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Predictive modeling and non-linear optimization techniques for composite materials design

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A B S T R A C T

With the rise in the use of composite materials for product design, research has been performed in determining the optimal way to produce materials for given desired outputs. As of now response surface methodology and the Taguchi method are the front-running methods for optimizing material production methods at the design level. This research investigates why these methods are not a one size fits all solution to optimizing composite materials production for material properties. It proposes utilizing predictive modeling and non-linear optimization techniques from historical manufacturing data of a non-highly controlled manufacturing process. The method is examined with the manufacturing and testing data of a local concrete product manufacturer. The models and optimization methods are validated with residual values to the true data and sensitivity analysis of the problem. The initial testing of the method offers promise to companies who have not found Taguchi or surface response methodology, applicable to their specific business solutions.

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1. Introduction

A common design problem that comes into play in product development is selecting the most appropriate material for a given application. The design begins with a basic list of requi rements by answering basic questions. Is the part going to be under a load? What is the predicted failure mode (tensile, compressive, buckling, impact, and other/additional failure modes)? Is there a weight restriction? Will the product undergo cycles of loads (tension, compression, heat, or electric)? Luckily after years of experience, engineers and product developers have become good at selecting materials. They know how to cost-effectively get a job done regardless of product longevity, or what is required to make a product last for generations. One of the biggest helping factors in this is material property charts. Due to continuous material testing by manufacturers, designers, and research institutions charts have been developed to identify material properties of alloy steels, types of aluminum, different polymers/elastomers, and other homogeneous materials. This however is not the same case for composite materials [1].

Composite materials have seen an extremely heavy rise in the last 100 years [2]. From concrete to nylon reinforced rubber products, to more mainstream uses like resin-reinforced fiberglass and carbon fiber. Composites are usually designed to utilize the material properties of more than one material [3]. Since composite materials are generally available on a make-to-purpose basis, it is not exactly easy to prototype with such materials, based on pre-made availability. Without extensive trial and error, how does an engineer decide how to design a part with composites that are both functional and efficient for cost and material use?

Traditionally there has been a few approaches to identifying what design changes affect material properties. The approach taken is often going to rely on resources and data available by the individuals working on it. The two main approaches to this are either a full factorial array, which tests each of the factors assumed to be contributors to the property or a Taguchi design of experiments (DOE). In many cases, if the ratio of signal to noise of factors to response is high, then the number of tests can be severely dropped by a Taguchi method. For example, 4-factor, 3-level arrays can be reduced from 81 tests to 27, while still testing all factors and levels, just not every factor at every level with every other factor-level combination. This greatly reduces the cost and time associated with producing samples and testing each sample.

Given that these methods are highly successful, it is hard to see where the use of a different method may be useful. Most of these companies already test their material by batch/load and have detailed information on the production process/ deviation from design specifications. Especially in a less controlled process, lots of natural variation in a production process can lead to extreme changes in material property. This of course is not always a good thing since it can lead to defective material, but it is extremely valuable for seeing how a material behaves in different production scenarios. On the other hand, being able to use all of this existing data in a Taguchi DOE is not always easy. Even with powerful statistical analysis tools, natural variation with high sample sizes often leads to there being too many levels in each factor for the

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Taguchi method to make sense.

One of the leading methods to design experiments to develop very application-specific composite materials is the Taguchi design. Taguchi robust design is a method developed by Genichi Taguchi, which utilizes a “p-diagram” and “signal to noise” ratios to identify testing factors when developing a design of experiments (DOE) [1]. The results from a Taguchi design dictate the array of factorials to be tested, less than a full factorial array, and utilize either physical or simulated experiments to see the effects within the DOE. The factors that showed significant contributions to the main function are defined as “control factors” and then optimum settings of the “control factors” are determined and tested for validity [4,5]. There are well-known software packages available to help with the more complicated setup of Taguchi [6]. Since most of the literature review revolved around testing composite materials, it was important to validate the research would be repeatable if others wanted to replicate the process for some of the more obscu re topics. For this, American Society for Testing and Materials (ASTM) standards were validated to ensure the testing procedures complied with internationally known standards [7-11]. A common topic of discussion was the long-term wear of specific composites in many pieces of research. Works in Inaguma [12] and Siddhartha et al. [13] focus on corrosion resistance due to wear on a Titania Epoxy mix which was found to be quite successful with only ~5% of error in the model. Similarly, a recent work performed by Savas [14] tests wears on an aluminum-based composite using the Taguchi method. That research [14] was performed to the same ASTM standard for the pin-on-disk wear testing. The great thing about utilizing the same standard is that these pieces of research, [12,13] and [14], can now be compared and looked at analytically, knowing that the data is not skewed due to different testing parameters. Keeping things like this standardized is also important when comparing different research approaches. This was the case for Salcido [15], who observed the validity of creating usable byproducts from restraint grease waste by comparing Taguchi and Response Surface Method (RSM) methodologies. Salcido was however not as successful with RSM as he had hoped which of course gives a slight advantage to Taguchi in which he was successful. Wang’s research [16] however suggests that the issue in a case like this may be due to the rotatability of the function and its parameters. Then, of course, is the debate on how to optimize the system once it is assumed to be accurately modeled. An option is to use linear optimization methodology, but it sadly only works for linear models [17]. Another option is to utilize generational algorithms that will improve a system’s variables with each attempt. In short, it is a sophisticated trial and error methodology, which means it suffers from the same faults. That being occasionally finding what turns out to be local optimums rather than global [18,19]. Another challenge is of course if a cost function has multiple objectives. There is a fundamental difference between solving a single objective problem vs a multi-objective problem, and the requirements of each. Often a multi-objective problem can be treated as two separate single objective problems with a weight attached to them for a final goal. Of course, if the objectives are opposites of one another, finding a true optimum for both at the same time is very difficult; constraining one of the two optimums can be explored as well [20,21].

In summary, most of the development in the composite design world utilizes two main methods. Either DOE uses a full/partial factorial array or utilizes Taguchi design to develop a smaller factorial array for DOE based on signal-to-noise ratios in pre-available data. The final steps after these DOE’s are generally quite unclear. Some researchers will simply select the best case scenario/trail from the DOE, and others take the optimization further by modeling the data from the DOE. The modeling is then either done with regression or by utilizing the ANOVA responses from the testing. The models can be used in either single or multiple objective approaches to achieve what is known by the researcher to be the best solution based on the design requirements. Overall the biggest issue is justifying large-scale testing by producing samples to be tested in a DOE.

The proposed method involves using predictive modeling based on existing manufacturing data, and the best way to utilize existing data for such models. The model will be used in conjunction with other variables as constraints in optimizing a cost function. Ideally, this method should be performed using simple, readily accessible tools, and not require extensive knowledge to attempt.

The world of material development moves almost as fast if not faster than the technology field. Many of the developments in technology are driven by material development. In industry, however, it takes extensive resources to develop materials, composite materials especially, at a pace that is at the demand of design industries. Because of this, engineers come up with techniques to develop materials with previous manufacturing/test data.

To confront the pitfalls of the research discussed above a new method needs to be assessed. Therefore, we propose an optimization-based predictive modeling method that heavily utilizes the already available production/ manufacturing data, and models trends without performing additionally testing with a DOE. We assume that the natural variation in the manufacturing process is measurable, accurate, and recorded, to give insights into creating a model to optimize, especially when seen across multiple product lines with similar processing. Our optimization model provides a good idea of data that would be lost between levels in a Taguchi design. The model is expressed as the best matching curve to the data, rather than simply using linear fits. This will include interactions between variables like is seen in the Taguchi model, but without all the additional testing and manufacturing of specific samples.

2. Methodology

In reviewing the works above, it appears as if in most cases a method was found that turned out to be successful for the research teams. Of course, two big differences separate these research papers and a large portion of real-life industry; access to a plethora of retrospective data, and the access to sufficient resources required to run a DOE rather than production. This is exactly the case for company “X” based in the United States that produces a product out of concrete. They have the capabilities to produce nearly 300 yards of concrete per day and keep relatively good records of the day-to-day production changes, as well as the test results from each lot/batch of material. They do not, however, have the resources available to produce individual-specific samples for a DOE, even if it was truncated like a Taguchi design.

In this case, the material property of interest is the compressive load of concrete without rebar that a test sample breaks at, and the air content of the concrete which helps for damping in cold operating conditions. The concrete is produced from 5 basic raw materials and with up to 4 additives. There are a few factors that are also identified as potential factors in the materials’ properties. The following are those materials and factors.

- Cement: Limestone that is refined, baked in a furnace, then ground down to a size specified by type. Measured in lbs.
- Dry rock: An aggregate that is a mix of granite and quartz stone. Measured in lbs.
- Dry sand: A natural fine aggregate rather than manufactured sand, which is specific sand for concrete manufacture. Measured in lbs.
- Fly ash: A refined byproduct of coal that when used with cement aids in bonding the composite together. “Class F” fly ash is used. Measured in lbs.
- Combination water: This is the combined water added to the mix, both the water intentionally added, as well as water that

is added in the form of moisture from the sand and rock. Measured in lbs.

- Sika 4100: A concrete additive “high range water reducer” used to help maintain water to cement ratio. Measured in Oz.
- Sika NC: A concrete additive used to accelerate the cure/setup of concrete so that it can be released from forms sooner. Measured in Oz.
- AEA sika air: A concrete additive used to help keep the air content of the concrete between 5-7% of the volume. Measured in Oz.
- Sika VF 2020: A concrete additive “medium-range water reducer” used to help maintain water to cement ratio. Measured in Oz.
- Moisture content: The measured amount of moisture is in either the sand or rock. Expressed as a percentage of the total weight of the aggregate.
- Air temperature: The temperature of the room where the concrete is being poured at the time of pouring into the molds. Measured in Fahrenheit.
- Concrete temperature: The temperature of the concrete at the time of pour once it is inside of the mold. Can be varied with heating coils inside of the mold bed. Measured in Fahrenheit.
- Air content: The percentage of volume in the concrete that is trapped in air bubbles.
- Time before test: This is the amount of time between the pour of concrete and the compressive break test on the concrete test cylinders. It is quite well known that concrete gets stronger over time. Company “X” would like to release the concrete from their molds as soon as possible, but they require a specific break pressure before they will begin the process. Measured in hours.
- Break pressure: The pressure at which a test cylinder fails under compression load. Measured in psi.

The basic operating process requires a mixture of cement, rock, sand, fly ash, and water. To meet specific requirements, the operators will add a sika additive to the mix. This is done largely based on the feel of the mix and is brought to a standard in the first few pours. The molds and test cylinders are cured for at least 16 hours based on operating hours, then are tested the next working day which can be up to 3 days later. If the test cylinder passes its 6,500 psi threshold, then the production lot is allowed to be released from the molds, and the molds can then be reused for the next day’s production. If the release pressure is not obtained on the first test, then additional time is required until the product can be released.

So, if company “X” is already producing their product reliably, why would they want to change how they manufacture? The simple answer is to save money. There might be a more efficient way to produce their product that still meets their design requirements that is less demanding on capital resources. By utilizing existing variations in their manufacturing process, they can analyze trends that may lead to a more efficient way of producing their product, either from a time standpoint or from one purely on material and operation costs.

The manufacturing data provided by company “X” was a dataset that had 1428 samples of manufacturing and test data to aid in the development of a model. The idea is to create a predictive model that simulated the changes in compressive break pressure and air content of the cylinders based on input factors of manufacturing. In the case of the data provided by company “X”, Minitab was the final software decided on to create the model, due to the simplicity of creating a model as quickly as possible with minimal effort using the stepwise regression tool. The raw data was loaded into Minitab after being conglomerated inside Excel. In general, there are assumptions that the stepwise feature of Minitab takes into account the need for independent variables, and removes any variables that are perfectly correlated to one another. This setting resulted in a decent-sized model with sufficient terms that could account for 99.04% (R^2) of the variability in the response of the material property.

The final model for compressive break pressure of the test cylinders is:

Compressive Break=

$$2.396\,(F)(S) + 0.2306\,(S_5)^3 - 0.000162\,(C)^2(F) + 0.000062(C)(R)(D) - 0.002301(R)(S_4)(S_5) - 0.000359(R)(W)(D) - 0.001324\,(S)(S_2)^2 + 0.000516(S)(W)(D) - 0.02319\,(S_3)(S_2)(S_4) + 0.02135\,(S_4)(S_3)^2 + 0.00695\,(S_4)(S_3)(T_A)$$

(Eq. 1)

The next factor to be modeled is the air content of the concrete mix. The same starting factors/predictors are used, with the same method of utilizing Minitab stepwise regression for this material property. The final model to come from the regression modeling had an R-sq. value of 98.65%, meaning that a good portion of the air content can be determined with the factors/predictors provided. Here is the final model:

$$\text{Air Content} = 41.43 - 0.3092(F) + 0.0534(S_4) - 0.0687(S_5) - 0.5145(T_A) + 0.004518(F)(T_A) + 0.00423(S_4)(S_5) - 0.000678(S_4)(T_A)$$

(Eq. 2)

Now that has been decided as the functions to describe how the compressive break pressure and air content are modeled, the next step is to optimize the system by minimizing the total manufacturing cost. We start by defining the terms used in the optimization model followed by the constraints and objective function to be optimized as shown in Table 1.An optimization can be set up in such a way as to maximize both profit and break pressure, but weights will have to be assigned to both the cost/profit function and the break function. The more realistic goal is to identify the manufacturing scenario that will result in the cheapest manufacturing cost, but also reliably result in successful/passing compressive break pressures as well as the other goals of the mix like air content that the composite will be held to. This will be accomplished using constraints in addition to the objective function, to reliably hold the required spec values of the concrete while maintaining cost as the focus. It is important to note that cost in itself is not only a function of how much of each material is used but also a function of outside factors like how expensive it is to heat or cool the building and hold temperature based on the current temperature.

Decision variables:

X: The amount of each raw material utilized in the mix.

T_A: The temperature of the air inside which is altered with an air conditioning system.

D: The amount of time between pouring and testing of the break cylinder.

Constraints (subject to) as listed in Table 2.

Now the question is how to minimize the optimization function with the given constraints. Usually, a quiet way to do optimizations is using the simplex method, but since the functions are not linear, this is not a viable option. Instead, Excel’s solver (GRG non-linear) was utilized to perform the optimization. With the optimization completed, a sensitivity analysis was performed to see how the air content, break pressure, and cost was affected by varying each of the variables known to be factors of the material properties. Additionally how targeting different material properties affected optimal cost. Luckily, since concrete is already a well-known material, the sensitivity analysis was confirmed with company “X” to be valid to their working knowledge. The Figures below are a good representation of the entirety of the sensitivity analysis. In most

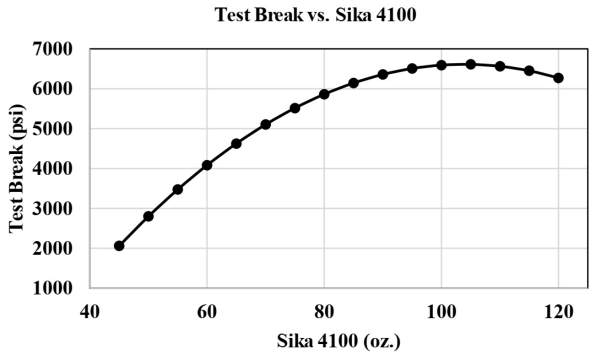

Fig. 1. Variation of Test Break with Sika 4100.

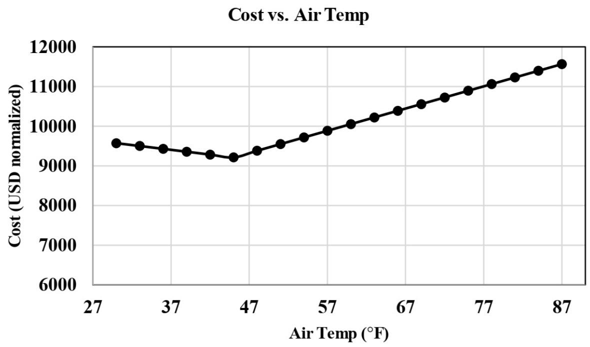

Fig. 2. Variation of Cost with Air Temp.

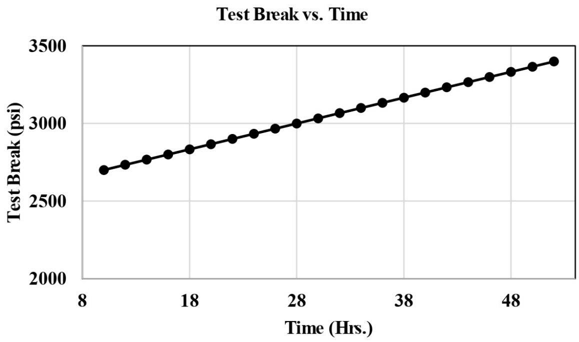

Fig. 3. Variation of Test Break with Time.

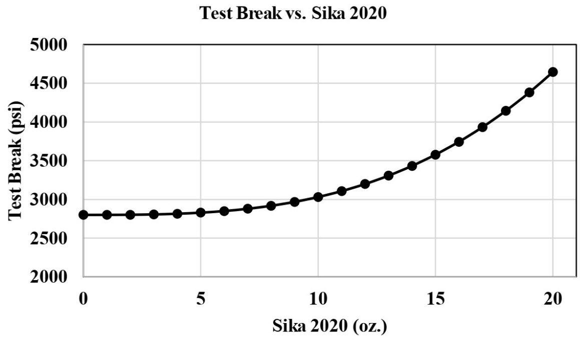

Fig. 4. Variation of Test Break with Sika 2020.

cases, 20 points were selected for each factor. Each point was individually tested to see how changing a factor affected the material property and the objective. The graphing of all of the 20 points was a good way to see the general trend of the changes, and to see if the model showed realistic changes to the material properties and functions, based on known information about the raw materials and other factors.

Table 1.
Definitions of terms used in the models.

Terms	Definitions
B	The pressure at which a concrete test cylinder breaks before releasing the product from its molds, (psi).
P	Price per unit of raw material or resource, (USD).
T_A	The air temperature inside the facility where concrete is being poured, (°F).
T_C	The temperature of wet concrete after pouring into molds, (°F).
T_O	Outside air temperature at the time of pour,(°F).
A	Air content: the volume of the concrete taken up by entrapped air, (%).
D	Duration of time from mix/pour to the breaking of the test cylinder, (hours).
X	Amount of raw material in each batch, (lbs or oz).
C	Cement: refined and baked limestone, (lbs).
S_1	Dry sand: natural sand which is specific to concrete manufacture, (lbs).
R	Dry rock: mix of Quartz and Granite stone, (lbs).
F	Fly ash: a byproduct of coal, utilized as a binding agent, (lbs).
S_2	Sika 4100: high-range water reducer utilized as a non-required additive, (oz).
S_3	Sika NC: a catalyst to speed up the curing process, which is a non-required additive, (oz).
S_4	Sika air: stabilizes the air content to between 5-7%, non-required additive, (oz).
S_5	Sika 2020 medium range water reducer utilized as a non-required additive, (oz).
W	Combo water: the amount of added water and water in the moisture of the rock and sand which is added unintentionally, (lbs).

3. Results and Analysis

In Figure 1, one of the additives was tested to see how it affects the test break pressure. The Sika 4100 additive is used to reduce the effects of water on the hardness of the concrete. Concrete with too much water is generally weak, but by adding this additive, the concrete is supposed to stay hard even when high amounts of water are used. Of course, as it is seen in the chart, there is a positive trending curve associated with the high use of sika 4100, then at around 105oz of use, adding more of the additive can start negatively affecting the concrete. This chart follows what has long been known about the additive, and confirms the validity of the model.

In Figure 2, the function of heating and cooling a building that is affected by outdoor temperatures are on display. The cost of which is generally going to be largely dependent on the desired temperature, and how large the delta between the two temperatures is. In the case of the graph, 45 °F outdoor temperature is in such a range that changing the desired temperature to lower or higher than that temperature presents two different functions (heating and cooling.) This follows the sample model developed for the cost associated with a cost for temperature variation but could be more accurately represented with real cost data associated with air conditioning.

In Figure 3, the most easily recognizable piece of concrete knowledge is on display. Concrete gets harder the longer it has to cure. That is exactly what we can see in the graph between 10 and 56 hours of cure

Figure 4 is similar in concept to Figure 1, as both additives are used as water reducers, but each for different ranges. The graph shows that while Sika 2020 does help to increase the break pressure of the test mold, it only becomes effective when more than 7oz of the additive is used.

Figure 5 was created by utilizing the optimizer to find the most

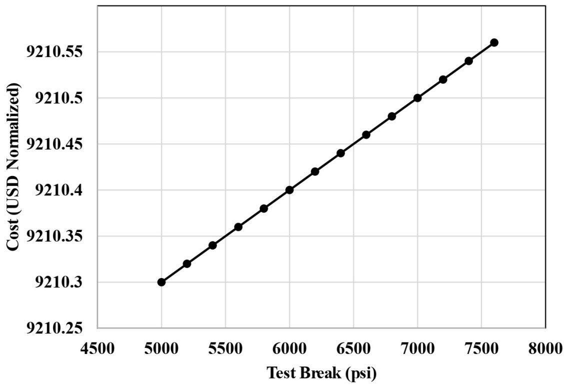

Fig. 5. Variation of Cost with Test Break.

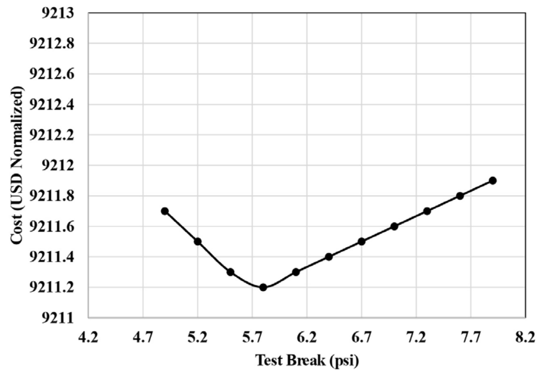

Fig. 6. Variation of cost with air content.

cost-effective way to make the product when the minimum desired test break is increased. The function ends up being non-linear, just like most terms in the test break predictive model/function. As expected, cost increases when targeting stronger concrete, but surprisingly it is not much more expensive to produce concrete that can withstand nearly 3000psi more than its cheaper counterparts.

Figure 6, utilizes a similar concept as that of Figure 5, but with a different material property. This time air content is tested, and interestingly there is a cost-effective optimum for producing concrete with an air content of ~5.55%. This is quite convenient since most customers are looking for concrete that is between 5 and 7% air by volume. The function shows how the cost is affected when desired air content is made lower or higher than that optimum value.

As seen, both functions are not linear. While the curve on the cost to break pressure is not very steep, the cost of on-air content varies quite extensively based on the constraints. There is an optimum air content achievable for cost, and with these constraints is around 5.55%. For the cost of test break pressure, in general, the lower desired test break pressure, the cheaper it is to produce the product.

The following discussion summary can be made from the testing, and recommendations for further research on the subject.

1) First thing is that the methodology was quick, efficient, and cheap as far as the tool being utilized. Regression is readily available through multiple pieces of software, from Microsoft excel, to free online regression tools. The methodology to filter data was quite easy, comparing the data and outliers with someone who understands the data was simple. Setting up the optimization method, in its simplest form in something like excel is quite simple. In the case of this material, almost every constraint was able to be defined by the raw material range that was tested already. For example, historical data only used between 171 lbs and 354 lbs of water in each batch of mix, so that is how the constraints were defined. The only other constraints were set to business requirements or customer-demanded material properties which were all calculated based on the regression models. Overall, this is simple and could be completed by nearly any "layperson" who understood the business and material requirements, and the meaning of the raw manufacturing data.

2) This method was also cost efficient in the way of time and money, as additional testing, by creating specific testing material, is not required. For the model that was created, if only 3 levels (which is low) would be utilized for all 9 factors in the model, a full factorial would re-

Table 2.
Description of equations used.

Equation	Description
Eq. 1	Compressive Break estimation regression model. This will be used as input to in Eq. 4
Eq. 2	As listed in the body (Air Content formula)
Eq. 3	(this states that the total amount of raw material put into each of batch, is greater than or equal to the required weight of concrete known to fill a mold. If a mold can't be fully filled the entire batch is wasted.
Eq. 4	$\text{Predictive Break P.Model output} \geq B_{total}$ (customer specification required to release)
Eq. 5	$A_{total} \geq$ Predictive Air Con. Model Output $\geq A_{total}$ (long-term product quality req.)
Eq. 6	$T \geq 16$ (operation single shift requirement)
Eq. 7	$120 \geq F \geq 110$ (highest and lowest ever used)
Eq. 8	$675 \geq C \geq 620$ (highest and lowest ever used)
Eq. 9	$354 \geq W \geq 171$ (highest and lowest ever used))
Eq. 10	$1080 \geq S_1 \geq 900$ (highest and lowest ever used))
Eq. 11	$2005 \geq R \geq 1750$ (highest and lowest ever used)
Eq. 12	$85 \geq T_A \geq 32$ (water freezes below 32, and workers are uncomfortable over 85)
Eq. 13	Predictive Break Pressure Model Output $= b_1 (F)S_4) + b_2 (S_5\ 3) - b_3 (C_2)(F) + b_4 (C)(R)(D) - b_5 (D)(S_4)(S_5) - b_6 (R)(W)(D) - b_7 (S_1)(S_2) + b_8 (S)(W)(D) - b_9 (S_4)(S_2 (S_3) + b_{10} (S_4)(S_3) + b_{11} (S_4)(S_3)(T_A)$
Eq. 14	Predictive Air Content Model Output $= b_0 - b_1 (F) + b_2 (S_4) - b_3 (S_5) - b_4 (T_A) + b_5 (F)(T_A) + b_6 (S_4)(S_5) - b_7 (S_4)(T_A)$
Eq. 15	Temperature Cost Model Output $= D(b_1 (T_o - T_A)(T_{OHot}) + b_2 (T_A - T_o)(T_{oCold}))$
Eq. 16	The objective function is to minimize the total cost to produce a single unit/batch of concrete., which is given as follows. Minimize: $P_{total} = \sum_D^q \sum_{T_A}^s + \sum_C^i \sum_R^j \sum_{S_1}^k \sum_F^l \sum_W^l \sum_{S_4}^m \sum_{S_3}^n \sum_{S_2}^o (X)(P)$ The right-hand side of the Eq. contains all of the controllable costs, not related to things like staff salaries.)

quire 3^9 or 19683 samples. A Taguchi method usually removes around one to two factors worth of tests from the number of test samples, largely depending on signal-to-noise ratios. In this case, reducing from to or tests, which is a nearly 80% reduction of tests to around 3787.995 tests. Even with only 3,800 tests, the amount of time and resources that it would take to perform such a test would take over a year of company "X's" full workforce, meaning they would make no money producing products during this time. The method of using only the natural variation of manufacturing the product and utilizing the historical data takes no product out of production and costs no additional money or time to create and evaluate specific test samples. This is a bit of a no-brainer if a company has no R&D department like this one.

3) Possibly the biggest issue with this methodology is that it lacks a validation run. Normally the easiest way to tell if a calculation is correct with this sort of method is to create material using what is called the optimal method and test to see if the calculated values are true. In this paper there were two reasons why the validation run cannot be created. The first reason is the timing of the paper coincided with the 2020 COVID-19 pandemic, which put strains on lots of businesses including company "X" and its operating conditions. Aside from the strains from the pandemic were also the issues of being able to control their operating process better. Most of the raw materials being added are done by hand and the ability to get the work done fast rather than extremely accurately does result in targeted numbers not always being achieved. For example, if 2000 pounds of dry rock is being targeted, an accuracy of ±20lbs might be achieved. While they could be more precise with adding the material, it would take additional operator time and care, especially while calculating the dry characteristics from the tested moisture content of the aggregate. Based on business demands, they could come up with better ways to ensure the raw material was added more accurately with automation or other measurement techniques. Needless to say, this style of research could give a company an idea of where to focus or minimize random/natural variation in their manufacturing process, which when completed can help to optimize a system. The natural variation at this stage is helpful in the modeling of a larger level range for each variable. Doing a validation run could have solidified many of the claims made in the paper as true, so it is a recommendation if future research is pursued.

Since that could not be done, the next best thing is to compare known material behavior with the sensitivity analysis of the models. Importantly as more of each material was added the cost increased, which makes sense to the objective function, but the other two functions that come from regression were overall more likely to have issues from an accuracy standpoint. Luckily as far as can be seen, all of the sensitivity analysis looks correct, even though it is all just first order changes, where most functions involved the interaction between variables. As an example, time should positively affect break psi, but not affect air content at all, and in the sensitivity analysis, this was the case. The same goes for the Sika add-ins. Sika Air for example should not affect break psi but does affect air content, which is the case in the sensitivity analysis. If multiple or any of the sensitivity analysis runs look incorrect, the models are likely incorrect in some way, or the historical assumption of something may be incorrect.

4. Conclusions

Based on the study, it can be said that the Taguchi method and SRM are not handy techniques to use in material process development for specific manufacturing scenarios such as for the company "X" described in this paper. Therefore, an alternative method was proposed to deal with producing a concrete product in large batches with many potential factors of variation. The method involved analyzing manufacturing data of a process that is not highly controlled. The data were used to create predictive models of material properties that affect product lifetime and performance via regression. The non-linear material property models were then used to optimize the system for cost, while also holding the material properties to high standards. Sensitivity analyses were utilized to give insight into the validity of the model's effectiveness in accurately representing the system changing with the input factors.

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