-5-6	Not Experienced	Manual	11.3	100	7.9 (46)	27.1 (3935.2)
31	6	S-6-1	Not Experienced	Vibrator	20.4	20	7.9 (46)	23.5 (3410.3)
32		S-6-2	Not Experienced	Vibrator	20.4	20	7.9 (46)	23.6 (3417.7)
33		S-6-3	Not Experienced	Vibrator	20.4	20	7.9 (46)	24.5 (3553.2)
34		S-6-4	Not Experienced	Vibrator	20.4	20	7.9 (46)	24.3 (3529.3)
35		S-6-5	Not Experienced	Vibrator	20.4	20	7.9 (46)	23.1 (3354.1)
36		S-6-6	Not Experienced	Vibrator	20.4	20	7.9 (46)	23 (3338.1)
37	7	S-7-1	Experienced	Vibrator	20.4	100	28.5 (83)	33.6 (4873.7)
38		S-7-2	Experienced	Vibrator	20.4	100	28.5 (83)	33.4 (4839.1)
39		S-7-3	Experienced	Vibrator	20.4	100	28.5 (83)	39.1 (5663.8)
40		S-7-4	Experienced	Vibrator	20.4	100	28.5 (83)	35.3 (5116.2)
41		S-7-5	Experienced	Vibrator	20.4	100	28.5 (83)	36.3 (5269.1)
42		S-7-6	Experienced	Vibrator	20.4	100	28.5 (83)	35.1 (5096)
43	8	S-8-1	Not Experienced	Vibrator	20.4	100	28.5 (83)	39.8 (5768.8)
44		S-8-2	Not Experienced	Vibrator	20.4	100	28.5 (83)	35.9 (5205.5)
45		S-8-3	Not Experienced	Vibrator	20.4	100	28.5 (83)	34.8 (5052.8)
46		S-8-4	Not Experienced	Vibrator	20.4	100	28.5 (83)	38.5 (5583.7)
47		S-8-5	Not Experienced	Vibrator	20.4	100	28.5 (83)	38.2 (5535.1)
48		S-8-6	Not Experienced	Vibrator	20.4	100	28.5 (83)	35.8 (5192.3)
49	9	S-9-1	Experienced	Vibrator	11.3	100	7.9 (46)	26.1 (3783.9)
50		S-9-2	Experienced	Vibrator	11.3	100	7.9 (46)	24.8 (3593)

51		S-9-3	Experienced	Vibrator	11.3	100	7.9 (46)	23.7 (3444.3)
52		S-9-4	Experienced	Vibrator	11.3	100	7.9 (46)	25.3 (3673.6)
53		S-9-5	Experienced	Vibrator	11.3	100	7.9 (46)	25 (3632.2)
54		S-9-6	Experienced	Vibrator	11.3	100	7.9 (46)	26.6 (3852.2)
55	10	S-10-1	Experienced	Manual	11.3	20	28.5 (83)	26.7 (3877.4)
56		S-10-2	Experienced	Manual	11.3	20	28.5 (83)	30.2 (4379.5)
57		S-10-3	Experienced	Manual	11.3	20	28.5 (83)	29.1 (4221.5)
58		S-10-4	Experienced	Manual	11.3	20	28.5 (83)	26.8 (3886.1)
59		S-10-5	Experienced	Manual	11.3	20	28.5 (83)	28.3 (4111.3)
60		S-10-6	Experienced	Manual	11.3	20	28.5 (83)	28.5 (4140.4)
61	11	S-11-1	Experienced	Vibrator	20.4	20	7.9 (46)	21.3 (3093)
62		S-11-2	Experienced	Vibrator	20.4	20	7.9 (46)	23.9 (3471.7)
63		S-11-3	Experienced	Vibrator	20.4	20	7.9 (46)	23.4 (3396.5)
64		S-11-4	Experienced	Vibrator	20.4	20	7.9 (46)	23.3 (3380.9)
65		S-11-5	Experienced	Vibrator	20.4	20	7.9 (46)	22.2 (3213.1)
66		S-11-6	Experienced	Vibrator	20.4	20	7.9 (46)	20.3 (2948)
67	12	S-12-1	Not Experienced	Manual	20.4	20	28.5 (83)	29.1 (4221.5)
68		S-12-2	Not Experienced	Manual	20.4	20	28.5 (83)	28.8 (4182)
69		S-12-3	Not Experienced	Manual	20.4	20	28.5 (83)	28.1 (4077.9)
70		S-12-4	Not Experienced	Manual	20.4	20	28.5 (83)	29.9 (4330.8)
71		S-12-5	Not Experienced	Manual	20.4	20	28.5 (83)	30.4 (4403.8)
72		S-12-6	Not Experienced	Manual	20.4	20	28.5 (83)	32.1 (4648.5)
73	13	S-13-1	Not Experienced	Vibrator	11.3	100	28.5 (83)	32.1 (4657)
74		S-13-2	Not Experienced	Vibrator	11.3	100	28.5 (83)	30.6 (4443)
75		S-13-3	Not Experienced	Vibrator	11.3	100	28.5 (83)	35.2 (5104.1)
76		S-13-4	Not Experienced	Vibrator	11.3	100	28.5 (83)	32.4 (4696.4)
77		S-13-5	Not Experienced	Vibrator	11.3	100	28.5 (83)	30.4 (4415.2)
78		S-13-6	Not Experienced	Vibrator	11.3	100	28.5 (83)	28.9 (4198.6)
79	14	S-14-1	Not Experienced	Vibrator	20.4	20	28.5 (83)	27.3 (3964.3)

80		S-14-2	Not Experienced	Vibrator	20.4	20	28.5 (83)	26.5 (3848.5)
81		S-14-3	Not Experienced	Vibrator	20.4	20	28.5 (83)	27.4 (3967.2)
82		S-14-4	Not Experienced	Vibrator	20.4	20	28.5 (83)	25.4 (3689.9)
83		S-14-5	Not Experienced	Vibrator	20.4	20	28.5 (83)	25.8 (3737.9)
84		S-14-6	Not Experienced	Vibrator	20.4	20	28.5 (83)	26 (3771)
85	15	S-15-1	Experienced	Vibrator	11.3	20	28.5 (83)	27.5 (3993.4)
86		S-15-2	Experienced	Vibrator	11.3	20	28.5 (83)	27.4 (3975.6)
87		S-15-3	Experienced	Vibrator	11.3	20	28.5 (83)	27.8 (4036)
88		S-15-4	Experienced	Vibrator	11.3	20	28.5 (83)	28 (4065.8)
89		S-15-5	Experienced	Vibrator	11.3	20	28.5 (83)	28.7 (4165.4)
90		S-15-6	Experienced	Vibrator	11.3	20	28.5 (83)	26.3 (3812.9)
91	16	S-16-1	Experienced	Vibrator	11.3	100	28.5 (83)	30.4 (4411.7)
92		S-16-2	Experienced	Vibrator	11.3	100	28.5 (83)	33 (4785.6)
93		S-16-3	Experienced	Vibrator	11.3	100	28.5 (83)	31.7 (4596.8)
94		S-16-4	Experienced	Vibrator	11.3	100	28.5 (83)	30.9 (4483.4)
95		S-16-5	Experienced	Vibrator	11.3	100	28.5 (83)	35.4 (5136.4)
96		S-16-6	Experienced	Vibrator	11.3	100	28.5 (83)	35.4 (5138.2)
97	17	S-17-1	Experienced	Manual	20.4	20	7.9 (46)	21.1 (3056.2)
98		S-17-2	Experienced	Manual	20.4	20	7.9 (46)	23 (3338.5)
99		S-17-3	Experienced	Manual	20.4	20	7.9 (46)	19.9 (2892.2)
100		S-17-4	Experienced	Manual	20.4	20	7.9 (46)	22.3 (3238.1)
101		S-17-5	Experienced	Manual	20.4	20	7.9 (46)	21.6 (3129.6)
102		S-17-6	Experienced	Manual	20.4	20	7.9 (46)	21.4 (3101.2)
103	18	S-18-1	Not Experienced	Vibrator	11.3	20	28.5 (83)	23.1 (3345.9)
104		S-18-2	Not Experienced	Vibrator	11.3	20	28.5 (83)	21.8 (3168.6)
105		S-18-3	Not Experienced	Vibrator	11.3	20	28.5 (83)	23.8 (3452.4)
106		S-18-4	Not Experienced	Vibrator	11.3	20	28.5 (83)	23.1 (3356.4)
107		S-18-5	Not Experienced	Vibrator	11.3	20	28.5 (83)	23.5 (3414.3)

108		S-18-6	Not Experienced	Vibrator	11.3	20	28.5 (83)	24 (3486.6)
109	19	S-19-1	Experienced	Manual	11.3	100	7.9 (46)	26 (3767.9)
110		S-19-2	Experienced	Manual	11.3	100	7.9 (46)	27 (3915.7)
111		S-19-3	Experienced	Manual	11.3	100	7.9 (46)	24.1 (3499.7)
112		S-19-4	Experienced	Manual	11.3	100	7.9 (46)	25 (3625.5)
113		S-19-5	Experienced	Manual	11.3	100	7.9 (46)	24.3 (3530)
114		S-19-6	Experienced	Manual	11.3	100	7.9 (46)	25.9 (3760.4)
115	20	S-20-1	Experienced	Vibrator	20.4	20	28.5 (83)	28.8 (4174.4)
116		S-20-2	Experienced	Vibrator	20.4	20	28.5 (83)	30.1 (4372.6)
117		S-20-3	Experienced	Vibrator	20.4	20	28.5 (83)	27.6 (4003)
118		S-20-4	Experienced	Vibrator	20.4	20	28.5 (83)	28 (4058.8)
119		S-20-5	Experienced	Vibrator	20.4	20	28.5 (83)	30.3 (4387.5)
120		S-20-6	Experienced	Vibrator	20.4	20	28.5 (83)	29 (4211.3)
121	21	S-21-1	Not Experienced	Manual	20.4	20	7.9 (46)	21.8 (3168.3)
122		S-21-2	Not Experienced	Manual	20.4	20	7.9 (46)	23.7 (3435.3)
123		S-21-3	Not Experienced	Manual	20.4	20	7.9 (46)	22.6 (3271.7)
124		S-21-4	Not Experienced	Manual	20.4	20	7.9 (46)	23 (3342.1)
125		S-21-5	Not Experienced	Manual	20.4	20	7.9 (46)	21.8 (3161.8)
126		S-21-6	Not Experienced	Manual	20.4	20	7.9 (46)	22 (3184)
127	22	S-22-1	Not Experienced	Manual	11.3	20	28.5 (83)	26.6 (3851.6)
128		S-22-2	Not Experienced	Manual	11.3	20	28.5 (83)	23.8 (3454.5)
129		S-22-3	Not Experienced	Manual	11.3	20	28.5 (83)	24 (3475.1)
130		S-22-4	Not Experienced	Manual	11.3	20	28.5 (83)	26.8 (3883.1)
131		S-22-5	Not Experienced	Manual	11.3	20	28.5 (83)	24.8 (3602.6)
132		S-22-6	Not Experienced	Manual	11.3	20	28.5 (83)	26.3 (3820)
133	23	S-23-1	Not Experienced	Vibrator	11.3	100	7.9 (46)	23.5 (3412.5)
134		S-23-2	Not Experienced	Vibrator	11.3	100	7.9 (46)	23.1 (3345.3)
135		S-23-3	Not Experienced	Vibrator	11.3	100	7.9 (46)	22 (3194.2)
136		S-23-4	Not Experienced	Vibrator	11.3	100	7.9 (46)	23.5 (3407.3)

137		S-23-5	Not Experienced	Vibrator	11.3	100	7.9 (46)	21.7 (3143.8)
138		S-23-6	Not Experienced	Vibrator	11.3	100	7.9 (46)	23.6 (3420.6)
139	24	S-24-1	Experienced	Manual	20.4	20	28.5 (83)	28.8 (4178.3)
140		S-24-2	Experienced	Manual	20.4	20	28.5 (83)	28 (4067.8)
141		S-24-3	Experienced	Manual	20.4	20	28.5 (83)	26.3 (3814.6)
142		S-24-4	Experienced	Manual	20.4	20	28.5 (83)	27.9 (4052.4)
143		S-24-5	Experienced	Manual	20.4	20	28.5 (83)	30.7 (4455.1)
144		S-24-6	Experienced	Manual	20.4	20	28.5 (83)	30.8 (4471.7)
145	25	S-25-1	Not Experienced	Vibrator	20.4	100	7.9 (46)	23.9 (3473.5)
146		S-25-2	Not Experienced	Vibrator	20.4	100	7.9 (46)	25.1 (3635.7)
147		S-25-3	Not Experienced	Vibrator	20.4	100	7.9 (46)	26.5 (3839.5)
148		S-25-4	Not Experienced	Vibrator	20.4	100	7.9 (46)	27.8 (4030.8)
149		S-25-5	Not Experienced	Vibrator	20.4	100	7.9 (46)	26.2 (3802)
150		S-25-6	Not Experienced	Vibrator	20.4	100	7.9 (46)	25.7 (3726.9)
151	26	S-26-1	Experienced	Vibrator	20.4	100	7.9 (46)	26.5 (3842.3)
152		S-26-2	Experienced	Vibrator	20.4	100	7.9 (46)	24.6 (3574.8)
153		S-26-3	Experienced	Vibrator	20.4	100	7.9 (46)	25.9 (3752.4)
154		S-26-4	Experienced	Vibrator	20.4	100	7.9 (46)	26.1 (3782.8)
155		S-26-5	Experienced	Vibrator	20.4	100	7.9 (46)	24.7 (3584.6)
156		S-26-6	Experienced	Vibrator	20.4	100	7.9 (46)	26.1 (3783.8)
157	27	S-27-1	Experienced	Vibrator	11.3	20	7.9 (46)	23.5 (3404.5)
158		S-27-2	Experienced	Vibrator	11.3	20	7.9 (46)	23.3 (3381.2)
159		S-27-3	Experienced	Vibrator	11.3	20	7.9 (46)	22.9 (3318.7)
160		S-27-4	Experienced	Vibrator	11.3	20	7.9 (46)	23 (3329.3)
161		S-27-5	Experienced	Vibrator	11.3	20	7.9 (46)	21.5 (3117.3)
162		S-27-6	Experienced	Vibrator	11.3	20	7.9 (46)	22.9 (3326.3)
163	28	S-28-1	Not Experienced	Manual	20.4	100	7.9 (46)	27.6 (4000.7)
164		S-28-2	Not Experienced	Manual	20.4	100	7.9 (46)	27.4 (3976.9)

165		S-28-3	Not Experienced	Manual	20.4	100	7.9 (46)	26.4 (3836.1)
166		S-28-4	Not Experienced	Manual	20.4	100	7.9 (46)	25.4 (3685.7)
167		S-28-5	Not Experienced	Manual	20.4	100	7.9 (46)	27.3 (3958.7)
168		S-28-6	Not Experienced	Manual	20.4	100	7.9 (46)	28 (4060.2)
169	29	S-29-1	Not Experienced	Manual	20.4	100	28.5 (83)	32.1 (4660.2)
170		S-29-2	Not Experienced	Manual	20.4	100	28.5 (83)	33.4 (4849.9)
171		S-29-3	Not Experienced	Manual	20.4	100	28.5 (83)	35.2 (5107.2)
172		S-29-4	Not Experienced	Manual	20.4	100	28.5 (83)	36.6 (5304.1)
173		S-29-5	Not Experienced	Manual	20.4	100	28.5 (83)	32.7 (4744.1)
174		S-29-6	Not Experienced	Manual	20.4	100	28.5 (83)	32.1 (4660.6)
175	30	S-30-1	Experienced	Manual	11.3	20	7.9 (46)	22.4 (3247.7)
176		S-30-2	Experienced	Manual	11.3	20	7.9 (46)	21.8 (3164.7)
177		S-30-3	Experienced	Manual	11.3	20	7.9 (46)	23.2 (3362.1)
178		S-30-4	Experienced	Manual	11.3	20	7.9 (46)	23.3 (3381.4)
179		S-30-5	Experienced	Manual	11.3	20	7.9 (46)	23.2 (3358.8)
180		S-30-6	Experienced	Manual	11.3	20	7.9 (46)	24 (3480.4)
181	31	S-31-1	Not Experienced	Manual	11.3	100	28.5 (83)	35.6 (5167.3)
182		S-31-2	Not Experienced	Manual	11.3	100	28.5 (83)	37.1 (5381.3)
183		S-31-3	Not Experienced	Manual	11.3	100	28.5 (83)	35.2 (5106.7)
184		S-31-4	Not Experienced	Manual	11.3	100	28.5 (83)	33.7 (4880.7)
185		S-31-5	Not Experienced	Manual	11.3	100	28.5 (83)	36.8 (5342.7)
186		S-31-6	Not Experienced	Manual	11.3	100	28.5 (83)	37.3 (5415.1)
187	32	S-32-1	Experienced	Manual	20.4	100	7.9 (46)	27.2 (3938.7)
188		S-32-2	Experienced	Manual	20.4	100	7.9 (46)	26.5 (3849.8)
189		S-32-3	Experienced	Manual	20.4	100	7.9 (46)	28.8 (4173.9)
190		S-32-4	Experienced	Manual	20.4	100	7.9 (46)	28.8 (4182.2)
191		S-32-5	Experienced	Manual	20.4	100	7.9 (46)	28.3 (4100.4)
192		S-32-6	Experienced	Manual	20.4	100	7.9 (46)	29.5 (4277.6)

Appendix B.8: Laboratory Setup

Hot dry environment (Relative humidity 20% and Temperature 29 ±1 °C)

Hot wet environment (Relative humidity 100% and Temperature 29 ±1 °C)

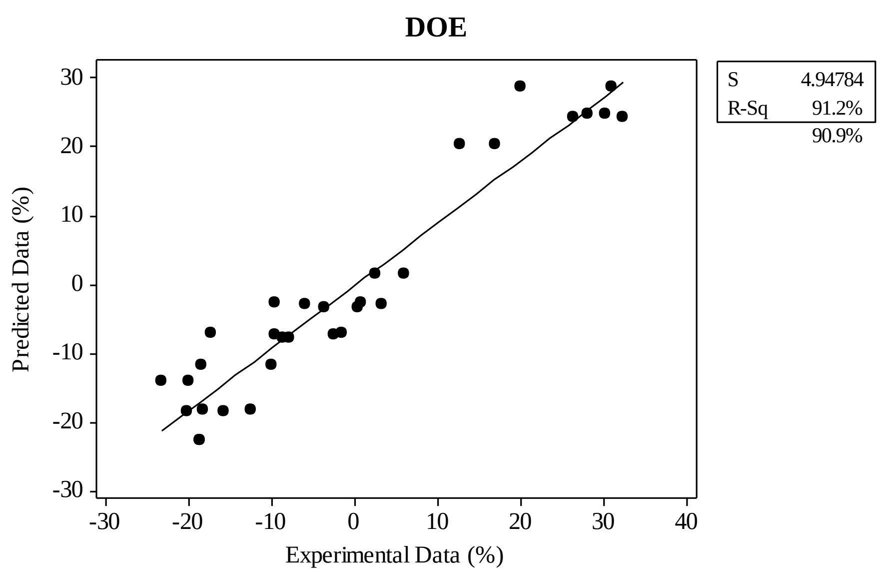
Cold room for dry and cold environments (Relative humidity 20%, Relative humidity 100% and Temperature 7 ±1 °C

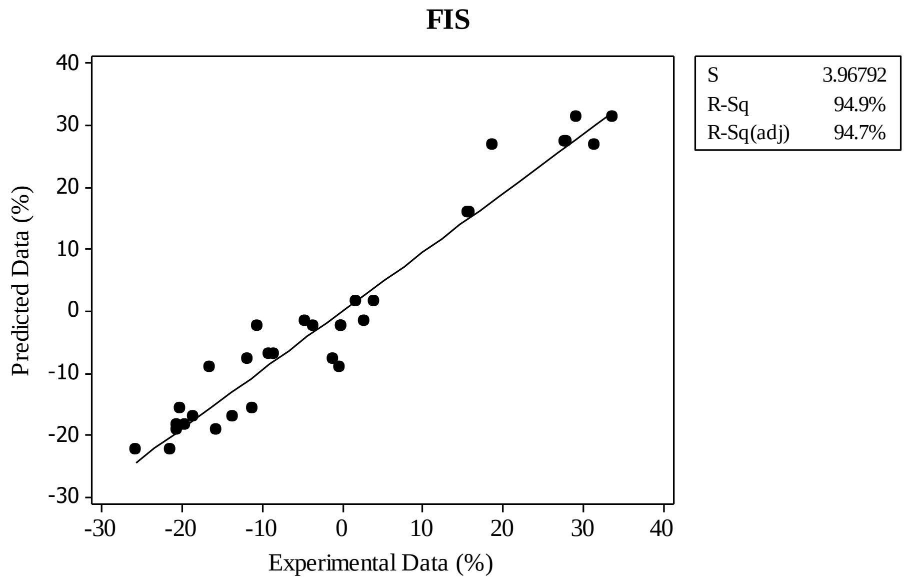
Appendix C: Comparison between Designed Experiments and Fuzzy Models for for Chapter 4

Table 34. Comparison of DOE regression models versus Fuzzy Inference Systems (FIS)

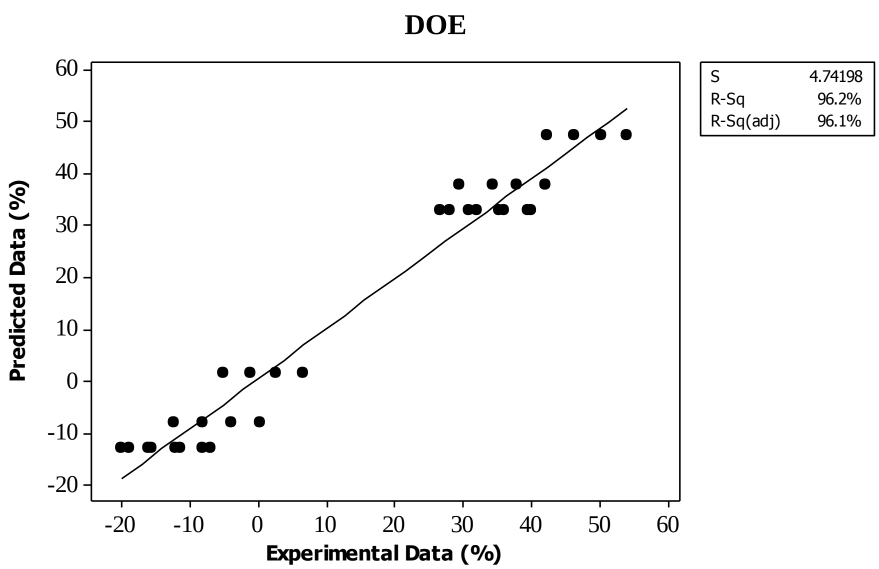
Statistic	Compressive strength effect		Cost Effect		Production Effect	
	DOE	Sugeno FIS	DOE	Sugeno FIS	DOE	Sugeno FIS
R^2	91.2%	94.9%	96.2%	97.5%	94.7%	96.5%
S	4.9	4.0	4.7	4.0	4.8	3.9
RMSE	5.0	7.9	4.7	3.8	4.7	3.7

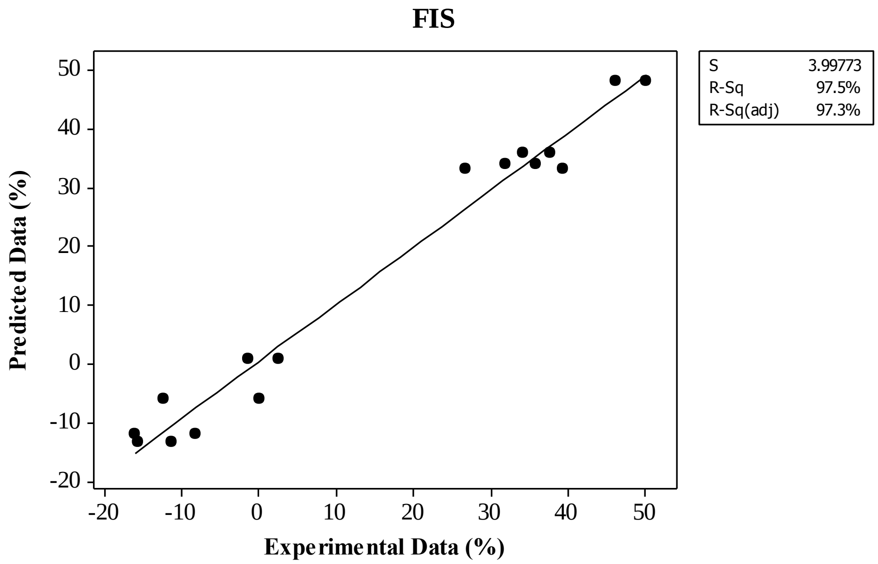
Appendix C.1: Predicted versus Experimental Data for Strength Effect



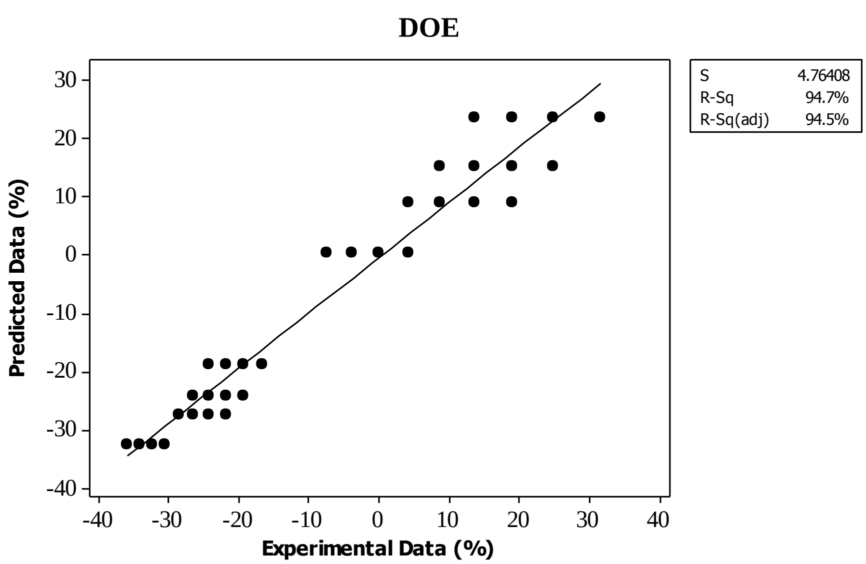


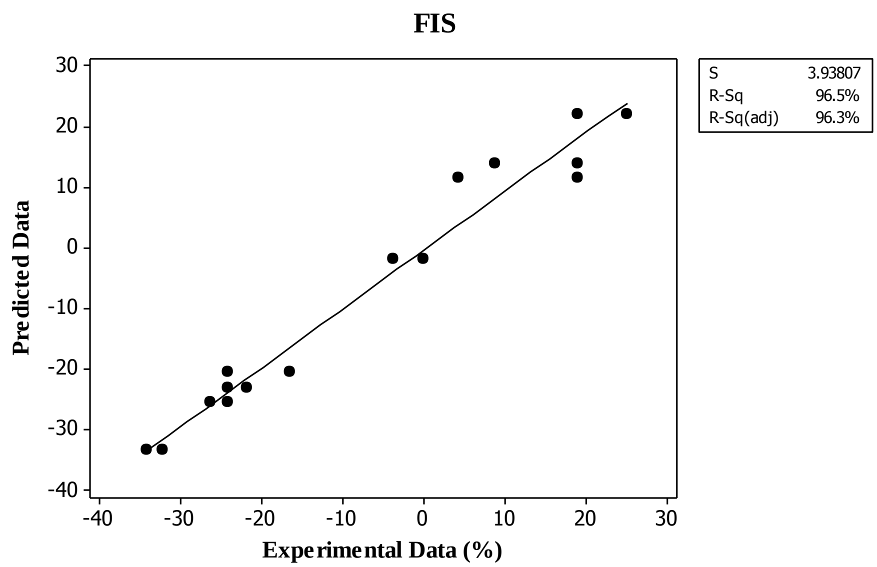
Appendix C.2: Predicted versus Experimental Data for Cost Effect





Appendix C.3: Predicted versus Experimental Data for Production Rate Effect




FIS
S 3.93807
R-Sq 96.5%
R-Sq(adj) 96.3%
Predicted Data
Experimental Data (%)
30
20
10
0
-10
-20
-30
-40
-40 -30 -20 -10 0 10 20 30