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DIGITAL CONCRETE QUALITY ASSURANCE

Possibilities for Data-driven Quality Assurance of Concrete in Production

Aku Wilenius, Pasi Karppinen, Juho Pättö

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Finnish Transport Infrastructure Agency
P.O.Box 33
FIN-00521 HELSINKI, Finland
Tel. +358 (0)295 34 3000

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Abstract

New technologies such as machine learning, continuously improving wireless and wired connectivity, as well as modern sensors for data collection, are being widely adopted by many industries. In concrete construction, digital solutions have the potential to help assure the quality of ready-mix concrete while increasing productivity in construction sites. Even if the data collection capabilities exist to implement data analytics and machine learning-based applications, the availability of proper, clean data from concrete production has often been a challenge in our early experiments, such as the trials by the DigiConcrete working group in Finland

This project aimed to understand what digital data collection opportunities there are in ready-mix concrete production and how data analytics, machine learning, and artificial intelligence techniques could be used to automate some of the concrete quality assurance tasks. The research was done by selecting, collecting, and analyzing data from a concrete production as well as studying literature and standards for the industry. We combined both existing data from the control systems of concrete mixing plants and data that were separately acquired by purposely installed measuring equipment. The data collection, acquisition, and analysis were made between December 2019 and June 2020.

The research that was completed by Caidio Oy for Finnish Transport Infrastructure Agency continues the work that has earlier been performed by the DigiConcrete working group in Finland in 2018 and 2019. Several Finnish organizations in concrete construction, such as Finnish Transport Infrastructure Agency, have collaborated in studying what possibilities the digitalization could offer to increase performance and decrease challenges in concrete construction. Caidio Oy, which is a technology startup specializing in artificial intelligence and industrial Internet solutions, has coordinated the DigiConcrete activities.

In this research, Caidio focused on four research activities. First, we analyzed which existing, and new data collection possibilities exist in concrete production. Second, we collected data from existing data sources in concrete production as well as added novel measurements in the process. Third, we cleaned the acquired data such that it could been used for machine learning and data analytics. Finally, we experimented with how data analytics and machine learning could potentially be used in concrete production and documented our findings.

The research indicated the possibilities of a data-centric approach for quality control but also highlighted the current gaps in a traditional production process. A standard concrete plant often lacks the open software interfaces for accessing the required production data in the right format, which makes the

development slower. For the machine learning approach to be successful, the production data needs to be lined up with the concrete quality test results from the laboratory as well, which requires proper planning and alignment between the stakeholders in an organization. Furthermore, for the computerized approach to be successful, more data needs to be collected from the process than what we had the opportunity to do. The research team is confident the data-centric method has a lot of potentials to work, but additional research, data acquisition, and development will still be needed.

Aku Wilenius, Pasi Karppinen ja Juho Pättö: Betonin digitaalinen laadunhallinta – Betonituotannon datapohjaisen laadunhallinnan mahdollisuuksia. Väylävirasto. Helsinki 2020. Väyläviraston julkaisuja 54/2020. 37 sivua ja 2 liitettä. ISSN 2490-0745, ISBN 978-952-317-815-1.

Avainsanat: betoni, betonitehdas, laatu, laadunvalvonta, testaus, digitalisaatio, tekoäly, koneoppiminen

Tiivistelmä

Uusia teknologioita, kuten esimerkiksi koneoppimista, tehokkaita langattomia ja kiinteitä verkkoyhteyksiä tai tiedonkeruuseen tehtyjä IoT-antureita, sovelletaan nykyään yleisesti monella teollisuuden alalla. Digitaaliset menetelmät voivat auttaa valmisbetonin laadunvarmistuksessa sekä lisätä tuottavuutta betonirakentamisessa työmailla. Vaikka data-analyytikan ja koneoppimisen tarvitsemaa tiedonkeruutekniikkaa on helposti saatavilla, algoritmien tarvitseman hyvälaatuisen datan käyttöön saaminen betonintuotannosta on monesti ollut työlästä aikaisen vaiheen DigiConcrete-testeissämme Suomessa.

Tämän projektin tarkoituksena oli kasvattaa ymmärrystä siitä, mitä tiedonkeruumahdollisuuksia valmisbetonin tuotannossa on ja millä tavalla tietoon pohjautuvaa data-analytiikkaa, koneoppimista ja tekoälyä voisi käyttää betonin laadunhallinnan automatisoimiseksi. Tutkimuksessa etsittiin mahdollisuuksia, kerättiin ja analysoitiin tietoa betonin tuotannosta sekä tutkittiin aiheeseen liittyvää kirjallisuutta ja teollisuuden standardeja. Yhdistimme tuotannon automaatiojärjestelmästä saatua olemassa olevaa dataa tietoon, jota kerättiin tuotannosta erikseen asennetuilla mittalaitteilla. Tiedot kerättiin ja analysoitiin joulukuun 2019 ja kesäkuun 2020 välisenä aikana.

Tutkimuksen suoritti Väyläviraston toimeksiannosta Caidio Oy ja se pohjautuu aikaisempaan niin kutsutun DigiConcrete-työryhmän Suomessa vuosina 2018 ja 2019 tekemään pohjatyöhön. Useat suomalaiset organisaatiot kuten esimerkiksi Väylävirasto, tekivät DigiConcrete-työryhmässä yhteistyötä tutkiakseen, mitä mahdollisuuksia digitalisaatio voisi tarjota tuottavuuden lisäämiseksi ja haasteiden vähentämiseksi betonirakentamisessa. Caidio, joka on suomalainen tekoälyyn ja teolliseen Internetiin panostava startup-yritys, on koordinoinut DigiConcrete-aktiviteetteja.

Tässä työssä Caidio keskittyi neljään tehtävään. Aluksi tutkittiin, mitä olemassa olevia sekä uusia tiedonkeruumahdollisuuksia tyypillisessä betonintuotannossa on. Tämän jälkeen kerättiin olemassa olevaa dataa valmistusprosessista sekä tehtiin täysin uudentyyppisiä mittauksia tuotannossa. Kolmanneksi kerätty data suodatettiin, jotta koneoppimisalgoritmeja ja data-analytiikkaa voitiin soveltaa tiedonkäsittelyssä. Lopuksi kokeiltiin koneoppimis- ja data-analytiikkamenetelmiä tiedon prosessoinnissa, jotta saataisiin käsitys, miten menetelmät voisivat toimia betonituotannossa.

Tutkimuksessa havaittiin, että dataan perustuvista laadunvalvontakeinoista voi olla hyötyä betonin automaattisessa laadunvalvonnassa. Haasteena kuitenkin todettiin olevan perinteisen tuotantolaitoksen automaatiojärjestelmän kankeus tarvittavan datan saamiseksi oikeassa muodossa algoritmien käyttöön. Avoimien tietorajapintojen puute voi hidastaa ja vaikeuttaa ohjelmistokehitystä.

Jotta tietokonepohjaiset koneoppimismenetelmät toimivat betonin laadunhallinnassa, malleja otettaessa tuotannosta kerättävä data sekä betonilaboration tekemät laatutestit pitää suorittaa samoista betonin tuotantoeristä. Tämä vaatii tarkkaa koordinointia yrityksen eri osastojen välillä.

Jotta tietokonepohjainen dataan pohjautuva menetelmä toimisi betonin laadunvalvonnassa, prosessista pitäisi kerätä enemmän tietoa kuin mihin tutkimuksessa oli mahdollisuus. Tutkimusryhmän mielestä tutkituilla menetelmillä on hyvät mahdollisuudet toimia, mutta ratkaisut tarvitsevat lisätutkimusta, tiedonkeruuta ja kehitystä.

Foreword

This report presents a summary of the research conducted and the results obtained in Caidio's data-centric approach for quality assurance of concrete production project for Finnish Transport Infrastructure Agency.

Caidio Oy carried out the project under the guidance of Finnish Transport Infrastructure Agency. The primary representatives of Caidio during this project were Pasi Karppinen and Aku Wilenius, supported by Caidio's IoT instrumentation and machine learning teams. The project builds on the DigiConcrete initiative in Finland, which has been a collaboration working group by several stakeholders in the Finnish concrete construction industry, including Finnish Transport Infrastructure Agency.

This project aims to promote the digitalization in the concrete construction industry. Both Finnish Transport Infrastructure Agency and Caidio Oy envision that modern tools have much potential to help the industry manage bottlenecks and assure quality in concrete construction.

Helsinki November 2020

Finnish Transport Infrastructure Agency

Content

1 Introduction

1.1 Background and objectives

Caidio conducted a research project for Finnish Transport Infrastructure Agency on the possibilities of using modern machine learning and data analytics techniques in the quality assurance of ready-mix concrete in production. The challenges that Finnish Transport Infrastructure Agency experienced in 2016 regarding the quality of ready-mix concrete are motivating this research.

The performance of artificial intelligence and machine learning-based systems is continuously evolving as the systems gather more data about the processes that are being managed. Caidio's research indicates that in a short time, with various algorithms, the AI systems can process a large amount of information gathered from raw materials, the production process, and the environment, and learn how to alert about possible problems with concrete quality parameters. AI systems can generate alarms and operational recommendations for concrete plant managers and other employees.

The general objective of this project was to understand what digital data collection opportunities and challenges there are in ready-mix concrete production and how data analytics, machine learning, and artificial intelligence can be used to automate the quality assurance of concrete in production. According to Caidio's experience, machine learning and AI system have the potential to detect the following quality management applications defects in the concrete production process:

- Changes in the quality parameters of aggregates
- Changes in the quality parameters of mixed concrete
- Incorrect sensor operation and sensor calibration error
- Predicting machine malfunctions situations

1.2 Research methodology

The research was done by selecting, collecting, and analyzing data from the concrete production industry as well as studying the existing literature and standards for the industry. We combined both current data from the control systems of concrete mixing plants and data that were separately acquired by purposely installed measuring equipment. The data collection, acquisition, and analysis were done between December 2019 and June 2020.

1.3 Structure of the report

This report has been created based on the template from Finnish Transport Infrastructure Agency. The research project has been divided into three phases, according to table 1.

Table 1. The research phases of the project

Phase	Reporting	Tasks
Data selection and acquisition	January 2020	The optional data sources for the research were listed, the most useful data sources were selected, and the collection of data was started.
Data acquisition, optimization, and analysis	March 2020	The data that was selected in the first phase of the project was acquired from a concrete production process. The filtering, processing, and analysis of the data was started.
Returning the research results	July 2020	The usability of data analytics, machine learning, and artificial intelligence methods for concrete quality assurance was studied and reported.

2 Overview of producing and testing the quality of concrete

The ready-mix concrete process, as shown in figure 1, consists of multiple stages. The concrete production starts by getting the raw materials such as cement, aggregates, water, and admixtures based on the recipe information for the concrete in the mixer where the materials are mixed. The mixing is done in batches, and each time a batch of concrete of concrete strength and concrete class is produced.

When testing the produced concrete for quality parameters, such as workability, density, or temperature, a small sample is taken from the batch of concrete and sent for testing in the local laboratory. The frequency and method of testing have been defined in the European standard EN 206, which has been adopted in the local Concrete Code guideline in Finland. After taking the test sample, the truck delivers the product to the construction site. The concrete is then cast, cured, and hardened at the worksite. The process is then repeated for the next order. An overview of this process is shown in Figure 1. The most relevant data gathering points for the purpose of this report are highlighted in yellow. The process and data points are further elaborated in Appendix 1.

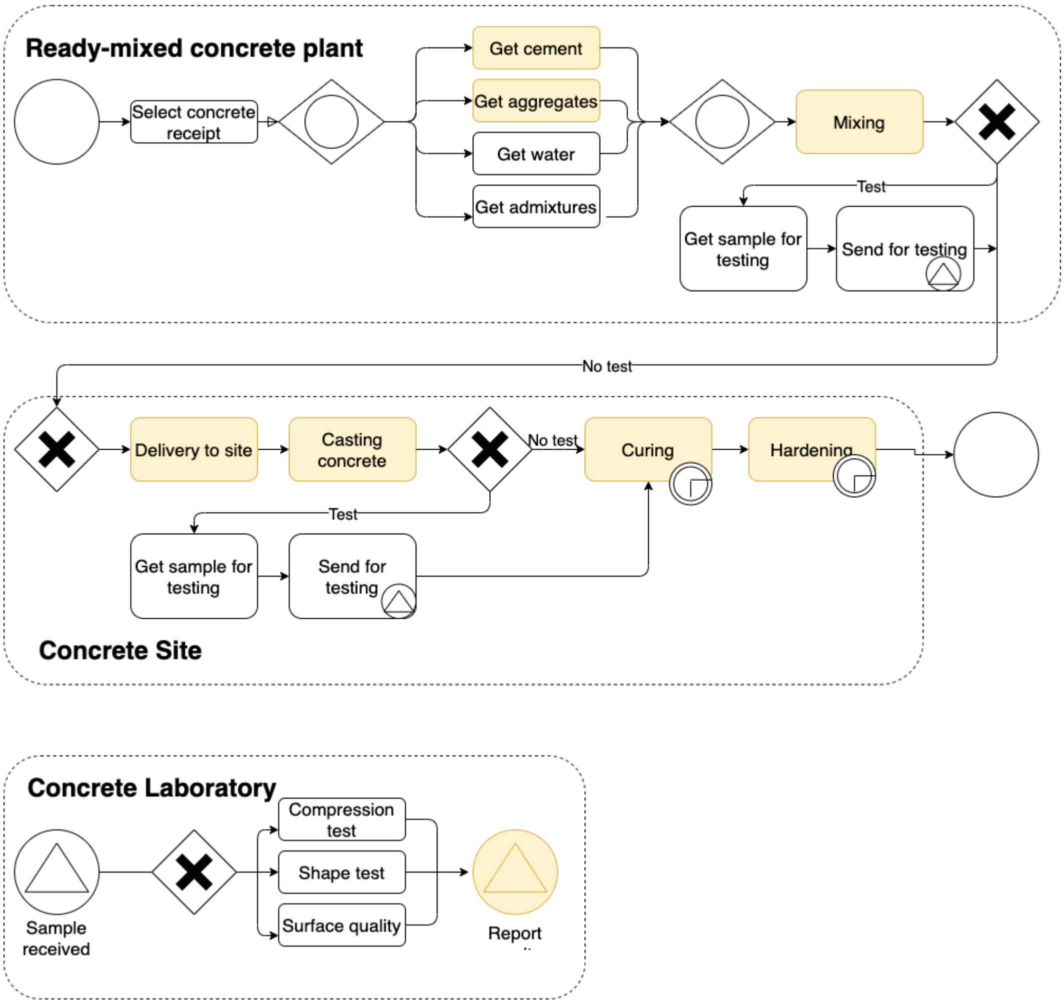


Figure 1. Ready Mixed Concrete process

2.1 Quality assurance of ready-mix concrete

Concrete Association of Finland describes the current quality assurance procedures of ready-mix concrete in Concrete Code 2016 publication, which is based on the European standard EN 206. The properties of concrete shall be controlled to the specified requirements, as given in Table 2. For some concretes, additional requirements for production control may be necessary. For example, the production of high-strength concrete requires special knowledge and experience of the contract documents that have defined special requirements for the concrete; the production control shall include appropriate actions in addition to those in Table 2. The actions presented in the table may be adapted in special cases to the conditions of a specific place of production and be replaced by actions that provide an equivalent level of control. For example, Finnish Transport Infrastructure Agency has published requirements for concrete production for their use.

Table 2. Quality control of production procedures of concrete properties.

	Type of test	**Inspection/ test**	**Purpose**	**Minimum frequency**	**Pro-duc-tion**
1	Properties of concrete	Initial test	To provide proof that specified properties are met by the proposed composition with an adequate margin	Before using a new concrete composition	No
2	Water content of fine aggregates	Continuous measuring system, drying test or equivalent	To determine the dry mass of aggregate and the water to be added	If not continual, daily. Depending on local and weather conditions more or less frequent tests may be required	Yes
3	Water content of coarse aggregates	Drying test or equivalent	To determine the dry mass of aggregate and the water to be added	Depending on local and weather conditions	Yes
4	Water content of fresh concrete	Check of the quantity of water added (b	To provide data for the water-cement ratio	Every batch or load	Yes
5	Chloride content of concrete	Initial determination by calculation	To ensure that the maximum chloride content is not exceeded	When performing initial test In case of an increase in the chloride content of the constituents	No

	Type of test	Inspection/ test	Purpose	Minimum frequency	Pro-duc-tion
6	Consistency	Visual inspection	For comparison with normal appearance	Every batch	Yes
7		Consistency test according to SFS-EN 12350-2 or SFS-EN 12350-5	To assess the achievement of the specified values of consistence and to check possible changes of water content	In connection with the production of test specimens for compressive strength When testing air content In case of doubt following visual inspections	Yes
8		Consistency test according to SFS-EN 12350-8:en		At least once a day In connection with the production of test specimens for compressive strength When testing air content In case of doubt following visual inspections	Yes
9	Viscosity of concrete	SFS-EN 12350-8 or SFS-EN 12350-9	To assess the achievement of the declared values of consistence	When performing initial test Before using a new concrete composition In case of a change in the constituents In case of doubt following visual inspections or slump-flow test	Yes
10	Passing ability	SFS-EN 12350-10 or SFS-EN 12350-12			
11	Segregation resistance	SFS-EN 12350-11			
12	Density of fresh concrete	Density test according to SFS-EN 12350-6	For lightweight and heavyweight concrete for supervision of batching and density control	Daily	Yes
13	Cement content of fresh concrete	Check the mass of cement batched (b	To check the cement content and to provide data for the water- cement ratio	Every batch or load	Yes

	Type of test	Inspection/ test	Purpose	Minimum frequency	Pro-duc-tion
14	Additions content of fresh concrete	Check the mass of additions batched (b	To check the additions content and to provide data for the w/c ratio (see Section 3.1.2)	Every batch or load	Yes
15	Admixture content of fresh concrete	Check the mass or volume of admixtures batched (b	To check the admixture content	Every batch or ad	Yes
16	Water-cement ratio of fresh concrete	By calculation or by test method	To assess the achievement of the specified water-cement ratio	Daily, where specified	Yes
17	Air content of fresh concrete where specified	Test according to SFS-EN 12350-7	To assess the achievement of the specified content of entrained air	In accordance with Appendix 4	Yes
18	Temperature of fresh concrete	Measure temperature	To assess the achievement of the minimum temperature of 5 °C or specified limit	In case of doubt Where temperature is specified: - periodically, dependent on the situation. - each batch or load where the concrete temperature is close to the limit	Yes
19	Density of hardened concrete	Test according to SFS-EN 12390-7(a	To assess the achievement of the specified density	Where density is specified, as frequently as compressive strength test	Yes
20	Compressive strength test on molded concrete specimen	Test according to SFS-EN 12390-3	To assess the achievement of the specified strength	Where compressive strength is specified; as frequently as for conformity control Recommended to be carried out always in connection with testing of test specimens for compressive strength	Yes
a) May also be tested in saturated conditions, where correlation to oven-dry density is established. b) Where recording equipment is not used and the batching tolerances for the batch or load are exceeded, record the batched quantity in the production record.					

In table 2, Concrete Association Finland describes 20 different quality inspection tests and minimum frequencies for ready-mix concrete. Of all of these, 16 tests are performed while producing concrete, and most of them require manual testing by personnel or testing providers. One of the purposes of this research is to study if these manual test phases could at least partly be replaced with digital techniques.

According to our interviews with industry experts, the root cause of the quality issues in the manufacturing process often originates from the malfunctioning machinery. In addition to testing the concrete directly for quality parameters, verifying the correct operation of the production machinery is also essential. Concrete Code 2016 publication describes, according to table 2, how, and how often different production machines need to be tested. Modern instrumentation and data-centric approach for testing the facility may offer new possibilities for automated ways for verifying the functionality of production machinery as well as performing predictive maintenance, which would allow the producer to schedule maintenance operations on time.

Table 3. Equipment control.

	Equipment	**Inspection/ test**	**Purpose**	**Minimum frequency**
1	Stockpiles, bins, etc.	Visual inspection	To ascertain conformity with the requirements	Once per week
2	Weighing equipment	Visual inspection of the performance	To ascertain that the weighing equipment is clean and functions correctly	Daily
3		Test of weighing equipment	To ensure the accuracy of the batching equipment	On installation Periodically (a depending on provisions valid in the place of use In case of doubt
4	Admixtures dispenser (including those mounted on truck mixers)	Visual inspection of the performance	To ascertain that the measuring equipment is clean and functions correctly	First day of use for each admixture
5		Test of measuring equipment and verification of batching amount	To ensure the functionality of the batching equipment	On installation Periodically (a after installation In case of doubt
6	Water meter and water dispenser mounted on truck mixer	Test of measuring equipment	To ensure the functionality of the batching equipment	On installation Periodically (a after installation In case of doubt

	Equipment	Inspection/ test	Purpose	Minimum frequency
7	Equipment for continuous measurement of water content of aggregates	Comparison of the actual amount with the reading of the meter	To ascertain correct values	On installation Periodically (a after installation In case of doubt
8	Batching system	Visual inspection	To ascertain that the batching equipment is functioning correctly	Daily
9		Comparison of the actual mass of the constituents in the batch with the target mass	To meet the requirements of Section 3.7.4.2	On installation In case of doubt Periodically (a after installation
10	Testing apparatus	Calibration according to relevant national or SFS-EN standards	To check the conformity	Periodically(a For strength testing apparatus, at least once per year
11	Mixers (including truck mixers)	Visual inspection	To check the wear of the mixing equipment	Periodically (a
a) The test/inspection frequency depends on the type of equipment, its sensitivity and the production conditions of the plant.				

3 Results

3.1 Data selection and acquisition

In this research, the plan was to select, collect and analyze existing data from ready-mix concrete production and combine it with the data that typically has not been made use of in concrete production, such as sound and video data. This research hypothesizes that by analyzing the information thus formed, it is possible to achieve a better understanding of the variables that cause variation in the quality of produced concrete as well as catch other problems in production.

Examples of measurement data that are already often available is the measurement data of the moisture content of aggregates and the amount of air in fresh concrete or the power consumption of the concrete mixer. New data that can be combined with these can be obtained, for example, from sound and vibration sensors and image and video recordings.

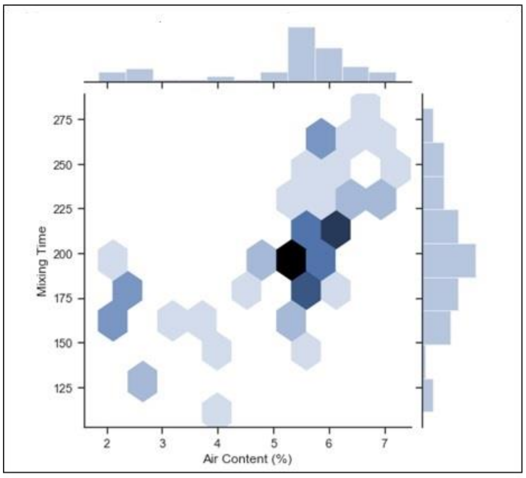
In typical concrete mixing plants, the meter readings are visible and manually usable by concrete plant operators, but the data or other measurement results are not usually connected in real-time to the process automation control software. By combining the data and measurement results, the information can be visualized in real-time, which makes it easier for the concrete producer to control the production and delivery process of concrete more precisely.

3.1.1 Air content analysis example

An example of the data that the concrete production plants collect from the concrete mixing process is the air content of the material. Air content affects the compressive strength of concrete and its workability. It increases the workability of concrete without much increase in the water-cement ratio. To reach the desired air content, the producers mix the concrete long enough to achieve the needed amount of air in the concrete.

The general assumption is that the more one mixes the concrete in production, the more air one gets in the product. The data in figure 2 illustrates the air content distribution of ready-mix concrete for two different production days. The amount of air in concrete was measured with AIRTRAC Air Control System.

On the first day, which is represented by the plot on the left, we can observe that most often, the air content of 5% was reached by mixing the concrete for 200 seconds. The darkest area on the plot represents production batches with the largest amount of same air content measurements. On day two instead, which is represented by the graph on the right-hand side of figure 2, we see that most often, the production made concrete with 6% air in it, which required a 180 second mixing time.



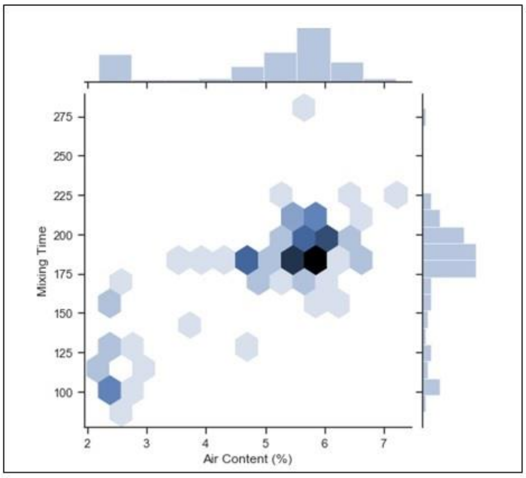


Figure 2. Concrete mixing time vs. air content

3.2 Existing data from the control system

A concrete plant, also known as a batch plant or batching plant or a concrete batching plant, is equipment that combines various ingredients to form concrete. Some of these inputs include water, air, admixtures, sand, aggregate, fly ash, silica fume, slag, and cement. A concrete plant can have a variety of parts and accessories, including mixers, cement batchers, aggregate batchers, conveyors, radial stackers, aggregate bins, cement bins, heaters, chillers, cement silos, batch plant controls, and dust collectors.

Concrete plants use the control system to control the working of the machine. The plants employ computer-aided control to assist in fast and accurate measurement of input constituents or ingredients. With concrete performance so dependent on accurate water measurement, systems often use digital scales for cementitious materials and aggregates, and moisture probes to measure aggregate water content as it enters the aggregate batcher to automatically compensate for the mix design water/cement ratio target.

3.2.1 Typical data available from the control system

A typical control system of a concrete mixing plant records the following data from the process, for example.

Table 4. Typical data recorded by the control system

Information	Description
Day	Date of producing the concrete
Order number	Order number of the delivery
Type of concrete	Type of concrete produced
Strength	Strength of concrete
Workability	Workability class of concrete

Information	Description
Amount of concrete	Amount of concrete
Temperature	Temperature of concrete
Target power	Target mixing power in kilowatts
Measured power	Measured mixing power in kilowatts

3.2.2 Laboratory measurement data

The quality analysis results for compressive strength of concrete from concrete testing laboratories will be useful for automated data analysis. Concrete Association Finland describes that any durability tests to be performed on hardened concrete shall be carried out by a qualified testing laboratory. The qualification can be demonstrated, for example, with an accredited durability test method.

The strength tests relating to concrete may be performed by the producer. In such a case, the verification of the testing of compressive strength shall be made yearly by a qualified testing laboratory in accordance with the instructions of the inspecting body.

The results of the strength test in a laboratory typically provide the following data, that can be matched with the data recorded in the mixing plant.

Table 5. Typical data recorded in the concrete testing laboratory

Information	Description and notes
Order number	Order number of the delivery
Date	Casting date of the sample
Number of the sample	Identification number of the sample which was taken for compressive strength test
Recipe number	Recipe number for the order
Amount of concrete	Amount of concrete produced
Concrete strength class	Compressive strength class of the sample
Workability	Workability of the sample
Maximum aggregate size	Maximum aggregate size of the sample
Slump	The result of the slump test of concrete

Information	**Description and notes**
Exposure classes	Describes the exposure class of concrete such as frost resistance
Temperature of concrete	Temperature of the concrete in °C
Temperature of the environment	Temperature of the environment in °C

3.3 Data that can be separately acquired from production

The research team believes that additional data must be acquired to catch and predict potential quality problems of concrete in production. The mixing plant provides several interesting data sources for computer algorithms, but this data needs to be acquired. The modern sensor and data acquisition technologies enable a high performance and cost-effective way of acquiring rich data from the machinery. In this chapter, we describe additional data sources that can potentially be used to estimate the quality parameters of concrete.

3.3.1 Water content measurement of aggregates

Coarse aggregates can contain 0-2% surface moisture by weight and fine aggregates, even up to 10%. Wet aggregates may contain moisture more than is desirable to preserve the water-cementitious material ratio (w/cm) in design limits. The uncertain and unstable moisture rate leads to a significant quality variation. In controlling the fault tolerance, extra cement is used to keep the product quality standard stable. So, this directly leads to adding excess cement for the fault tolerance of producing concrete.

Accurately measured moisture in aggregates allows optimizing concrete mix design, durability, and shrinkage of concrete products without overdosing cement. The moisture content of aggregates must be known to fractions of a percent to minimize variability in concrete quality, to enable optimal usage of cement, and to reach cost efficiency in concrete production.

In this research, optical measurement sensors have been used. Optical measurement is based on the absorption of water molecules. It employs near-infrared wavelengths with a measurement distance of 1-2 m. Since the measured material does not get in contact with the sensor, it does not resort to wear and tear. It allows measuring water content in real-time and is sensitive to rapid changes.

3.3.2 Vibration data

Measuring the vibration of concrete mixers can prove a valuable source of information for detecting machinery failures and wearing in the process. The research team assumes that the vibration data, when combined with other types of information from the mixing process, can be used to monitor the quality parameters of concrete when combined with modern algorithms.

In this project, we acquired the vibration data of the mixer. A vibration sensor was placed at the mixer, which was attached to a data logger at the factory site. The data logger was responsible for transferring the data to the FTP server every minute for a week. The data was then transferred to the software platform, as shown in the following figure. The sample rate of the data was 96kHz.

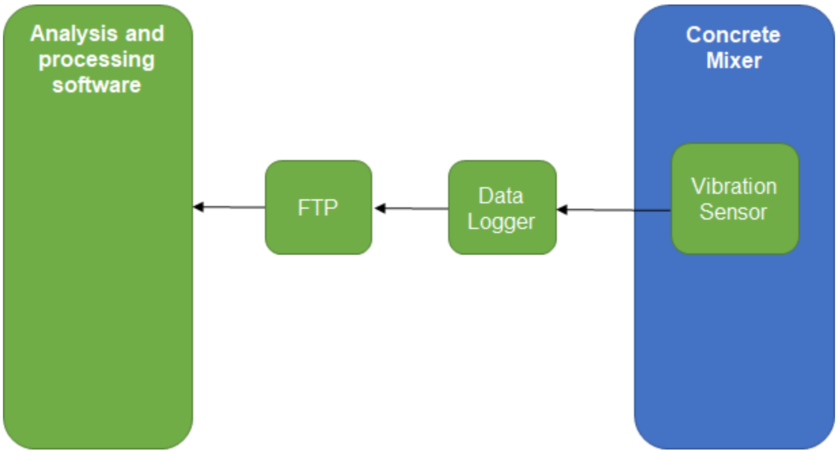


Figure 3. Vibration measurement setup

Figure 4 visualizes the physical installation of the vibration sensor in the mixing plant.

Figure 4. Vibration sensor installation

3.3.3 Audio data

One of the hypotheses of the research team is that the audio information of the mixing process can provide useful information on the operation of the mixing process. We wanted to study this more and a sound recorder was placed at the concrete factory site in the mixing room to monitor the mixing sounds of the ready mixed concrete. The main idea behind the data collection was to identify the mixing and non-mixing events from audio data, which is summarized in figure 5. The data was collected over a week, and a USB memory stick was attached as persistent data storage. The memory stick was then removed after a week from the site, and data was transferred to the software platform for analysis. The sample rate of the acquisition was 22KHz.

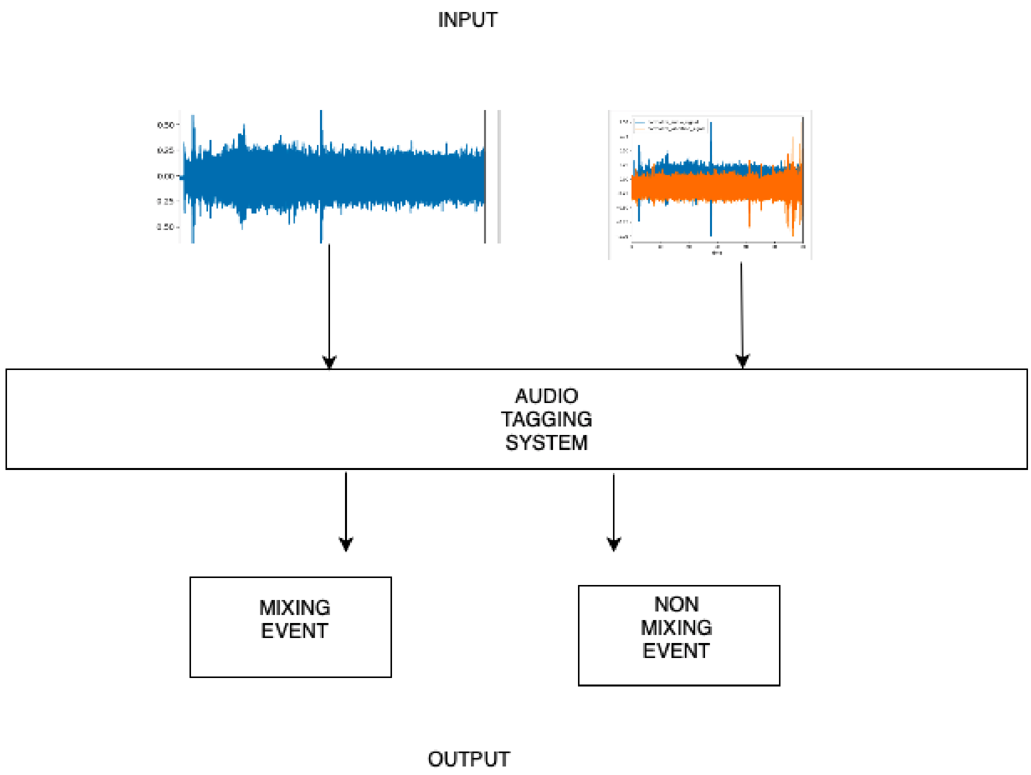


Figure 5. Using an audio measurement to detect mixing events

3.3.4 Video data

The research team believes video data can prove useful in analyzing the workability of the concrete or to detect anomalies in the process. The video feed of ready mixed concrete from the mixer can be used in conjunction with object detection algorithms to locate the concrete from the video and estimate the workability. Moreover, video information can also be used in identifying alien materials in process such as foreign materials on conveyor belts, which can introduce problems in the process.

3.3.5 Current data

We also measured the mixer current during the concrete mixing process. The data acquisition unit was used to record the current directly from the mixer motor. The purpose of recording the current data from the mixing plant was to see how much current the mixer is drawing and compare that to the mixing process. Mixing and the current readings are directly proportional to each other, as shown in Figure 6. Continuous current measurements could be used to identify the stage of the mixer and to detect anomalies during the mixing process, as opposed to the usual procedure where only the final current value is read.

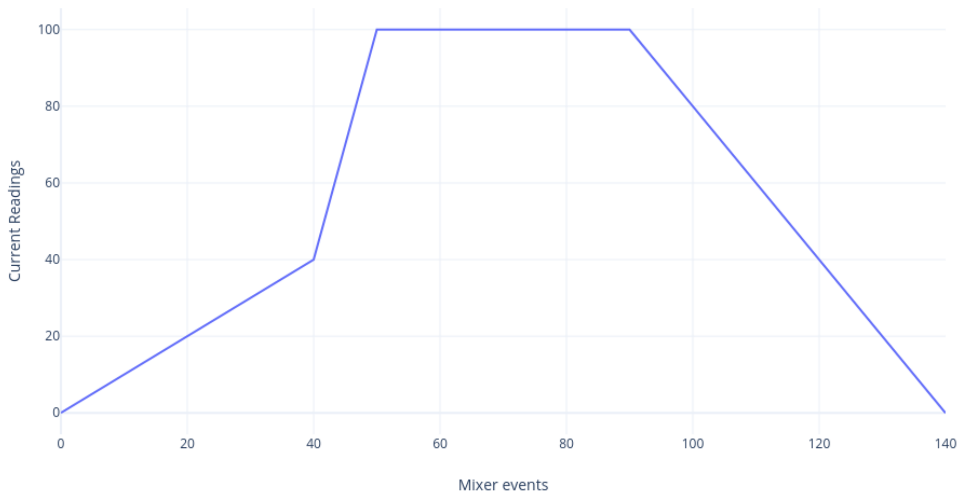


Figure 6. The relationship between the mixing events and motor current measurements

The figure demonstrates the relationship between the mixing events and current readings. Initially, it shows an upward trend when the mixer starts; then it rises exponentially when it starts mixing with materials in the mixer and becomes stagnant for some time when the concrete is being mixed. It eventually drops down to zero, after the mixer has been unloaded.

3.4 Other potential data sources

In addition to the standard information that can be collected from the process control system or acquired separately by using separately installed measurement instruments, there may be other available useful open data sources one can use. For example, in real life, millers in the mixing adjust the process when it is raining because the aggregates are moister than in more dry conditions. This kind of information can be automatically fetched to the software algorithms from the open weather data sources, such as the open data API of the Finnish Meteorological Institute.

4 Introduction to machine learning

In this project, we performed data analytics on the data we collected from different sources in concrete production. The goal of data analysis was primarily to understand the current state of a typical concrete production to be able to plan for future enhancements and activities. The analysis at this stage was performed on the separately measured audio data, with data from an existing control system and the data from laboratory measurements. We attempted to apply extensive data analysis techniques to understand the data and discover any meaningful patterns in it for developing automation systems in the future. Besides data analytics, machine learning is another technique we apply in the analysis.

Data analytics, as a research method, is growing and is being widely used in different fields for exploring systematic patterns and relationships in data. With many businesses and industries generating more data in recent times, the application of data analysis has been effective and growing. It provides businesses and organizations the possibility to extract information from their data that assist them in generating rules for decision making. Along with data analytics, the use of machine learning for analysis and decision making is rapidly growing, and it has proven to be successful in creating automation systems in different fields. Machine learning in the presence of big data can extract patterns from data that can help in creating systems to automate decision making and reduce errors.

Machine learning, in general, is a collection of tools that can learn from data automatically. The data for our analysis can be retrieved from multiple sources, as described in section 3. Machine learning models are usually fed in with training data to detect patterns in data with the help of some mathematical models so that they can make predictions on new data without explicitly being programmed. Broadly classifying, machine learning can be of supervised and unsupervised learning. In supervised learning, machine learning models are trained with data with known outputs so that they can be used in future for prediction on similar data. For unsupervised learning, machine learning models are simply fed with data without output to find any structure in the data that can be used for grouping or clustering of data points.

With many benefits and applicability of machine learning, it can be utilized in the concrete production process to supervise some stages in the production. Since at present most of the processes in the production are handled with human expertise and manual process, machine learning can help in optimizing the output with reduced time and fewer human errors. Through data collected from different sources during concrete production, machine learning can be applied to systematically identify patterns for any fault detection or irregularities in the machine. Similarly, they can be used for controlling the quality parameters of the raw materials for obtaining a certain level of quality of concrete.

4.1 Using Machine Learning with Audio Data

In this part, we aim to extract several mixing cases from the audio data that were acquired at the concrete factory. This would allow a fine and real-time check on the concrete mixing process and report any irregularities. In addition to the mixing stages, the audio information also can provide us information on the condition of the machinery. In machine learning, receiving rich data of different sources of the process is essential due to which we wanted to experiment collecting and processing the audio information, too.

For example, in the next figure we can see the frequency response of two randomly picked samples:

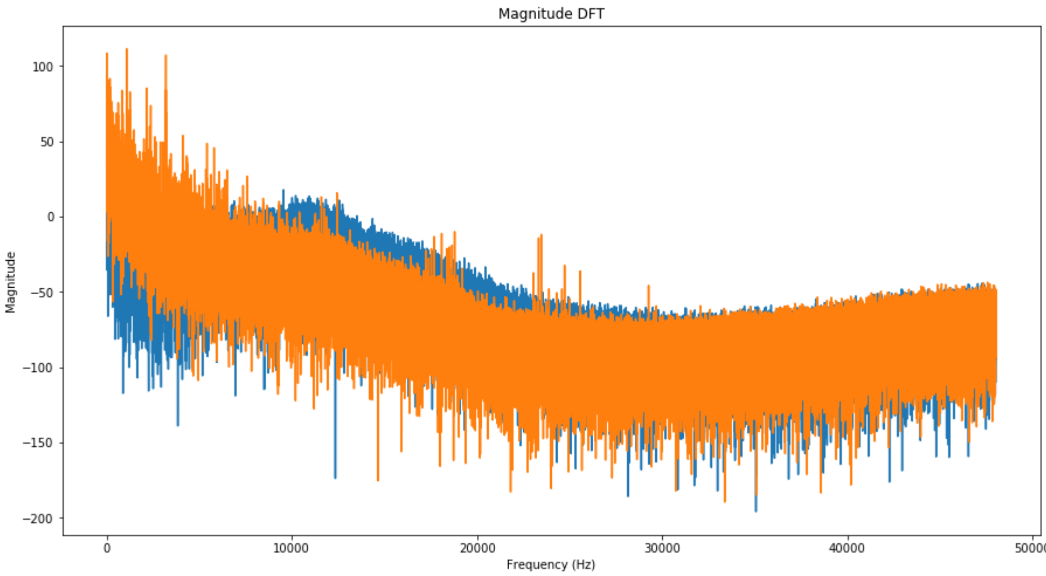


Figure 7. Audio frequency response of concrete mixing

As the audio data is not linked to other kinds of data, such as a concrete recipe or time-lapse of mixing events, mixing cases were selected manually by cutting the raw audio data into three seconds samples labeled as “mixer off”, “mixer on, not mixing” and “mixer on, mixing”. Our goal is to create an algorithm that would find additional mixing cases. Therefore, the algorithm should consist of a classification algorithm.

4.1.1 Measurement setup

The audio data was acquired using a TASCAM DR-05 hand recorder. The audio was recorded with a sampling frequency of 96 kHz, which means we can study the audio data up to 48 kHz.

The learning data is made of 2100 audio samples of 3 seconds length, including 700 of each manually picked case.

4.1.2 Pre-treatment

To reduce the total amount of data without losing high-frequency information as down-sampling would do, we generate a band-pass filter bank (see Appendix 2).

What we want to do now is to create a collection of values linked to audio samples. We call the collection of values a sound level vector. Each value corresponds to the sound level in one specific frequency band. This allows us to look at the audio data with sections of its spectrum. For example, one frequency band "looks" at what is happening in the low frequency, while another one focuses on high frequencies.

Figure 8 shows the result of the pre-treatment on all samples of the audio data. Each sound level vector has 35 values of sound level, from low frequencies to high frequencies.

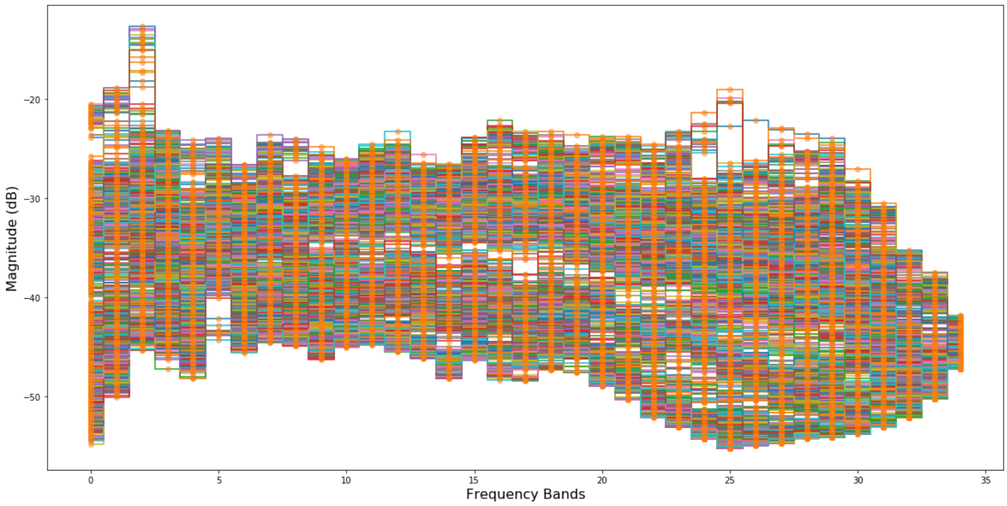


Figure 8: 2100 sound level vectors, 700 from group "mixer off", 700 for "mixer on, not mixing", 700 from "mixer on, mixing"

We can already see empty areas and a few isolated cases. It is from those sound level vectors that we will be able to compute classification vectors. Those classification vectors are very similar to sound level vectors by their shape, and each classification vector should represent a group of sound level vectors.

4.1.3 Algorithm

The algorithm is similar to the K-nearest neighbors' algorithm. The K-nearest neighbors' algorithm is a simple supervised machine learning algorithm. Provided a set of classification factors such as a classification vector, it will label an input data based on their distance from classification vectors. For more details on the K-nearest neighbors, please read this article by Onel Harrison.

Our algorithm will determine classification vectors by minimizing their distance with sound level vectors. The idea is to start with a significant amount of empty classification vectors, which will be updated after each iteration of the algorithm or removed if they don't match a required amount of sound level vectors from the learning data set.

Classification vectors are updated to minimize their distance from sound level vectors from the learning data set until two consecutive iterations provide the same classification vectors. It means that the algorithm converged, and classification vectors will not change anymore.

4.1.4 Results

The algorithm converges after 38 iterations, and we are down to 9 classification vectors, as shown on figure 9:

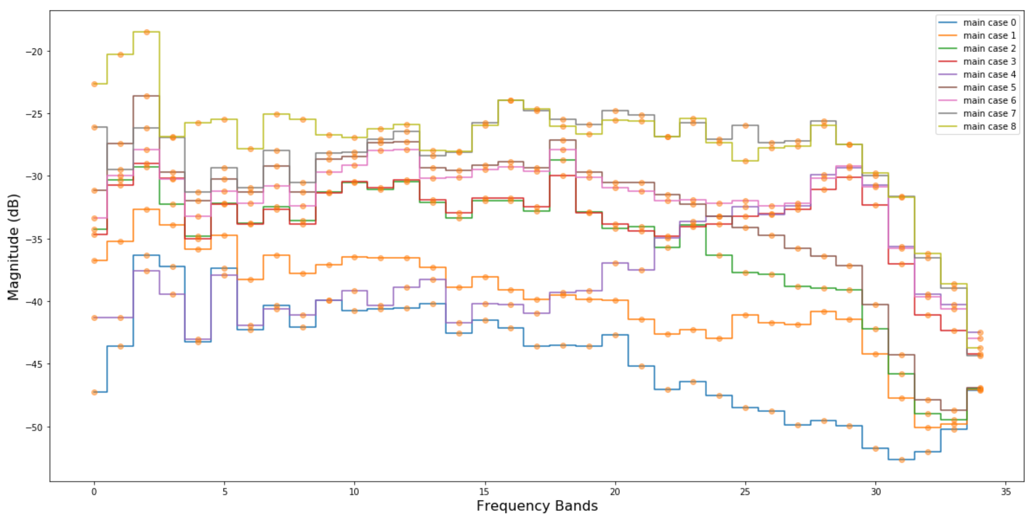


Figure 9. Resulting classification vectors

We can see that identification vectors are well separated, and while some of them seem to follow the same behavior in some frequency areas, they do show different behaviors eventually.

The repartition is unbalanced, however. They are not associated with the same amount of sound level vectors. This can be explained as not all the events during the mixing process have the same length or the same amount of occurrences.

For example, the first classification vector, labeled main case 0 on figure 9, is the lowest sound level classification vector overall, and matches audio files where the mixer is off, so it is quite understandable that it matches over 600 audio files.

If we associate the audio data with data considering the quality of the concrete, it would be possible to determine an optimal sound response from the mixer and therefore detect irregularities early in the mixing process.

Figure 10 is showing all 2100 energy vectors, for two frequency bands, one color for each mixing case or group. We can see here that some frequency bands can show good results for some groups. For instance, the purple group seems very well separated from other groups considering those two frequencies.

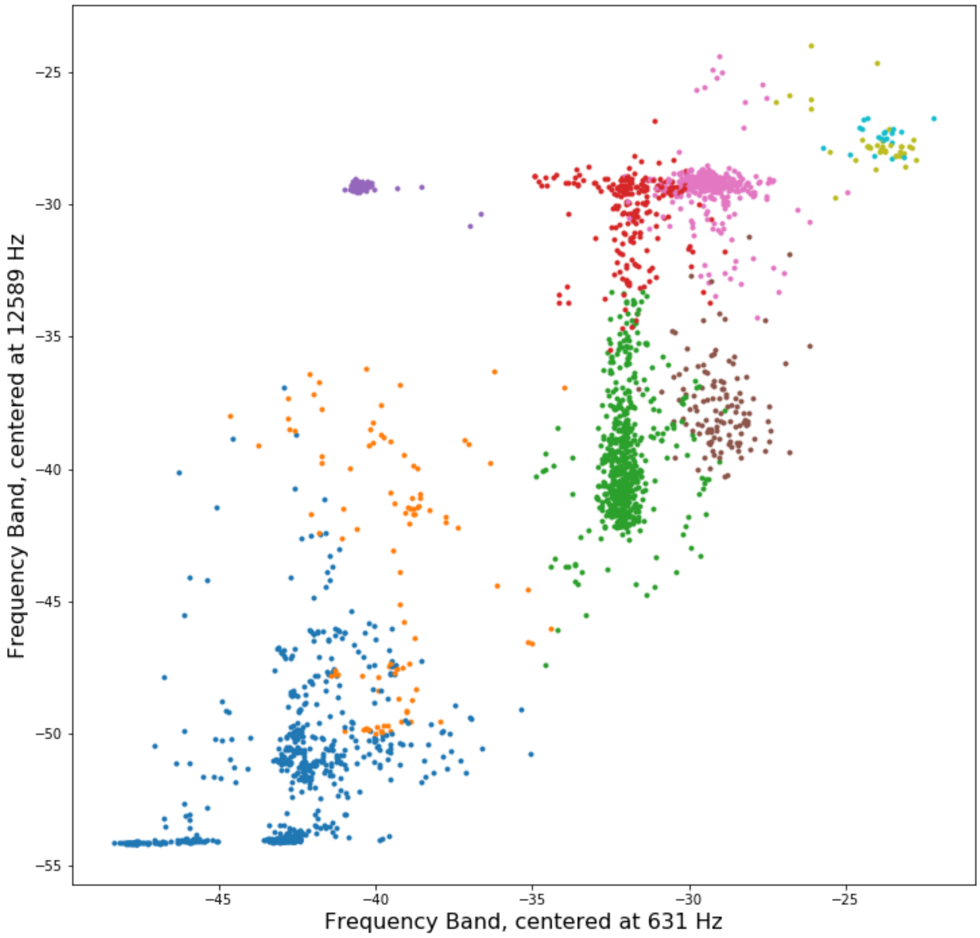


Figure 10. Example with two frequency bands

4.2 Power Calibration with machine learning

The workability is an essential quality parameter of ready-mix concrete. It is the property of freshly mixed concrete which determines the ease and homogeneity with which it can be mixed, placed, consolidated and finished. One of the factors impacting the workability is the mixing time of the concrete in the mixing machinery. The workability can be estimated by the power usage and mixing time of the electrical motor of the concrete mixer. In general, the motor draws less power for high workability concrete and more power for low workability concrete.

For every concrete type and workability class, the concrete producer has a target power level, which is used as a benchmark to obtain a certain level of workability while mixing the concrete in the mixer. The target power value is calibrated to address any changes in the machine, materials, or external factors. The calibration takes place by making batches of concrete and then performing slump tests in the concrete testing laboratory to analyze the workability of samples. If the laboratory tests indicate a need for calibrating target power level, they will then be calibrated based on the differences in the target workability and tested workability. This manual testing and calibration process can be prone to human errors, and therefore automating this process can help in reducing the time and error in the measurements. Hence, in this part, the objective was to analyze the data to detect if calibration of the target power value is required, and by what value should the calibration potentially be performed. Developing the automated calibration solution itself, was out of the scope of this research.

Workability is represented by a numerical value in the data. In the data that we used, the interpretation of these numerical values to describe workability is inverse compared to the current standards due to the way the older automation system that was used in the plant reported these values. Hence, the higher value assigned to represent workability is referred to as concrete having low workability and lower values represents higher workability.

4.2.1 Method

To understand the calibration process and its requirement, we made use of two data sources, one from the concrete plant control system and the other from the concrete testing results from the laboratory. The data from the concrete plant control system holds the information related to the concrete and the mixing process as described in Table 4. Their corresponding laboratory results are obtained from the data containing the concrete testing results, which has the information, as shown in Table 5. In this analysis, we mainly focused on exploratory data analysis from the two data sources, the concrete plant control system, and the laboratory measurements as the initial process with the aim of understanding the effect of different variables on the power calibration process.

The concretes in the data are categorized into different groups, referred to as curves in the data. There are six different concrete groups in the data, which are shown in Table 6. However, we only present the analysis results on Curve 3 concretes because in the data we had available for our research, there were very few data points available for other groups.

Table 6. Concrete Groups

Curve	Concrete Description
1	Floor concrete
2	Air-entrained concrete
3	Watertight concrete
4	Very fluid concrete
5	Type of concrete with no strength class
6	Special frost resistant concrete

4.2.2 Target and Measured Power Value

The target power value and measured power value of the concrete mixer indicate correlation with each other, as shown in figure 11. There is a moderately strong correlation (Pearson correlation) of 0.546. We did not have data available from a newly calibrated concrete mixer, but from the data, it looks likely that the equipment could benefit of calibration as their measured power value was often differentiating highly from the target power value.

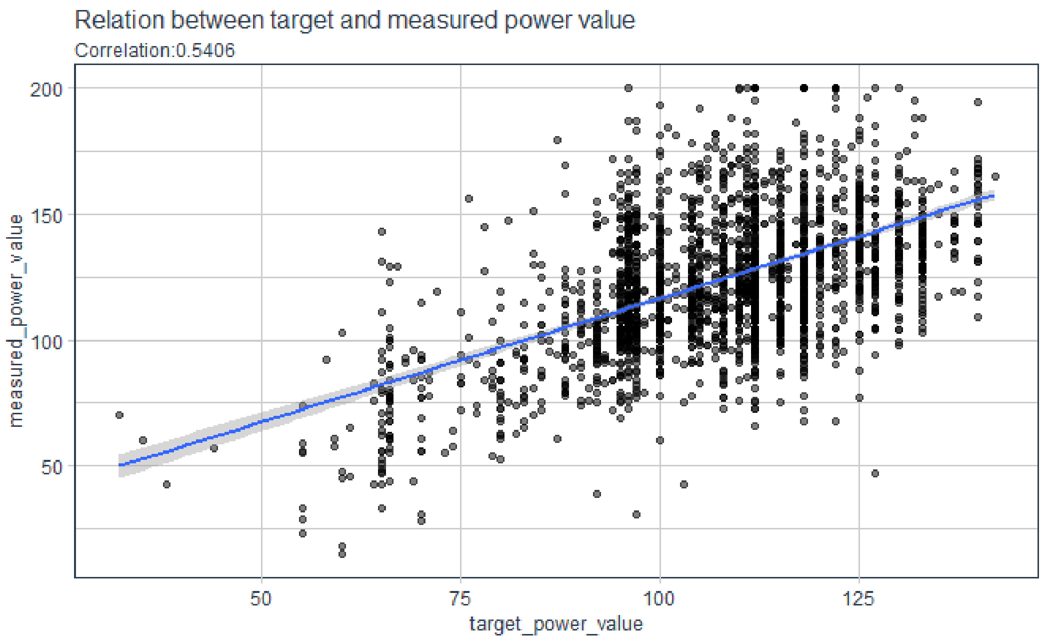


Figure 11. Relation between target and measured power value

In addition to most of the batches having differences in measured and target power value, most of the cases show that the measured power value is higher than the target power value as shown in figure 12. The reason for the increase in the power value could be due to the condition of the mixing machine. However, in our data for this analysis, we do not have any information about the condition of the machine, and hence any relation with it could not be analyzed.

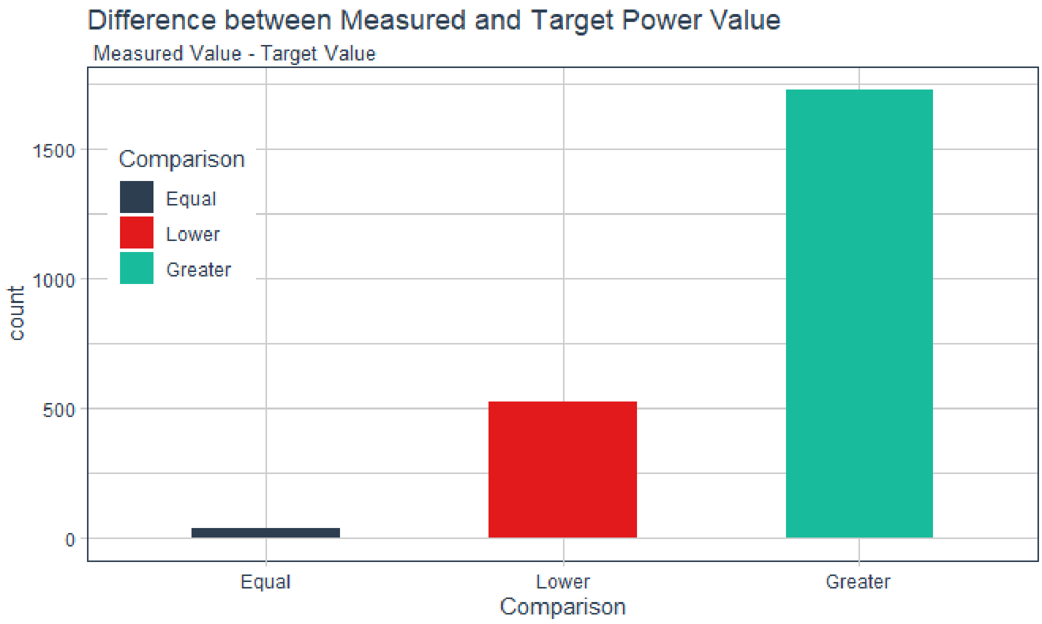


Figure 12. Difference between Measured and Target Power value

The range of power difference for Curve 3 concretes is shown in figure 13. From the histogram, we can see that most of the concretes in Curve 3 have a power difference of between -10 to 40. In addition, there are a high number of concretes that have a power difference between 5 and 25. Overall the average absolute power difference is 22.12.

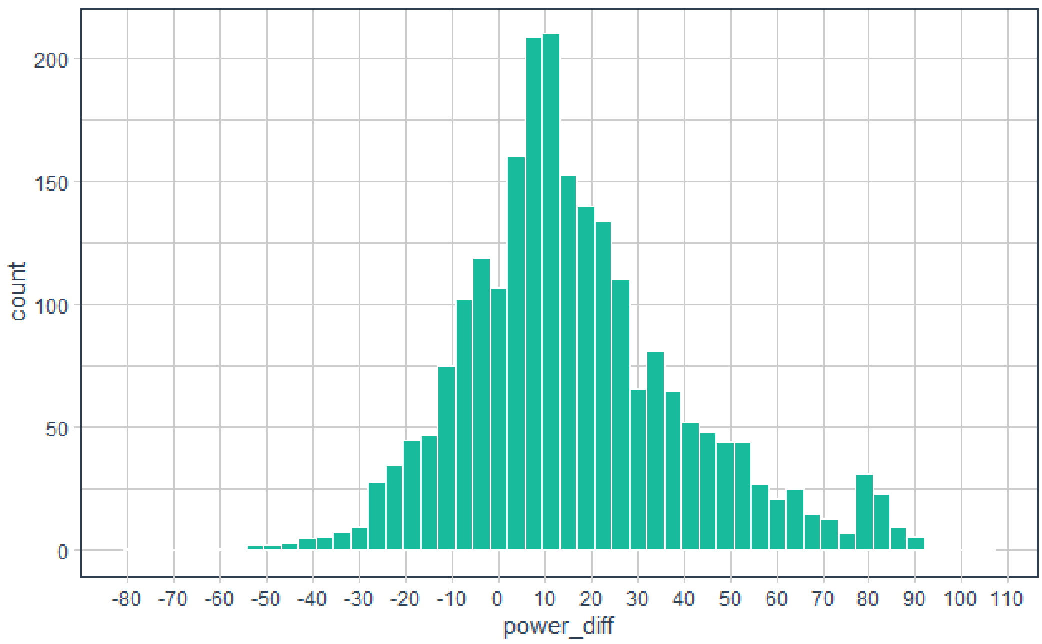


Figure 13. Power value difference for Curve 3 concretes

4.2.3 Power value and workability

In general, the higher the workability, the less power is required for mixing the concrete. As we mentioned earlier, the representation of numeric values to define workability is inverse in our data because of the older control system the production facility was using. Therefore, going by this representation it is evident from the data as shown in figure 14, that low workability concretes that are represented by high numbers require high power and high workability concretes that are represented by low numbers require less power.

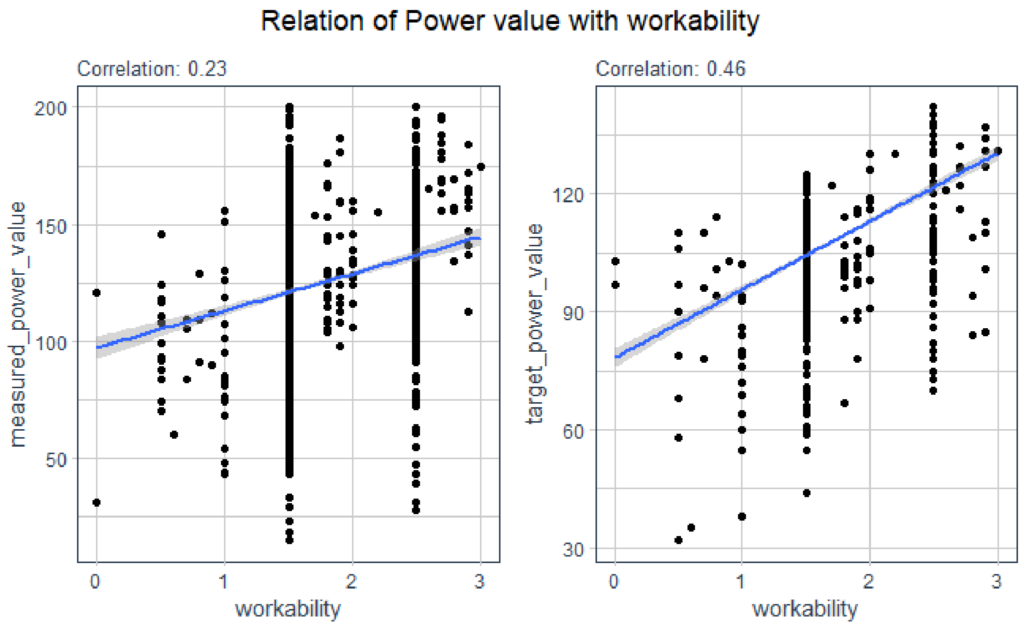


Figure 14. Relation of power values with workability.

4.2.3.1 Slump Test

A slump test is performed in the laboratory to check the workability of the concrete produced. The fresh concrete produced in the concrete plant is taken to the lab, and the workability is tested manually with a special slump cone. The slump test gives the result as a measurement value in millimeters, based on which the workability of the concrete is verified. In general, these values are higher for higher workability concretes and low for lower workability concretes.

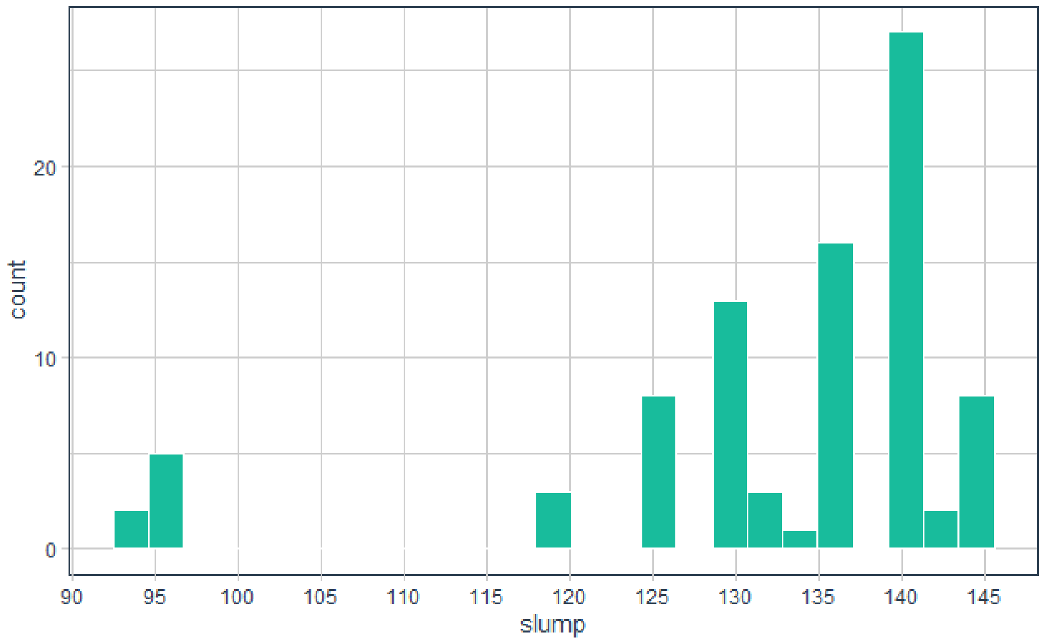


Figure 15. *Slump Test Distribution for S3 class*

In figure 15, we can see the slump test distribution of the concretes in the workability class S3. Again, here due to low amount of data for other classes we only present the result for S3 class. We see that the slump is distributed mostly between 130 to 140 mm. The high slump test is expected as S3 class corresponds to higher workability. As seen from the distribution, a higher number of concretes have a slump value of 140 mm. The mean slum value is observed at 132 mm, where minimum value is 94 mm and maximum is 145 mm. Also, very few concretes have a comparatively low slump value between 94 mm to 97 mm.

In figure 16 the histogram of the workability difference (required workability - lab workability) from the laboratory testing is presented for Curve 3 concretes. The difference in workability is presented for the cases when the lab and the required workabilities are not matching. In most of the cases, the difference is 0.5, that states that the laboratory tested workability was less than the required workability.

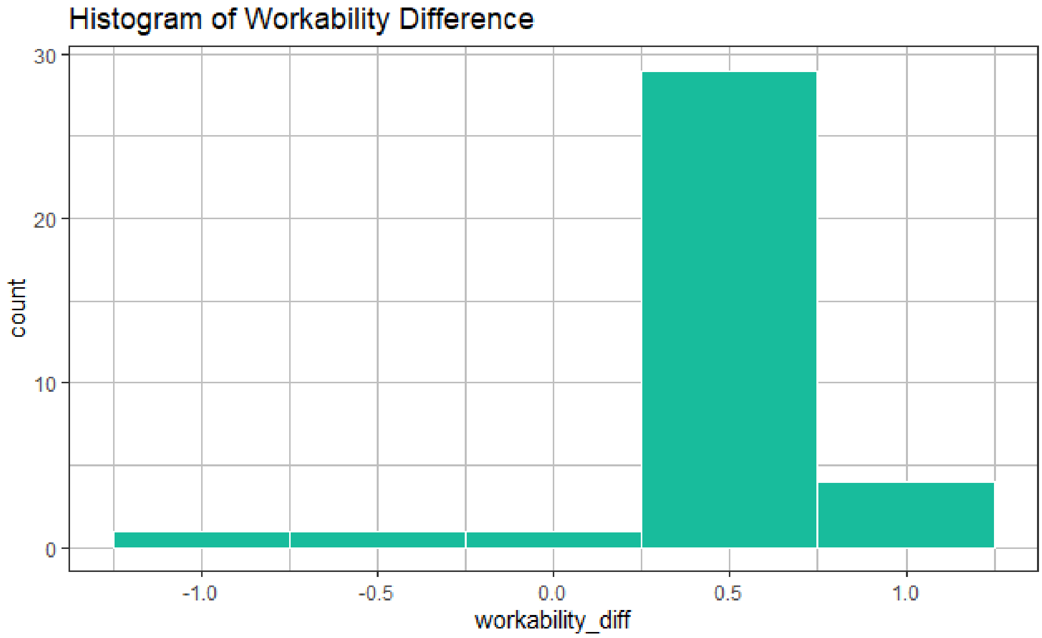


Figure 16. Comparison of lab workability to required workability.

4.3 Discussion

In the analysis with the audio data, the algorithm can identify nine mixing cases, including events occurring less than others. However, it is forcing identification vectors to match all audio data, regardless if some are unique such as someone talking next to the microphone, heavy object falling, etc. One thing to do would be to implement a maximal distance beyond which an audio file would not be associated with any classification vectors and be treated as an error.

One big question is also the fidelity. It is possible that classification vectors are space specific. While it is possible to calibrate microphones and vibration sensors, the shape of a concrete production facility can greatly influence the frequency spectrum of the recorded audio. It might be that a new set of classification vectors should be computed for each installation. To find this out, additional research needs to be made.

It is also possible that the room response of factories are slowly changing due to the dust accumulation, objects changing places and so on. If that is the case, we should think of a proper way to automatically update the identification vectors.

The analysis for power consumption was performed with the data from Curve 3 concrete groups. The results show that in most of the cases there were differences in the target and measured power values resulting in the calibration of the power. Most of the cases required higher power value compared to the target power. Due to the limitation of the amount of data, we were not able to make good use of machine learning techniques for studying the calibration process of power values, which we plan to overcome with more data collection in a subsequent research project.

The calibration of power levels of mixing machinery depends on the condition of the mixing machinery along with the concrete types and external factors. However, in the analysis of the calibration, the data did not have any information on the condition of the machine. Hence, in the future, information on the mixing machine can be combined for better understanding of the calibration process.

For combining the data sources in the next phase, we plan to record the audio data and the power data of the concrete mixer at the same time to synchronize the data for the analysis. With the data sources being synchronized, we could see if some frequency bands have any meaningful relation to the testing results from the laboratory. Furthermore, since we had very less data for all the concrete groups, we could not perform an extended study on all the concrete groups and only focused on Curve 3 concrete type. The analysis in the next phase could be performed, focusing on comparison between the concrete groups to identify any significant differences in the results. In addition, in the next phase, with more data, we aim at applying machine learning techniques to start and test the automation system with predictive modeling.

5 Conclusion

In this research, we have studied which data collection opportunities there are in ready-mix concrete production that could be used as the basis for data analytics and machine learning-based quality assurance. Of the data we had in use, we analyzed the audio data of the concrete mixing machine and the calibration of power values of mixing machinery as well as concrete workability values from a concrete testing laboratory. As described in the results, the analysis was able to identify some important patterns in the data with the help of data analytics and machine learning.

From the audio data, we saw that without any information on the data, it is possible to extract several classes of sound behavior. However, both the analyses were performed separately, and there was no connection established in the data sources to combine the results. Hence, the focus of the next phase of the analysis would be to create a relationship between the two data sources and analyze them as a single entity. In addition to combining the analysis, we aim at collecting more data, especially for the power calibration part that would help in broadening the analysis with machine learning.

To increase the potential of data-based quality control in managing the quality of concrete in production, based on our research, there is much need for more open data sources in the industry. Currently the control systems of concrete production have access to the process control values, but this useful information is not straightforwardly accessible to data-analytics developers. Machine learning algorithms also need feedback from the laboratory tests, to be able to qualify how well the production has succeeded in producing quality concrete in different production conditions. Because concrete is based on natural materials, which also have quality variations, we believe the algorithms need feedback from the raw material streams as well. The more data the algorithms have access to, the better possibilities the machine learning algorithms must predict quality issues taking place in concrete production.

References

Haavasoja, Taisto: Optical Moisture Measurement in Concrete Aggregates. Nordic Research PUBLICATION NO44 (2011): 1-10.

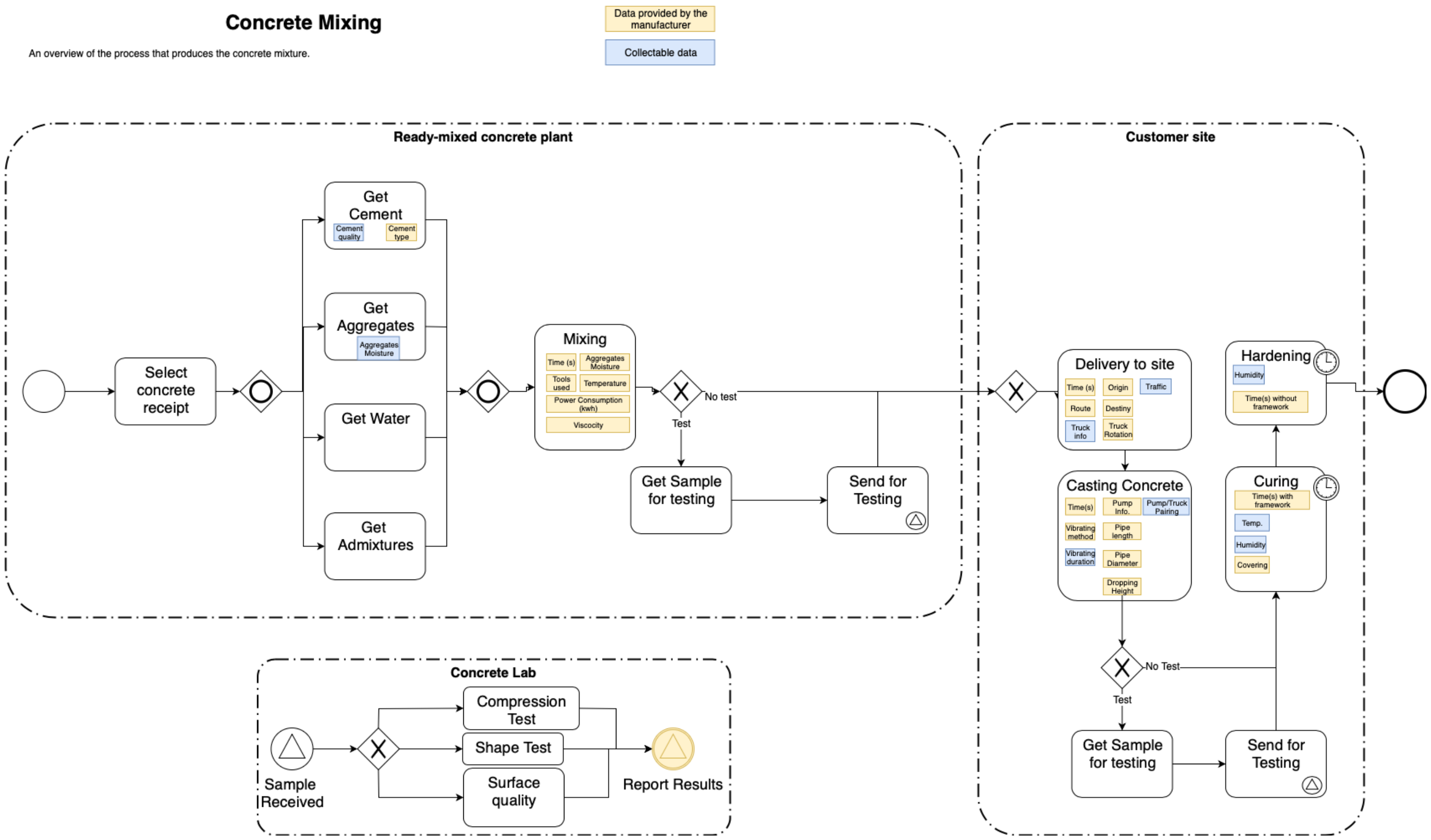
Finnish Weather data

Third-octave bands

K-nearest neighbors algorithm

Distance equations

Ready-mix concrete process



Band-pass filter bank

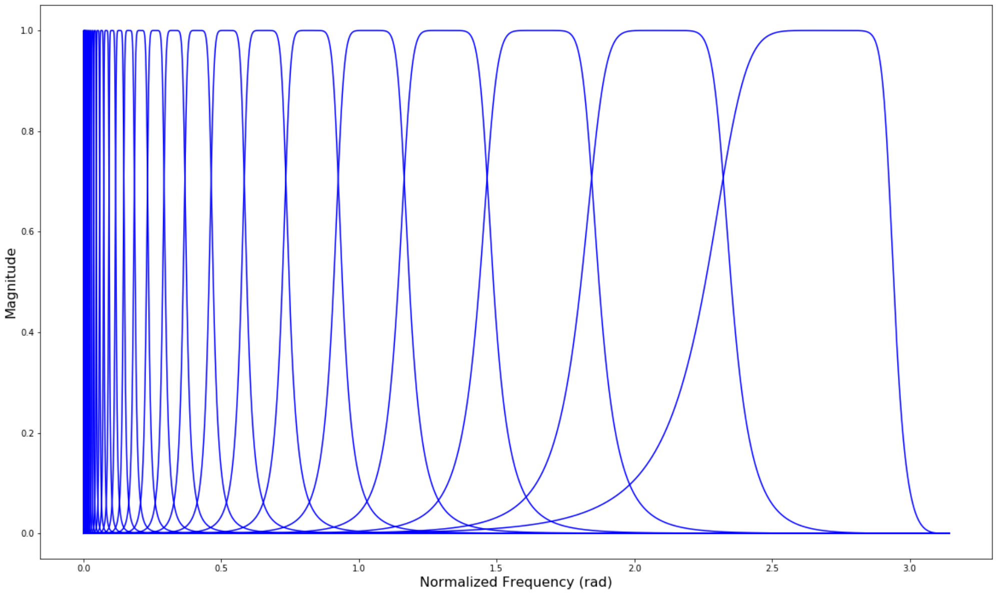


Figure: Band-Pass Filter Bank

This filter bank contains 35 bands, they are third octave spaced (link to Specification for octave-band and fractional-octave-band analog and digital filters)

Central frequencies for bands are going from around 16 Hz up to around 40 kHz.

Each filter allows us to focus on one specific part of the sample frequency spectrum.

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