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Dimensional Decision Support System

Developing A Decision Support System For 3D Concrete Printing

Colophon

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Preface

Before you lies the fruit of my master graduation project about “developing a Decision Support System for 3D concrete printing”. It has been worked through in Eindhoven University of Technology, with the collaboration of Construction Management and Engineering (CME) and Structural Design (SD) department. This research and development project is conducted within the multidisciplinary 3D Concrete Printing (3DCP) team.

I wish to express my appreciations to dr. Dipl.-Ing. Jakob Beetz, my supervisor in CME department, who inspired me constantly during the project in interesting meetings we had, guidance and feedbacks on the developments of the project. It is a pleasure to be able to benefit from his point of view and experiences during the project.

I wish to express my gratitude to prof.dr.ir. Theo Salet, my supervisor from the chair of Concrete Structures in SD department, who realised the dream of concrete printing with his guidance on 3DCP team. He has been always giving me great motivation, inspiration, and new ideas not only in the context of the project but also beyond it. It is an honour for me to be able to learn and work closely with Prof. Salet, which resulted in a great flow of enthusiasm and commitment to me and my project.

I would like to thank Zeeshan Yunes Ahmed, my supervisor and doctoral candidate of SD and one of the Ph.D. students leading graduate students in 3DCP team. His critical point of view in addition to practical inputs to the project was a valuable opportunity for me and the project.

I would like to appreciate valuable contributions of Rob Wolfs doctoral candidate of SD and another leader of 3DCP graduation atelier. I would also like to thank 3DCP team, because of all interesting discussions we had during meetings.

I would like to thank Kiana, my girlfriend for her great supports which made this hard working month beautiful and memorable. Also lots of thanks to my friend, Kiarash, who had valuable impacts on my work. At the end, I would like to thank my parents and my sisters that even though they are far away from me, they have always had a strong presence in my life and a high influence on my work.

I wish readers enjoy reading this thesis, find it inspiring and helpful for further developments in the field of 3D concrete printing.

Sahand Asgarpour

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Summary

Efficiency, sustainability, and safety are the drivers for the construction industry to seek automation, where has been adopted for a long time in other industries. Additive manufacturing and specifically 3D concrete printing have been studied in the last two decades, showing numerous potentials in reducing waste, increasing the time of construction, increasing precision in construction, reducing CO_2 emission, while increasing labour safety. Mass customization is another motivation brought by the opportunity of 3D printing, which results in realising structures without extensive and expensive formworks. Concrete as a most used material in the construction industry is a reliable material, is focused to be integrated into 3D printing. It is the final aim to make two stages of design and construction closer, reaching the ability to be able to print the designed structure.

3D concrete printing, however, is a complex process, which numerous parameters are interacting, and defining the final quality and properties. Material properties, design parameters, process parameters and manufacturing constraints are interacting with each other and defining the characteristics of the final product. Process parameters are classified in the category, about which there is the least knowledge available, while having an influential role in bridging design and production phase, realizing the as-planned design. *Process parameters* like Pint speed, Nozzle type, and Pump pressure are interacting with each other and have a big influence on *process targets* such as dimensional accuracy and mechanical properties of the final product.

Print speed, Pump degree, and Nozzle distance have been selected as process parameters which influence deformation and cross section of a printed layer. Layer cross section and deformations affect stability, functionality and aesthetics of the final product, while it is most likely not to meet dimensional requirements, defined in the design phase. There are more factors may affecting dimensional accuracy, but the mentioned parameters are those which can be modified for the printing process, hence they are the first set of parameters to be investigated.

In order to investigate the effect of mentioned parameters, the possibility to change the parameters in different levels played an influential role in selecting the process parameter. Due to the scope of the research and development graduation project, three mentioned parameters are selected. Further developments can look at the effects of other parameters investigated in this research.

The main objective of this research and development project is to *improve the process and product of 3D concrete printing* by

I. Depicting a *clear understanding* of the interrelated process parameters;
II. Develop a Decision Support System to provide the possibility of *conscious leverage* of process parameters.

As a result, the following steps has been taken by employing RSM a type of experimental design to reach the objective of this project.

I. Generate efficient number of concrete printed data as means of interrelation studies,

II. Distinguish influential process parameters according to defined process targets,
III. Specify level of influence of process parameters,
IV. Establishing precise relationship among process parameters and targets (empirical model).
V. Visualize results for a better and clearer understanding,
VI. Develop dimensional Decision Support System

Derived models relating process parameters to dimensions of a printed layer, then are used in a framework developed to support users' decisions in making process-related decisions. dimensional Decision Support System (dDSS) is developed to bridge design and production stage by tracking decisions virtually and visually.

As a result, proper process parameters to reach specific dimensional performances can be selected, without trial and error experimentations. More importantly, understanding the process of concrete printing has been increased. By conscious leveraging of process setting, dimensional requirements of a printed layer are met and quality of the product is ensured to be satisfactory.

Moreover, collaborations between two technical and managerial level can be improved and facilitated. Because from one level, the interactions between decisions and consequences are translatable to another level, due to their high interrelations. So better understanding of the dimensional requirements of 3D concrete printing will be gained.

dDSS and in general proposed methodology and framework for experimentation, analysis, and Decision Support System, improve concrete printing process, bridging design and production stage, reducing efforts of post processing and finally improve the final product quality.

This research and development graduation project is the first effort to develop a Decision Support System for 3Dconcrete printing and seeks to establish an approach of studying underlying relationships and support process-related decisions.

Abstract

3D concrete printing as an additive manufacturing method can bring a revolution to the construction industry by increasing sustainability, efficiency, and safety. Concrete printing is a complex process influenced by numerous parameters from different disciplines and stages of design and construction. Among them, process parameters have a great role in defining the final product quality, and there are least known about their interrelations and effect on process and product quality criteria. A printed layer dimensional performance is chosen to be studied in order to increase stability, precision and compliant with requirements, in addition, to proposing a methodology to investigate the effect of process parameters on final product quality of concrete printing process. The design of Experiment methodology is employed to derive empirical models and be used as the core of developed Decision Support Systems. dimensional Decision Support System (dDSS) is developed to assists decision makers' decision regarding process parameters to reach defined dimensional performance, and improve concrete printing g process and product. Decisions in both managerial and technical level can benefit from dDSS, increase the traceability of concrete printing process by technical decision makers and also managers.

Keywords: *3D concrete printing, Process parameter, Decision Support Systems, Design of experiment, dimensional performance, dDSS*

1. Reading guide

Research has been categorised in 5 main steps as it can be seen in the figure below.

The first step is taken in chapter 2 with introduction and elaboration on the main motivation of conducting research. Moreover, the overall research problem is defined, analysed and main research objectives and questions are described.

Chapter 3 is glossary explaining used terminology related to the context of the project.

Then, In the Investigation phase with literature review in chapter 4, main elements of the research are thoroughly investigated, which creates an extensive ground to narrow down the research questions and tackle defined problem in this research and development project.

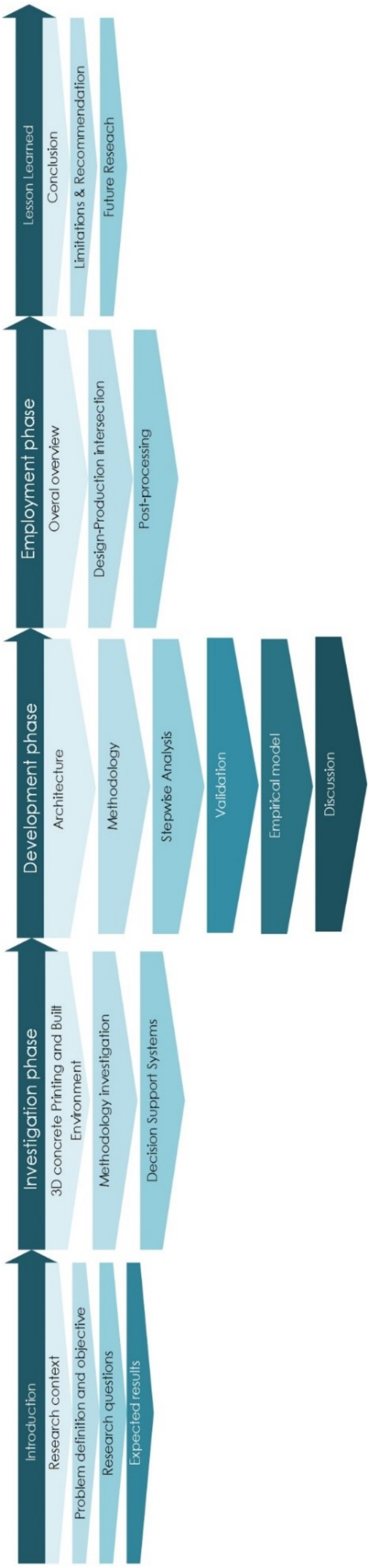
Development phase described in chapter 5 defines the detailed technical and managerial issues in the current phase of 3D concrete printing project, elaborates on methodology, employ data and analyse data sets, and reach to the most precise outcomes by validation. Finally, the Decision Support System is developed.

Employment phase explained in chapter 6 elaborates on the applications of the developed Decision Support System in the context and process of 3D concrete printing.

And finally in the step of Lessons Learned elaborated in chapter 7, research questions are answered, conclusions are derived and recommendations for improvement and also further research are suggested.

The graph below shows the research outline for this research and development project.

Figure 1: Research outline



2. Introduction

In this chapter, first, the research context will be discussed. In the problem definition, then the main research question will be defined after analysing the research problem. And eventually, research sub-questions are recognized to reply on the main research questions. This chapter is closed by presenting the expected results of the research.

2.1. Research context: Toward an automated industry

The construction industry is known as a more or less conservative industry to implement innovative technologies. It is partly because of cost-benefit considerations, inherent complexities and numerous steps and involved stakeholders. But at the same time, construction industry faces several challenges, such as inefficient processes, health threats against labours and complex, time-consuming collaboration among numerous players.

Hence there is a great need to pave the path of the industry toward more efficient, traceable and safer performance. Hence, automated manufacturing is an inevitable approach to reduces labours, construction costs, and time, increases efficiency, safety and freedom in design (S. Lim et al., 2012).

Within automated manufacturing approaches, there are Subtractive and Additive methods. The first approach starts off with a big block of material (wood, metal, or anything else), and a machine tool shaves off pieces to create what you want. Additive Manufacturing (AM) techniques like 3D printing instead, add material layer-wise to create something (Horvath & Cameron, 2015).

One of the major advantages of the latter case is the absolute reduction of waste in the construction process. Moreover, the method brings the opportunity to realise non-repetitive complex shapes and designs which conventional construction methods are unable to offer. Bridging design and construction in large scale is the essence of the approach.

3D printing which brought in the 90s is a term identified more with the Consumer Goods and home appliances while AM term describes the method and refers to industry applications (Vallés, 2014). Nowadays 3D printing term is also used in its different applications in different industries which vary from healthcare to food industry, automotive to ornamental accessories. Another application of the 3D printers, in general, is Prototyping, as it visualises the design, while production time and cost can be reduced.

So, there is a wide range of materials used in 3D printing to and this trend is attracting more diverse materials to enter new industries.

The construction industry is adopting this technology to profit from the advantages to lead the industry toward a smarter, faster and more efficient environment. Nowadays, enthusiastic start-ups, research institutes, and universities are investigating different material with various type of 3D printers, from glass to steel, from bioplastics to concrete.

3D printing is a wise choice to link the most used construction material, concrete in the industry with the state-of-the-art technology of 3D printing, which eliminates the obstacles of conventional methods and enable the designer to think free about the design and more efficient use of material, by distributing it where is needed.

As it can be witnessed that advantages of 3D printing in the construction industry bring a great necessity to dig into the field and face the challenges of the new field.

Hence, *the aim of this research and development graduation project is to develop the implementation of 3D concrete printing at the current stage, and more importantly, propose a methodology for constant improvement of the process and clarifying underlying relationships between its various elements .*

2.2. Problem definition and objective

3D Concrete printing process a complex process, in which numerous parameters and variables are interacting with each other on results of the process. These different parameters are within different categories:

I. Material characteristics,
II. Structural and Architectural design and analysis
III. Process parameters

3D model or shape, characteristics of the printable material (concrete), loads and boundary conditions, and decisions regarding different printing strategies influence each other in the process of 3D concrete printing. However, the interrelations are unknown at this stage.

Optimum suggestions among various settings within the decision variables in the process lead us to deal with the changing and uncertain environment of 3D concrete printing. As a result, lots of time and energy are saved by knowing possible shapes regarding the specific printing strategies and according to specific characteristics of the concrete compositions, for instance.

While mostly the interactions between the mentioned factors are investigated by time and energy consuming experiments, limited to a specific case, while one variable is varied and investigated at the time. For another design or element, even if the same settings are going to be used, again resources are dedicated to finding the proper setting among variables(like printing speed and pumping degree).

As a result, the aim is to develop a *Decision Support System* to leverage interconnected parameters, those which are related to printing process and strategy. Such a leverage brings up an opportunity in the changing environment of 3D printer implementation which defines objectives of:

I. DEPICTING A CLEAR UNDERSTANDING IN 3D CONCRETE PRINTING PROCESS, AMONG THE INTERRELATED PROCESS PARAMETERS;

II. DEVELOP A DECISION SUPPORT SYSTEM TO PROVIDE THE POSSIBILITY OF CONSCIOUS LEVERAGE OF PROCESS PARAMETERS.

As a result, tedious trial-error efforts are no longer necessary find the required, proper setting during the 3D concrete printing process. Thus, both process and product of 3D concrete printing will be improved, by supporting the designer in process-related decisions.

The main objective of the research:

PRODUCT AND PROCESS IMPROVEMENT OF 3D CONCRETE PRINTING.

2.3. Research question(s)

In order to reach the main objective and motivation of the research and development graduation project mentioned above, it is important to investigate:

I. HOW CAN CONCRETE PRINTING PROCESS BE IMPROVED IN THE MANNER WHICH ENHANCE THE FINAL PRODUCT OF THE PROCESS?

In the broader sense, 3D concrete printer should be seen as a process which intersects different stages of *construction and design*. So parameters in one stage affect decisions in another, creating a loop which integrates decisions in both stages. By improving the process in a way that decisions and their consequences can be predicted, an intermediator stage is shaped which can clarify decisions in two other stages of design and construction (concrete printing the product).

In order to reach the aim of developing a Decision Support System, design and construction should be linked, so that a concurrent flow between these two steps can be constructed. So here raises the second research question:

II. HOW IS IT POSSIBLE TO BRIDGE THE DESIGN AND PRODUCTION PHASE IN 3D CONCRETE PRINTING PROCESS?

Here arise sub-questions, which are necessary to be answered to reach the answer of the above-mentioned question:

i. Which levels of decisions in design and production phase would be necessary at the current stage, to be focused?
ii. What type of tool or system should be developed to act as the intermediator between design and construction?
iii. What are the components of the system?
iv. Who are the target groups of such Decision Support System?

Moreover, in order to be able to improve the process of concrete printing, production process should be investigated and important relations between important parameters should be understood. Hence the third research question is:

III. HOW IS IT POSSIBLE TO ESTABLISH A BETTER UNDERSTANDING OVER THE 3D CONCRETE PRINTING PROCESS?

It is important to elaborate on the following sub-questions to tackle the research question mentioned above:

i. What are key process decisions and targets in 3D concrete printing?
ii. How is it possible to identify the significant parameters regarding a specific process target?
iii. What are the criteria for a method to be used in the system, which lead to efficient, understandable and explainable predictions of process decisions and targets?

2.4. Expected results

Results of this research project will cover two expectations:

First, in order to increase the awareness of 3D concrete printing process, there will be derived relationships between key variables and performance criteria of 3D concrete printing process. In this relationships, the mutual effect of design and production (construction) will be investigated.

Second expectation will be fulfilled by establishing an understanding among, process parameters and targets. As a result, decision makers, researchers and process operators will be aware of trade-offs for process-related decisions and their consequences are traced virtually.

3. Glossary

3D Concrete Printing (3DCP)

Additive Manufacturing (AM)

Adequacy check

Analysis of Variance (ANOVA)

Artificial Neural Networks (AAN)

Bayesian Belief Networks (BBN)

Blocking

Central Composite Design (CCD)

Circumscribed Central Composite (CCC)

Coding

Cuboidal Region

Database

Data pre-processing

Decision Support System (DSS)

Design of experiment

Design region

Dimensional performance of a printed layer

Face centred Central Composite (CCF)

First order approximation

Frame-Based Systems (FBS)

Full Factorial design (FF)

Fuzzy Logic (FL)

Genetic Algorithms (GA)

Gray Rational Analysis (GRA)

Inscribed Central Composite (CCI)

Layer dimension : Height, Top width, Bottom width

Mass customization

Model fitting

Model Management System

Model-based Decision Support System

NdPr model

Optimum response

Problem Processing System (PPS)

Process parameters

Process target

PuPr model

Randomizing

Response Surface Methodology (RSM)

Rotatability

Rule-Based Systems (RBS)

Second order approximation

Sequential procedure

Taguchi method

User Interface (UI)

4. Literature study

Literature study is the investigation phase mentioned in research outline of chapter 1. The aim of the literature study is to elaborate on 3D concrete printing process and identifying key parameters affecting the product. As a result, a proper overview is reached to understand the interaction among parameters and their effect on characteristics of the final product.

In order to reach the main objective, literature study has been conducted to investigate the process improvement of Additive Manufacturing(AM) process, in general. Such an attempts are not numerous and there has been no research done in the field of concrete printing. So this section reviews efforts performed to improve AM in different industries. An important section in this chapter investigates important methods used to depict an understanding among parameters of unknown relationships. Finally, methods are compared and important criteria are defined to select the most suitable method for this research and development project.

After understanding 3D concrete process and elements, and investigating the methods and requirements of additive manufacturing improvement, to complete the knowledge which leads to the objectives, is studying architecture, elements and different types of Decision Support Systems(DSS). DSS is the platform, which defines the relation of key parameter in 3D concrete printing, and interacts with its user to support related decisions in the *design, printing process, and post processing*.

4.1. 3D Concrete Printing and built environment

Three-dimensional (3D) printing has been used in the different industrial sector as a manner in order to automated manufacturing process, while accelerating production and diminish waste. 3D printing makes it possible to produce various types of objects. These objects range from Tissues with blood vessels to the prototype of a new engine in an automotive company (Perkins & Skitmore, 2015). By decreasing the costs of 3D printing, such technology is finding its way to different industries. Construction is an industry, which is in need of reducing waste, increasing mass customization, decreasing the time of construction, while reduces injuries during the construction process.

3D printing brings new opportunities to concrete and cementitious material construction. The possibility to construct structures without extensive formwork is of the important advantages in terms of rate of construction, freedom of design and cost reduction, as formwork dedicates 35–60 % of the overall costs to itself (Perrot, Rangeard, & Pierre, 2015a).

Concrete Printing is an extrusion-based Additive Manufacturing (AM), using cement mortar, however, the process has been developed to retain 3-dimensional freedom and has a small resolution of deposition comparing to another large scale AM in the construction industry. It provides the possibility of a greater control of internal and external geometries(S. Lim et al., 2012).

Figure 2: TU/e 3D Concrete printer

4.1.1. 3D concrete printing process

The process is similar to other additive manufacturing processes. The general steps are:

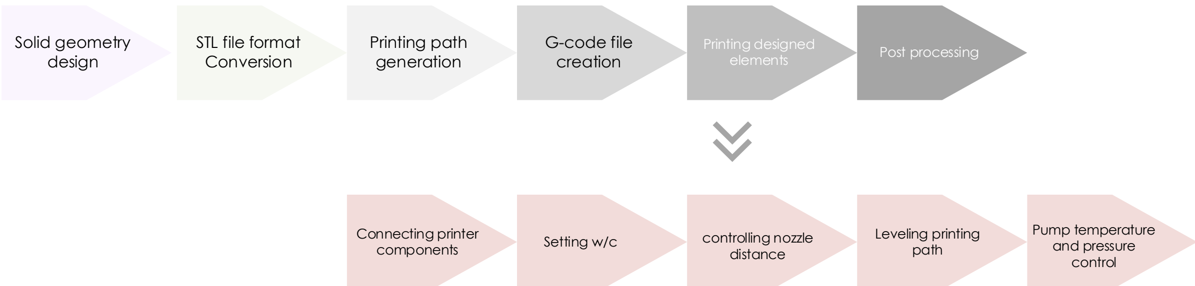


Figure 3: 3D concrete printing process

A printing element is designed as a CAD model, converted as an STL file format, sliced with the desired layer thickness, a printing tool path for every layer generated, and a G-Code file for printing created (Sungwoo Lim et al., 2011).

The finishing and post-processing of concrete printing differ because it produces the characteristic ribbed finish. This effect can also be controlled by using zero slump concrete, or leveraging process parameters to minimize the need to adjust dimensions. Such a finishing can be designed to be exploited the effect. In the case that a smooth surface is required, either the wet material is trowelled during the building process or the printed finish is ground to a smooth surface (S. Lim et al., 2012). Attaching a trowel to the nozzle can smoothen the printed layer.

In order to print the element, the printer should be assembled, by attaching different parts such as connections, hose, pump. Then, according water to cement ratio is set, normally it is set constant for different printings, to keep the characteristics of the concrete constant. This is because of the fact that the behaviour of material in the wider range of the normal w/c ratio is unknown.

Nozzle distance is the distance between printing surface and nozzle head of the printer. It is done to check the levelling of the printing path after that printing surface is levelled. During the printing process, pump temperature and pressure are constantly measured at the connection where the hose meets mixer. So that abnormal fluctuations can be traced and if needed show proper reaction.

4.1.2. 3D concrete printing key parameters

There are numerous parameters influencing printing process and the characteristics of the final product. Moreover, these parameters have interactions with each other in their influence on *process targets or performance criteria*. Key parameters are categorised as following.

Design phase parameters are those by which element are structurally or architecturally

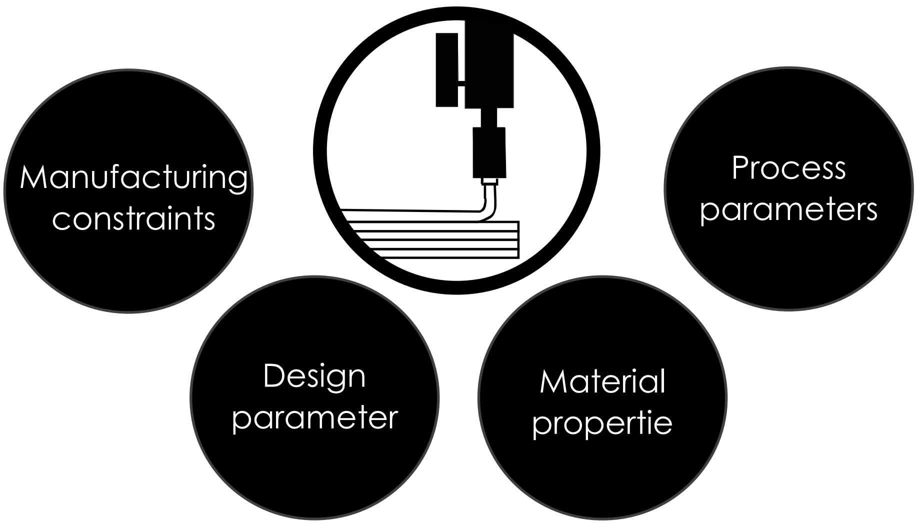


Figure 4: Process key parameters

designed, in order to response properly to the operational and constructional requirements. Imposed loads and external forces which define the design of the element are also considered in this category. Moreover, design parameters are also referred to parameters which define shape and form, material type and distribution and density and boundary conditions of the element are important parameters of the design phase.

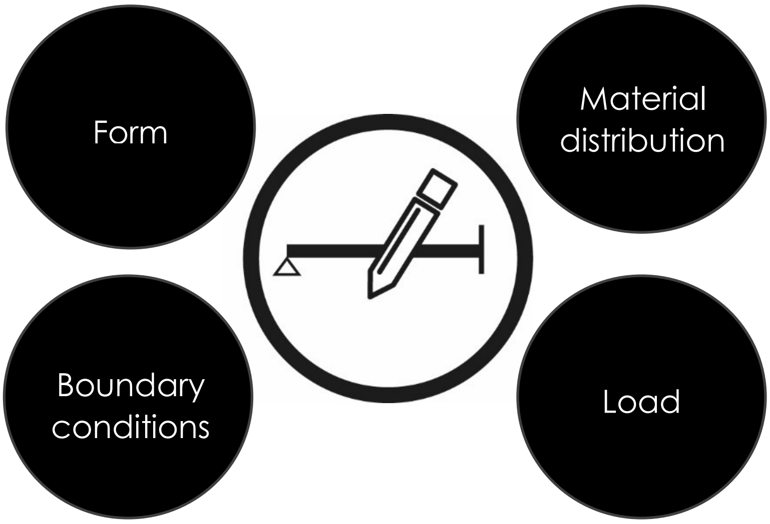


Figure 5: Design phase parameters

Manufacturing constraints are those parameters which define the printability of a design. Some of the most important ones are defined by machinery limitations, material properties, fineness of printed layer, minimum dimensions of openings, maximum overhang, performance speed of synchronised activities. The latter case has an effect on the print speed, and it decreases the speed, at a certain point such as corners, when several printer inputs change.

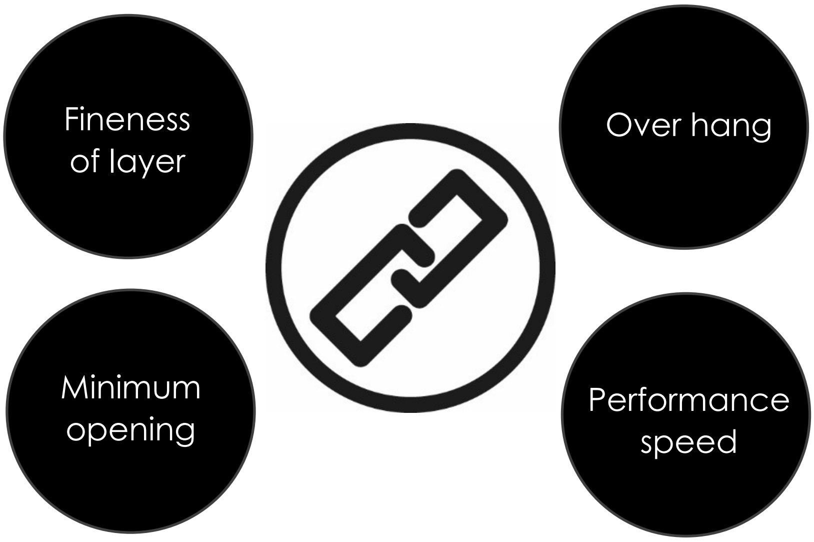


Figure 6: Manufacturing constraints

Material properties are categorized as a state, fresh and hardened properties. During 3D concrete printing process, fresh properties are the dominant factor.

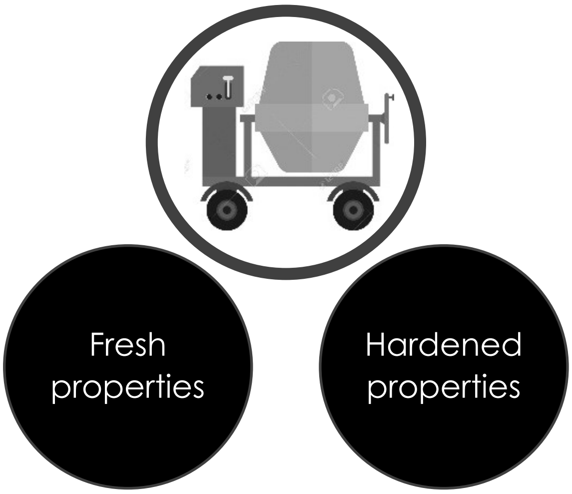


Figure 7: Material properties

In literature, fresh properties of concrete are divided into four key fresh properties (S. Lim et al., 2012) Here, state parameters which explain the basic state of printed material, is as considered as the category of fresh properties. affecting the development of hardened properties of concrete. So fresh properties of printed concrete contain the following characteristics.

I. Workability : The ease and reliability with which material is moved through the delivery system;
II. Extrudability :The ease and reliability of depositing material through a deposition device;
III. Buildability : The resistance of deposited wet material to deformation under load; and
IV. Open time : The period where the above properties are consistent within acceptable tolerances.
V. State parameters: Parameters reflecting fundamental properties of concrete, which are time dependent and required to develop the structure of the concrete in different stages.

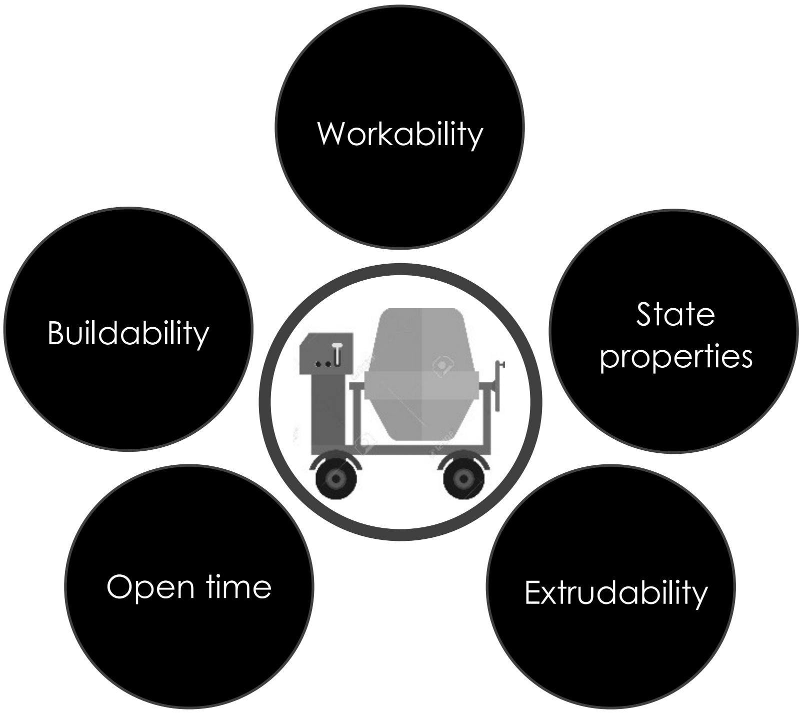


Figure 8: Fresh material properties

State parameters are concrete related parameters, which reflects properties of concrete such as temperature and moisture content in time, which form the internal reactions for cement hydration. Cement hydrates through reactions with water inside the concrete mix, produce Calcium silicate hydrate (C-S-H) C-S-H is the primary reason of concrete strength, and binding aggregates in the concrete mix, with a rock shape texture. Through initial setting, cement particles are agglomerated, forming the material in a way that it is not workable and extrudable anymore, but the links within particles can be broken by stirring the mix or material. Then the final setting starts which strong links are being made among agglomerated cement C-S-H particles and the one-way reactions are being constructed to form the solid binding material, holding aggregates together.

The total contained moisture amount within the concrete mix, as water or water vapour, is known as the *moisture content* and is indicated as a percentage of the concrete mass. It is an important parameter as provides water content required for setting and hardening process of concrete.

The maturity of concrete is a human-made state parameter defined usually by the product of time and temperature of the concrete in time. Maturity then is used to understand the strength development of concrete. Maturity is calculated by tracing variations in temperature of fresh concrete during the time. Each concrete mix has its own strength-maturity relationship, which can be used for strength estimation of the mixture after printing.

In 3D concrete printing, the placement of concrete is layer wise. Due to the discrete manner of concrete placement, state parameters of layers may vary. Such a variation affects the interaction among layer. In the other words, layers are facing each other in different states, which arise the necessity to study state properties among layers as well.

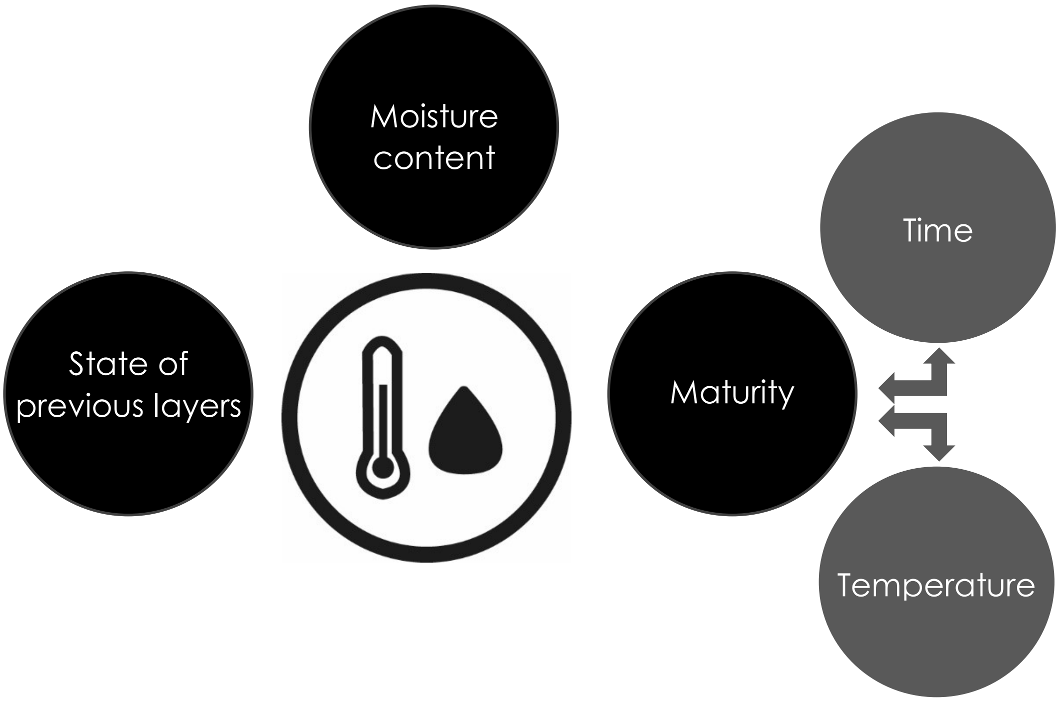


Figure 9: State properties

It is important to notice the fact that environmental condition indirectly affects state properties of concrete. Environmental parameters are those which are related to the condition in which the printing process is performed. It can be *controlled* or *uncontrolled*. Controlled environment reached by placing facilities to keep the conditions of the printing environment controlled and at desired levels. Such a facilities can be humidifiers, shelters to protect against rain (outdoor construction), heaters, and provisions for better curing of the printed elements.

The uncontrolled environment is printing conditions, which environmental parameters are changing in a manner which there is a minimum control on them, such are printing on site, in outdoor situations, or in the laboratory when there is no control over the environmental variables variations.

The most important environmental parameters are temperature and relative humidity.

In the operation phase, hardened properties of *density, compressive strength, flexural strength , tensile bond strength between layers* are dominant factors, which affect the characteristics of the printed elements (T. T. Le et al., 2012).

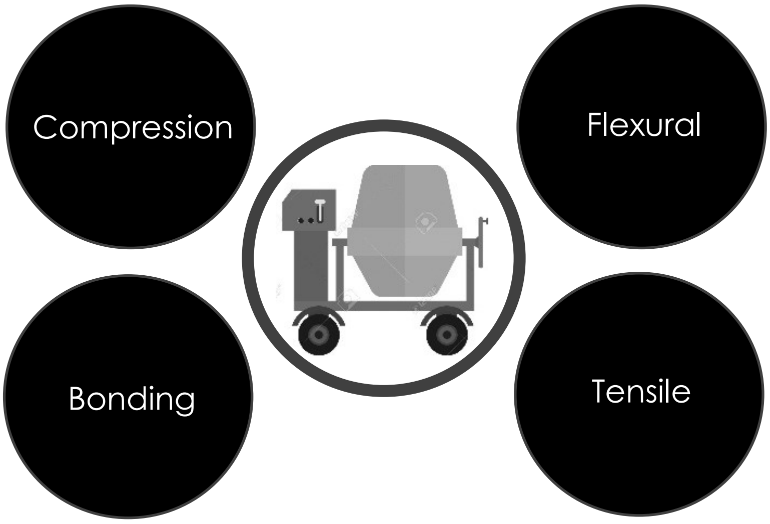


Figure 10: Hardened material properties

Process parameters are those which are defined by the printing strategy and approach to manufacturing, defining proper settings for a printing process, in order to realise as planned elements as designed as possible. Such parameters range from printer physical components such as nozzle type to printer material deposition regime, such as print speed. Such a parameters define layer height for instance, or how fast materials placed at a certain point, which affects the final characteristics of printed element. The properties of built components depend on settings of different process parameters fixed at the time of manufacturing (Panda, 2009). In 3D concrete printing, the following process parameters are key process parameters:

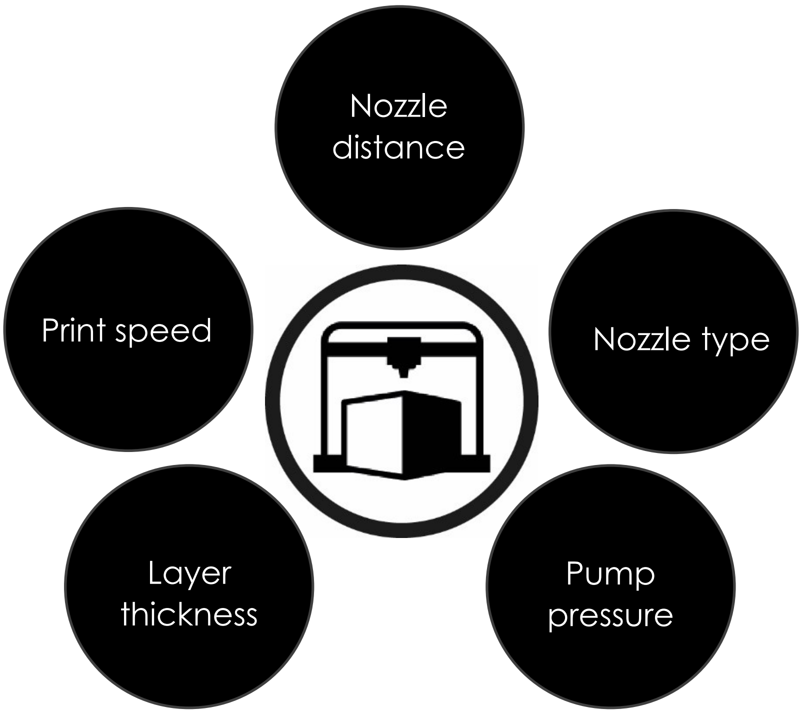


Figure 11: Process parameters

Above mentioned parameters have close interaction with each other and are interrelated. In a way that material properties have an influence on design parameter determination. Process parameters define the strategy to realize designed elements and have a great impact on final characteristics of printed element. Above all, manufacturing constraints define the possibility and the extent which the printing process can comply to as-designed parameters. As a result, such a fact affects the design and creates a loop into the design phase. Even direction of printing and direction of the element operation under load is determining the extent which the element will response to the expected external condition.

Printing speed should be set in a way that concrete remains wet enough to provide the sufficient coherent bond between layers, while it is stiff enough to carry loads of upper layers without collapsing, cracking or unwanted deformations. So it affects the buildability of the concrete. Printing speed also affects the workability and as a result extrudability of the concrete as it affects the printing gap which specifies the hardening of the concrete. In the case of low printing speeds and long printing gap, workability, and extrudability decrease so the chance of blockage in the tube, as well as a crack in the printed elements increases. Moreover, it will decrease the bond strength and hence the strength development. In the fast printing speeds, the maturity of the concrete element is affected and layers accept loads in early stages of maturity, hence strength cannot be developed sufficiently which result in the lower loading capacity of the final product (Wolfs, 2015). So printing speed is an important factor to be investigated.

Nozzle type/shape has an influence on bonding strength between layer as it defines the effective surface of layers' cross section. Hence the type of nozzle has a strong impact on strength development of the printed element. Moreover, different nozzle types result in the different final surface of the product, it the other words, it affects the smoothness of the surface and so the application of the printed product. As a result, nozzle type will reflect considerations made according to the applications and requirements of the product, and also its expected load bearing capacity.

Layer height is determined by Nozzle type/shape and affects the final surface of the product which is one of the factors that define its application. Overall printing process speed is also influenced by layer height. In higher layer heights, element reaches to the defined height faster which also has an impact on loading capacity. As the printed product is loaded faster or in the earlier stages of the maturity process, so strength development is affected. Layer height influences both fresh and hardened properties of the concrete.

Printing strategy factors, as it is mentioned has a close relationship with concrete as the material of the process. Fresh and hardened properties of the concrete affect directly buildability, workability, extrudability and open time of the concrete. Thus, it specifies the application, structural and design aspects and construction time of the process.

For example, print speed defines the open time of a layer, affecting the bond strength of layers, which also is affected by the humidity of environment during the curing process. There are numerous complex interaction and interrelation which creates a ***web of interlinked parameters***, which via several loops, their value changes and affect others and show their collective influence on final criteria, such as element stiffness, bonding strength or final realized height of a printed wall.

As a result, it is necessary to establish the relationship among and within the categories of parameters. So correction loops among categories of parameters will be established, and effects of parameters' variation will be traced in and modifications will be implemented.

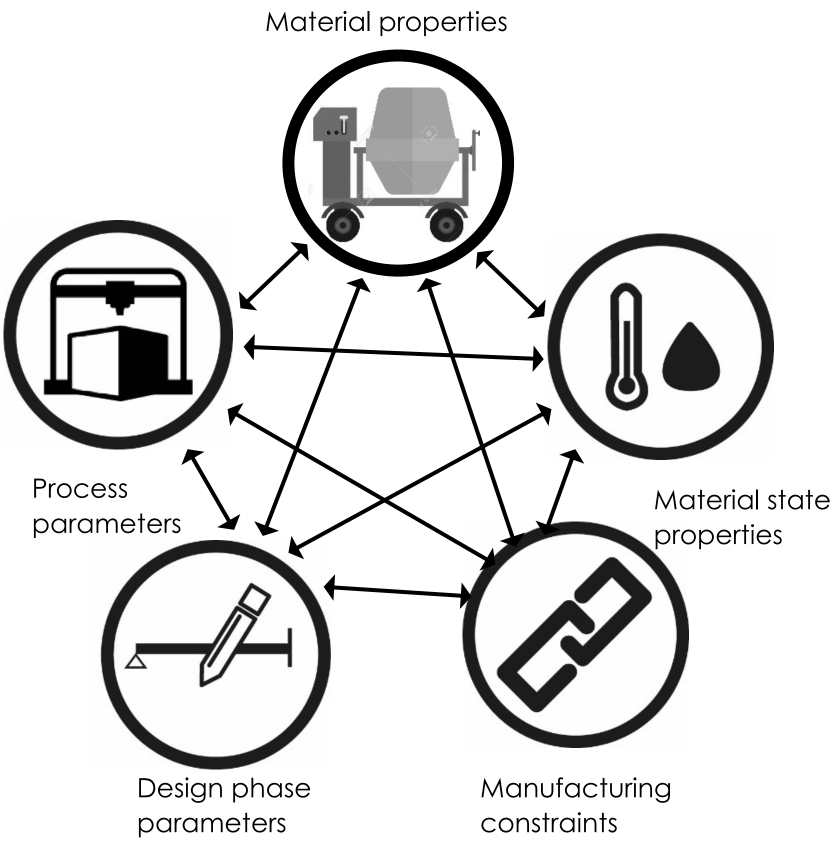


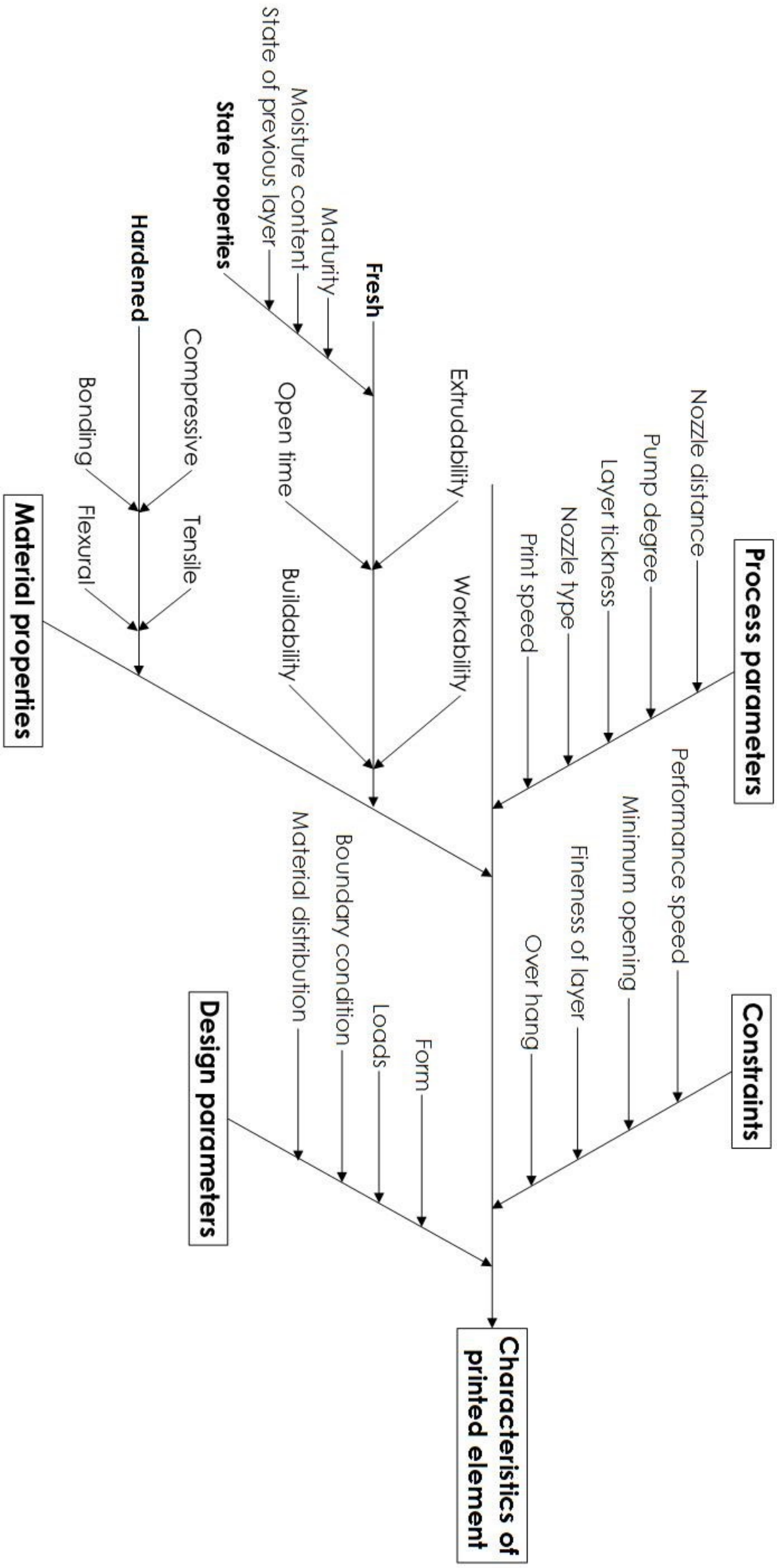
Figure 13: Interrelated parameters

4.1.3. 3D concrete printing: Cause and effect analysis

There are several parameters affecting the behaviour of a printed element, such factors can be depicted in cause and effect or Ishikawa diagram. Cause–effect diagrams depict the relationship between a given negative effect and its causes (Dumas, 2013). Parameters are grouped into categories and, such categories are helpful to lead the search for causes.

A cause–effect diagram contains main horizontal line (the trunk) from which a number of branches stem. At one end of the trunk is the effect that is being analysed.

Figure 14: Cause-effect diagram



4.2. Methodology investigation

In this section, methodology study has been conducted in order to find the most proper method in order to develop the Decision Support System for the context of 3D concrete printing.

Methodology study has been performed by (i) investigating the previous efforts for additive manufacturing process improvements and (ii) overall methodology study on the most common Decision Support Systems.

4.2.1. Process improvement in Additive manufacturing

In this section, previous studies are investigated which have been conducted to improve different types of Additive Manufacturing (AM). Hence, methods which are used to increase the understanding of AM are studied here. Literature study here was conducted to cover methods as broad as possible, and the main goal is to show the implementation of theories, get an insight over their added values and limitations.

The improvement of the efficiency of 3D printing rapid prototyping is investigated by Feng et al (Li-jie FENG, 2013), considering the strong effect of complexity and interlocking nature of 3D printing system. In this research, the interactional and inter-constraint influences of the factors within 3D printing process are countered. These factors are the degree of specialization of the operator, advanced level of the equipment, the characteristics of the moulding material, the complexity of the moulding object, construction of 3D model, effects of environmental factors (Li-jie FENG, 2013).

In the research, entropy weight method as an objective method of defining the weight of influencing factors. The method can calculate the entropy weight of every index by using information entropy and through the entropy weight to revise the weight of each index and obtain more objective index weight (Li-jie FENG, 2013).

In addition to that, System Dynamics modelling is used to model the interrelation of the factors and tracking the dynamics of the process. System dynamics describes the structure of a nonlinear, multi-feedback systems by feedback loops. Hence, the research model 3D printing process in system dynamics and explore different factors on the impact of 3D printing rapid prototyping system and then direct the enterprise to improve the efficiency of 3 d printing rapid prototyping system (Li-jie FENG, 2013).

Data used to structure the model and calculate entropy weights are gathered through expert evaluation method, which means that 50 experts in the field analyse and obtain relevant certain value through experience and 3 years of data from 2011 to 2013.

The scope of this research is in managerial level, categorizing factors and looking at them from a higher level, rather than investigating the parameters in technical level. Hence the underlying relations within the factors are known and include calculate entropy weights of the factors, current and previous value of factors, defined by expert evaluation method.

While for the case of 3D concrete printing, first, the focus is on the process parameters, which are at the technical level. Second the underlying relations are unknown and desired to be defined. Hence such an entropy method cannot fully satisfy the needs in 3D concrete printing context. On the other hand, system dynamic modelling can be used to structure the managerial model of the thesis, which is links to quality, time and cost of the process, emanated from the outcomes of the proposed settings in the technical model. Because the relations to calculate cost and time of construction are easy to derive, while the dynamic changes and trade-offs can be tracked which are of importance.

Regarding investigating the effect of process variables on the quality and characteristics of the printed parts and elements, lots of researches have been done for Fused deposition modelling (FDM). FDM Fused deposition modelling (FDM) is a fast growing rapid prototyping (RP) technology due to its ability to build functional parts having a complex geometrical shape in the reasonable time period (Anoop Kumar Sood, 2010). In the FDM process, the material is selectively deposited from the liquefier head, which melts the material such as acrylonitrile butadiene styrene (ABS), polycarbonate (PC), and PC-ABS blend.

Same as the 3D concrete printing process, the key success of FDM process depends on the suitable setting of process parameters (Mohamed, Syed H. Masood, & Jahar L. Bhowmik, 2015). In the researchers conducted to establish a model and understanding the relations among process parameters and properties of the printed elements, the main focus is to optimize the derived model. So optimum set of parameters is found regarding certain multi-objective properties of FDM product.

The mentioned focus on determining the optimum process conditions results in the ensured quality of products, improved dimensional precision, reduced wastes, increased productivity and reduced cost and time (Mohamed, Syed H. Masood, & Jahar L. Bhowmik, 2015).

Moreover, the complex process of FDM or additive manufacturing, in general, makes finding the optimum parameters hard, as there are conflicting parameters involved. The presence of those conflicting parameters affects the *Part quality & Mechanical properties.* The part quality and mechanical properties of fabricated part can be attributed to proper selection of process parameters (Mohamed, Syed H. Masood, & Jahar L. Bhowmik, 2015). There are efforts done for FDM process which can tackle the mentioned challenge in the process optimization.

According to the mentioned points, methods used for FDM additive manufacturing are proper examples of investigating, modelling and optimizing process parameters to gain satisfying product characteristics. Below summarized methods used for FDM process are compared by Mohamed et al (Mohamed, Syed H. Masood, & Jahar L. Bhowmik, 2015).

Table 1: Comparison of Methods used n FDM process (Mohamed, Syed H. Masood, & Jahar L. Bhowmik, 2015)

Capability	Techniques						
	Taguchi method	GA	Fuzzy logic	Gray relational	ANN	Factorial design	RSM
Understanding	Normal	Difficult	Difficult	Normal	Moderate	Easy	Moderate
Multi-response optimization	No	Yes	Yes	Yes	Yes	No	Yes
Uses	Widely	Rarely	Rarely	Widely	Widely	Widely	Widely
Shape of the experimental region	Regular or irregular	Regular or irregular	Regular or irregular	Regular or irregular	Regular or irregular	Regular only	Regular only
Computational time	Short	Very long	Very long	Short	Long	Short	Short
Prediction accuracy	Low	High	High	Normal	Very high	Normal	Very high
Models linear dynamics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Models non-linear dynamics	No	Yes	Yes	No	Yes	No	Yes
Developing of mathematical model	No	No	Yes	No	Yes	Yes	Yes
Data requirement for a given output	Mid	High	High	Mid	High	Mid	Low
Optimal solution	Straight	Straight	Through model	Straight	Through model	Straight	Through model
Ability to study interaction effects between variables	Yes	No	No	Yes	No	Yes	Yes
Availability in simulation software	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Taguchi method is an effective tool for optimizing process parameters which provide a simple, reliable and effective approach in practical applications to improve the product quality at low cost. It is relatively normal to understand, has short computational time with minimum amount of data needed for modelling. Taguchi method leads to the non-optimal global solution because of the confounded interactions. This method cannot handle multiple-response quality criteria, so this fact limits its application for predictive model creation (Mohamed, Syed H. Masood, & Jahar L. Bhowmik, 2015). Moreover, the level of prediction derived from the method is low.

The ***Response Surface Methods (RSM)*** is a collection of mathematical and statistical techniques useful for the modelling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response (Montgomery, 2012).

RSM is considered to be a more promising method for optimization as it gives very low standard error towards experimental verification. It can be noted that RSM is a powerful optimization design allowing multi-objective optimization in cases that are required to optimize more than one response.

In addition, RSM is strong- in identifying the critical parameters, the main and interaction effects of parameters which provide enough information for experimental studies (Montgomery, 2012). Furthermore, the significance of interactions and square terms of variables are more clearly predicted in RSM (Mohamed, Syed H. Masood, & Jahar L. Bhowmik, 2015). Also, the prediction accuracy is high, a provide a graphical representation of responses and parameters and their interaction.

Full factorial design (FF) allows investigating the influence on response outputs by process parameters. The main disadvantage of the method is the need of more experimental data to reach a better accuracy in the model (Montgomery, 2012), which make the model creation process more expensive. Fraction factorial design requires less number of runs, but due to confounded interaction, optimum process setting cannot be determined accurately (Mohamed, Syed H. Masood, & Jahar L. Bhowmik, 2015). Moreover, the method cannot handle multiple responses, which has a negative impact on its applications.

Gray Rational Analysis (GRA) is used to measure the relationship between process parameters, while as a result of confounded interaction possibility, finding the optimal setting is very slow (Mohamed, Syed H. Masood, & Jahar L. Bhowmik, 2015).

Artificial Neural Networks (ANN) is the most popular empirical modelling applied to express the mathematical relationship between the process parameters and quality characteristics (Mohamed, Syed H. Masood, & Jahar L. Bhowmik, 2015). ANN uses human brain reasoning model to understand the most proper relation between inputs and predicting the outcome or output. The network creates model according to input-output training data set, while having the ability to establish a complex non-linear relationship between process parameters and quality characteristics. ANN requires a large number of training data, which increases the computational time and hence the expenses of the experiment. This method cannot be retrained in the case of adding data to an existing network. It should be noted that ANN provides enough information about factors and their effects on the output responses only if screen experimental designs are done in addition to ANN (Mohamed, Syed H. Masood, & Jahar L. Bhowmik, 2015).

Genetic Algorithms (GA) are classes of Evolutionary Algorithms (EA), which model genetic evolution. Evolutionary computation (EC) has as its objective of survival of the fittest: the weak must give way to the strong (Onwubolu, 2009). GA does not need deep knowledge in mathematics, while requiring long computational time and high amount of data.

Fuzzy sets and ***Fuzzy Logic (FL)*** allow approximate reasoning, with these uncertain facts to infer new facts, with a degree of certainty associated with each fact. In a sense, fuzzy sets and logic allow the modelling of common sense. The uncertainty associated with fuzzy logics differs from what statistical one. Statistical uncertainty is resolved through observations, while fuzzy uncertainty is due to vagueness, imprecision and/or ambiguity (Onwubolu, 2009). Hence it is suitable for the complex process of 3D concrete printing, as it is associated with high uncertainties, due to the presence of large amount of variables, in which there is limited control.

However, the fuzzy logic approach requires developing rule and database. Thus, having in-depth knowledge of mathematics is necessary. Moreover, fuzzy logic requires a large amount of data storage, which may slow down the process (Mohamed, Syed H. Masood, & Jahar L. Bhowmik, 2015).

It can be concluded that method of AM improvement depends on the scope of variables under study, availability of data, the level of precision and the expected aim from relationships. Such a relationships, clarify the influence of parameters involved in AM process, on final product properties, which leads to facilitate decision-making process to find the proper setting, In order to satisfy defined performance of the product. These methods can be used in a platform, to construct Decision Support System, which s elaborated in the next section.

4.2.2. Overall methodology study

In this section, five main methods used in developing Decision Support Systems and expert systems are investigated and described. The aim here is to study methods used in common systems and find their relevance to the context of this research.

It is expected from 3D concrete printing decision support model to derive supports in the decisions required to realize the desired product. Hence *a program is required to make reasoned judgements or give assistance in a complex area in which human skills are fallible or scarce*(Todd, 1992). Here is the point where *expert systems* are applied in addition to Decision Support Systems, in order to assist the designer in leveraging interacting factors properly so that the desired outcome get produced without trial and error, using the strength of learning in the system. Within the expert systems, the following methods are studied: (i) Rule-Based Systems(RBS), (ii) Frame-Based Systems (FBS), (iii) Bayesian Belief Networks (BBN), (iv) Artificial Neural Network (ANN).

4.2.2.1. Rule-Based Systems (RBS)

In this approach, problem-solving knowledge is expressed in sets of rules which consist of antecedents as conditions and they result in consequences if conditions have a true statement.

IF <antecedent> THEN <consequents>

They incorporate practical human knowledge in conditional if-then rules(Hayes-Roth, 1985). In the other words, it follows the human reasoning for problem-solving and decision-making. RBSs adaptively determine the best sequence of rules to execute. Moreover, they explain their conclusions by retracing their actual lines of reasoning and translating the logic of each rule employed into natural language(Hayes-Roth, 1985). Hence, it is understandable and transparent to experts(designers, operators, and researchers in the 3D concrete printing). Each rule shapes the path within the branching sets of nodes. By tracing the special path the system performs, so RBSs are known as modular know-how. Hence, knowledge can be refined and new sets can be added to improve the performance of the system.

RBS consists of the *knowledge base* which contains rules and facts and *inference engine* which interpret current states, understand the meaning of rules and hence apply appropriate rules. The latter component is also known as rule interpreter.

Rules can be used in different approaches to be applicable in different situations. They can be used as deductive knowledge, which supports the inference, verification or evaluation tasks(Hayes-Roth, 1985). On the other hand, they can use to be goal(s)-oriented and seeks through the knowledge to reach defined goal(s). More importantly, they can dig into *what if* scenarios, as they get employed to address causal relations. Two latter cases are interesting for the 3D concrete printing context as it is possible to derive causal relations and reach predefined outcomes by leveraging interacting shape, material, printing strategy and force factors.

RBSs leave space to incorporate a large amount of judgement, heuristic and experimental knowledge, which in 3D concrete printing is an ideal situation, as relations should be understood by further experimental data. Moreover, Knowledge derived from experiments can be used to feed the knowledge base in the same format. In the other words, they require little processing to be implemented. Transparency ad tractability of the approach is positive points which come from the similarity of the approach to human reasoning. The rule is known as a relatively independent piece or chunk of know-how. Chunks are elementary patterns in perception and thinking that people use to make sophisticated high-level decisions(Hayes-Roth, 1985).

One of the disadvantages of RBSs is that it is often difficult to represent knowledge in terms of rules(Ramsey, Reggia, Nau, & Ferrentino, 1986). In the 3D concrete printing context, the limitation applies when it is needed to implement knowledge of an expert, who uses his/her experience as the main reference. Moreover, all the necessary context for a rule's application should be provided in its antecedents clauses(Ramsey et al., 1986). Especially in our case, due to the number of interacting factors, and lack of knowledge dominance, it is not possible to provide all required antecedents to construct the rule sets completely. Even if we can provide all necessary contextual information, a large number of rule sets should be generated and integrated. Another main disadvantage is the "directionality " of rule production in RBS and intuitive inference by experts. In a way that in the presence of a certain *cause,* specific *manifestation* occurs:

IF < cause> THEN < manifestation >

In the context of this proposal, it can be "reducing w/c in the mixture of concrete (as a decision variable or causes), crack in the printed layer occurs (manifestation)". There are certainty factors associated in this direction of derived knowledge This is the opposite direction of the rule generation in RDSs, which uses manifestations as conditions to fire the rule. If the prior probabilities of causes are available, one could derive certainty factors from the given information, but without that knowledge, it is often difficult to determine them, and subsequently the certainty factors used in real-world expert systems are, at best, rather arbitrary(Ramsey et al., 1986). Hence, one abstract solution can be the introduction of non-intuitive intermediate problem features for bookkeeping the purposes.

On the basis of the points mentioned above, RBS is suitable to integrate a large number of judgments, heuristics and experimental knowledge, which in the context of the research *large number of experiments* is necessary. Moreover, the format of the derived knowledge will be kept. The method works properly when the organization of the knowledge is branching logic, Rules, Description/tables (Ramsey et al., 1986) , which in the case of implementation in the context, it would be a table.

In addition, there should be few problem features defined as input with small context-dependency, otherwise, writing a set of rules would be difficult because all of the contexts for using each rule would have to be included in the antecedents of that rule. Even assuming that one could identify a priori all of this relevant context, the resulting knowledge base would be a potentially huge set of rules(Ramsey et al., 1986). In 3D concrete printing , features influencing the process and outcomes are numerous in the shadow of rules' *high context-*

dependency. Even if few features get involved in building the primary version of the decision support tool, further development of the system will be limited according to this method, as it will be complicated *to integrated numerous features* as input.

In 3D concrete printing , outcomes such as a cross section of a layer and stability of the layer are dependent. Hence, the strength of the Decision Support System will be increased if these multiple simultaneous outcomes could be integrated. RBS is suitable to incorporate dependent outcomes as well as mutually exclusive ones. Both mentioned assumptions can be used for categorical and combination of categorical and probabilistic outcomes, which the latter case seems the most suitable for the context of the research. The reason is because there is still limited control and knowledge over influential parameters involved in the 3D printing process.

4.2.2.2. Frame-Based Systems (FBS)

FBSs are a type of knowledge representation that uses frames as their primary element of knowledge representation. A frame is a structure of a concept, situation or scenario representation, which contains all kind of information needed to describe, define and satisfy the certain sets of outcomes and causes in the specific situation. Frames are an application of object-oriented programming for expert systems. In the other words, a frame lists various attributes and characteristics of the situation, which is treated as an object.

Using descriptive knowledge representation, FBSs perform inference according to hypothesize-and-test cycles. Given one or more initial problem features, the expert system generates a set of potential hypotheses or "causes" which can explain the problem features. These hypotheses are then tested by (i) the use of various procedures which measure their ability to account for the known features, and (ii) the generation of new questions which will help to discriminate among the most likely hypotheses. This cycle is then repeated with the additional information acquired(Ramsey et al., 1986). This approach is based on human reasoning and natural abduction, which tends to come up with the best explanation according to the most likely observed outcomes.

To project the implementation of this approach in the context of 3D concrete printing , it is proposed to use the same logic for medical diagnosis problem-solving expert systems. In order to simulate hypothesize-and-test reasoning, this system employs a generalized-set-covering model in which there is a universe of all possible manifestations(symptoms) and a universe which contains all possible causes (disorders). For each possible cause, there is a set of manifestations which the cause can explain. Likewise, for each possible manifestation, there is a set of causes which results in the manifestation. Given a diagnostic problem with a specific set of manifestations which are present, the inference mechanism finds all sets of causes with minimum cardinality which could "explain" (cover) all of the manifestations(Ramsey et al., 1986).

In the context of the proposal, manifestations turn into evaluation and performance criteria defined by the designer to satisfy specific needs and applications. Causes turn into decision variables during printing such as printing speed, pump pressure, layer height, nozzle shape, and dimension.

One of the advantages of such an approach is that frame generation is easy and natural and can be derived from descriptive information, which in this case eliminate the need of data process to input the knowledge. Another advantage is that information and relatives causes are placed in one frame, hence, that fact makes it suitable for a problem with high context-dependency, associated with multiple problem features as input. Furthermore, this method works very well when multiple cause/disorders/selection are involved in a large selection/diagnosis problem(Ramsey et al., 1986). This feature really fits the goal in the 3D concrete printing context, as there are multiple selections of decision variables associated with interrelated causes. Those causes can be categorical or the combination of categorical and probabilistic, as FBS work well same as RBSs. What makes this approach even more useful for the context is the fact that it can be associated with statistical methods to flow between the frames.

Finally, the hypothesize-and-test algorithms focus on the most likely outcome, thereby less time is consumed in a question-answering session with a user. In addition, people sometimes feel more comfortable using such systems because they can understand the reasoning of the system(Ramsey et al., 1986).

On the other hand, there are serious problems associated with FBSs which arise from the fact that this method is experimental and few real world applications tested the performance of the method. There are technical issues that limit the performance of such methods, such as the point that the questioning process terminates and the decision is generated. Especially when the method looks for the most likely outcomes and hypothesize-and-test limits the number of questions. Another area of doubt is how to select optimally next questions to ask. Finally, the algorithms of abductive inference are complex and have time-consuming decision-making processes(Ramsey et al., 1986).

4.2.2.3. Bayesian Belief Networks(BBN)

The following explanation gives a proper insight about BBN: “The Bayesian Belief Network (BBN) provides a technique to (i) represent knowledge and uncertainties in a causal network and (ii) use the network for probabilistic reasoning.” (Arentze)

BBN shape Directed Acyclic Graph (DAG) which are defined by nodes and directed edges. Nodes represent variables and direct edges show the statistical conditional relation between two directed nodes, In particular, an edge from node Xi to node X_j indicates that a value taken by variable X_j depends on the value taken by variable Xi. Roughly speaking that variable Xi or parent node, “influences” X_j, the child node (Ben-Gal, Ruggeri, Faltin, & Kenett, 2007).

The quantitative part of BBNs is represented as tables of probabilities or Conditional Probability Distribution (CPD) which represent the local probability that a child node takes on each of the feasible values – for each combination of values of its parents (Ben-Gal, Ruggeri, Faltin, & Kenett, 2007). Feasible values mean the defined states for each variable in the network, which can be continuous or discrete. The graph of a BBN represents n variables of X_1 , X_2, …, X_n if:

$$P\,(X1, X2, \dots, Xn) = \prod_{j=1}^{n} P\,(X\,|parents(Xj))$$

Where parents(X_j) denotes the set of all variables X_j , such that there is an arc from node i to node j in the graph (Pourret & Naim, 2008).

Employing Bayesian Belief Network (BBN) helps to understand the causal relationships of Situational, Decisions and outcome variables while considering the associated uncertainties. Moreover, thanks to the theory behind BBN, by knowing states of some variables, it is possible to calculate distributions of other variables according to certain defined objective or maximized utility.

By using the probabilistic distribution derived from the uncertain environment, the system finds the right path to reach a specific goal. For instance, by knowing the shape, material, print speed and compressive strength, the required thickness of printed layer will be suggested. The further step can be automated in the printer and results in an automated modification in the batch, mixture and printing strategies.

One of the main advantages of such a method is the reasoning process can operate on BBNs by propagating information in any direction, in spite of the fact that the arrows represent the direct causal connection between the variables(Ben-Gal, Ruggeri, Faltin, & Kenett, 2007), both backward and forward reasoning. This is because of the strength of Bayes probability theorem in addressing conditional probability(Arentze):

$$P(A|B)P(B)=P(A,B)$$

$$P(B|A)P(A)=P(A,B)$$

It follows that:

$$P(A|B)=(P(B|A)P(A))/P(B)$$

As a result, Bayes' rule enables us to compute P(A|B) in terms of P(B|A). In the context of 3D concrete printing , this feature is so helpful, in a way that in the light of existence evidence in each layer of the network, unknown factor or decision variable could be determined.

Another advantage is that this method encounters knowledge that experts are not aware of or cannot verbalize. This is because of the fact that BBNs use statistical data and information to build their network.

One of the biggest disadvantages of BBNs is that they require the availability of exact probabilities, which is a time-consuming and costly process(Ramsey et al., 1986). In the context of 3D concrete printing , we stand in a Boolean position, if the selected decision and attribute variables require several machine resetting, it is not feasible to derive needed data. On the other hand, if variables get selected in a way that they can be changed in a continuous printing tool path, producing that huge sets of data would be easy as there will be no need of resetting the printer, while investigating different states of the variables in the experiment.

In the same manner, evaluation criteria or utility derived from BBNs should be easily valuable since there are going to be numerous data production and hence there would be the need of evaluation for each case.

Another problem is that the unrealistic assumptions should be made in order to use BBN. One of them is that the outcomes should be mutually exclusive(Ramsey et al., 1986), which in the context of the proposal it brings up limitations, especially for the further developments of the system. The other one is that the problem features should be independent, which this assumption can degrade the performance.

4.2.2.4. Artificial Neural Network (ANN)

Like other methods of expert systems, ANN uses human brain reasoning model to understand the most proper relation between inputs and predicting the outcome or output. As it can be inferred from the name, this method models brain neural network which is fired by inputs and build the logical relations among the network in a way which neural networks in human brain transmit messages.

The human brain consists about 10 billion interconnected set of nerves called neurons, which are basic information-processing units and are connected by 60 trillion synapses(Arentze). This huge network makes the brain a powerful processing centre, while it is made by basic structures of interconnected neurons. A neuron consists of a cell body, soma, a number of fibres called dendrites, and a single long fibre called the axon. While dendrites branch into a network around the soma, the axon stretches out to the dendrites and somas of other neurons. Signals are propagated from one neuron to another by electrochemical reactions which release chemical substances from the synapses and cause a change in the electrical potential of the soma. When the potential reaches its threshold action potential is sent down through the axon. The pulse spreads out and eventually reaches synapses, causing them to increase or decrease their potential(Arentze). Hence, neural networks contribute to the learning process by changing the relations by weakening or strengthen their connections through experience.

Analogous to neural networks, ANN consists of neurons as processors which are interconnected by weighted links passing signals or inputs from one neuron to another. The output signal is transmitted through the neuron's outgoing connection which corresponds to the biological axon. The outgoing connection splits into a number of branches that transmit the same signal. Those branches terminate at the incoming connections of other neurons in the network(Arentze).

The neuron computes the weighted sum of the input signals and compares the result with a threshold value, θ which is corresponding to the electrical potential of the biological neuron. If the net input is less than the threshold, the neuron output is -1. But if the net input is greater than or equal to the threshold, the neuron becomes activated and its output attains a value +1.

$$X = \sum_{i=1}^{n} xi \times wi$$

$$Y = \begin{cases} +1 & \text{if } X \geq \theta \\ -1 & \text{if } X \leq \theta \end{cases}$$

where X is the net weighted input to the neuron, x_i is the value of input i, w_i is the weight of input i, n is the number of neuron inputs, and Y is the output of the neuron. This type of activation function is called a sign function). Other activation functions of step, linear and sigmoid functions can be also used according to the applications.

The most common way that the perceptron algorithm is used for learning from a batch of training instances is to run the algorithm repeatedly through the training set until it finds a prediction vector which is correct on all of the training set. This prediction rule is then used for predicting the labels on the test set (Kotsiantis, 2007).

On the basis of the points mentioned above, by introducing inputs to a black box modelling neural network approach to learning, continuous outputs will be derived from predictions of a dataset. In the context of 3D concrete printing, predictions about the buildable number of layers can be made according to the inputs such as shape, printing speed, and type of concrete. In the case of multiple outcome predictions, ANN responds sequential, in a way that predicts outcomes one after the other, although ANN omits the limitation of linear modelling. This is the limitation of the methods in comparison with BBN, which predicts multiple outcomes simultaneously.

4.2.3. Method comparison

In this section methods discussed above are compared according to criteria in order to select the method which leads to efficient data generation and processing in terms of time and quantities. Moreover, the proper method should meet specific requirements, mentioned as following:

VII. Generate efficient number of concrete printed data as means of interrelation studies,
VIII. Distinguish influential process parameters after parameter study (parameter screening), according to defined target of 3D concrete printing,
IX. Specify level of influence of process parameters (significance study),
X. Establishing relationship among process parameters and targets (empirical model).
XI. Incorporate possible non-linearity in the models and study interaction among parameters,
XII. Provide precise prediction of process and target parameters,
XIII. Visualize results for a better and clearer understanding,
XIV. Pave the way of analysis toward process optimization.

As a result, a method which satisfies the criteria mentioned above to an acceptable extent leads to reaching the main objectives of this research and development project. The main goal is to *improve the product and process of 3D concrete printing* by :

I. Depicting a *clear understanding* of the interrelated process parameters;

II. Develop a Decision Support System to provide the possibility of *conscious leverage* of process parameters.

Finally, the method should be understandable enough and are able to depict clear relationships which can be traceable, and explainable by physical and mechanistic law, involved in 3D concrete printing. Some methods such as ANN, establish relationships in a black box, which is usually hard to be interpreted by researchers and experts. Such a methods are considered to be unsuitable as explaining the constructed relationships are hard ad do not follow mechanistic logics.

According to the results of the comparison shown in the table below, RSM method, which is a type of Design of Experiment (DoE) is the most suitable method. Some literature argues the prediction accuracy of RSM. He prediction accuracy of RSM depends on the defined range of experiment and its direction and/or the distance from the centre of the design region. If the relatively small region of design is selected, RSM will perform good predictions. RSM method will be elaborated more in next chapter.

After studying methods, general components of Decision Support Systems, as the main framework of the tool is investigated in the next section.

Table 2: Comparison table

Criteria	Methods									
	Taguchi	GA	FL	GRA	FF	RSM	RBS	FBS	BBN	ANN
Complexity	Moderate	High	High	Normal	Low	Moderate	Low	Low	Moderate	High
Explainability	High	Low	High	High	High	High	High	High	High	Low
Computation time	Short	Long	Long	Short	Short	Short	Moderate	Moderate	Moderate	Long
Empirical model	No	No	Yes	No	Yes	Yes	No	No	No	Yes
Required data	Mid	High	High	Mid	Mid	Low	High	High	Mid-High	High
Non-linear modelling	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Interaction study	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
parameter screening	Yes	No	No	Yes	Yes	Yes	No	No	No	No
significance study	Yes	No	No	Yes	Yes	Yes	No	No	No	No
Accuracy	Low	High	High	Mid	Mid	Mid	Mid	Mid	High	High
Optimization	Straight	Straight	Through model	Straight	Straight	Through model	No	No	No	Through model

4.3. Decision Support Systems

Computerized Decision Support Systems practically became to exist with minicomputers development, timeshare operating systems, and distributed computing, and got implemented in the mid-1960s, when researchers began systematically studying the use of computerized quantitative models t assist in decision making and planning (Burstein & Holsapple, 2008).

“ *Decision Support System(DSS) is an interactive computer program that uses analytical methods and models to help decision – makers to formulate alternatives for large unstructured problems, analyse their impacts and then select appropriate solutions for implementation.* (Kumar, B, & Pragti, Decison Support System: An Overview, 2006) ”

DSS makes the right information available for decision- makers at the right time, provide model-based reasoning capabilities, enable users to generate and select an alternative solution for a given problem in a given scenario (Kumar, B, & Saxena, Decision Support System: An Overview, 2006).

As a result, more practical solutions with more cost effectively efforts are suggested, improving the quality of decision-making process. Moreover, interactive DSS provides the opportunity to establish an interactive dialogue between user and system, incorporating dynamics of the process, and improving what-if scenario generation and presentation.

DSS provide knowledge and/or knowledge- processing capability that is necessary for making decisions or making sense of decision situations (Holsapple, 2008).

Graph bellow, represents a decision process, can be sliced into Simon’s three stages *of intelligence, design, and choice*, which contains specific decision procedure and a mechanism such as optimization. In decision process, actions of DSS and user can be involved concurrently. The decision sponsor, participant(s), implementer, and the consumer may be individuals, or groups, having more than one role mentioned above (Holsapple, 2008). By involving DSS in the process of decision making, the process is affected and its outputs lay in at least one of PAIRS direction (productivity, agility, innovation, reputation, satisfaction) (Holsapple, 2008).

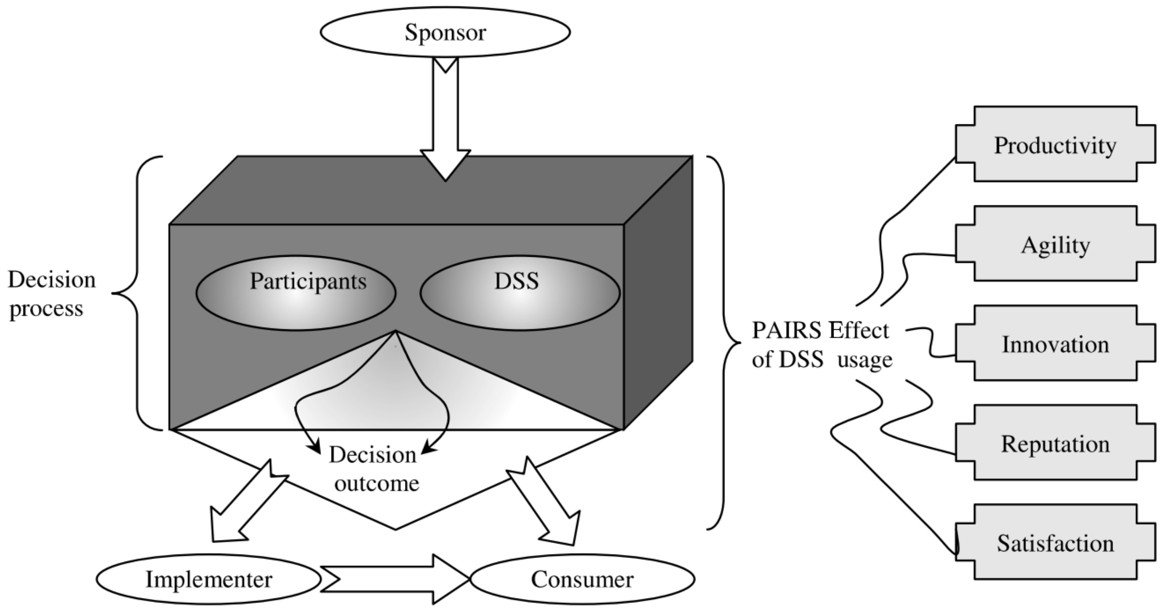


Figure 15: Decision process (Holsapple, 2008)

4.3.1. Decision Support System types

Over the evolution of DSS, developers made use of various concepts like spreadsheets, database, networks, hypermedia, expert systems (ES), visual programming, intelligent agents, neural networks, Artificial Intelligence and statistical methods (Kumar, B, & Saxena, Decision Support System: An Overview, 2006), in order to develop DSS with different applications

Here there is the main variant of the DSS, are studied in order to investigate best options to use in the context of 3D concrete printing, according to defined objectives (see chapter 2).

I. Model-driven DSSs emphasize access to and manipulation of financial, optimization, in addition to simulation models. Quantitative models provide the most fundamental level of functionality. Model-driven DSSs use limited data and parameters provided in the decision-making process, to aid decision makers in analysing a process, but in general, large databases are not needed for model-driven DSSs (Department, 2008).

II. Data-Driven DSS emphasize access to and manipulation of a time series of internal and external data in addition to real-time data. Simple file systems accessed by the query and retrieval tools provide the most basic level of functionality. Database systems that provide the possibility of manipulation of data by computerized systems fitted to a specific setting or by more general tools and operators bring more functionality. Data-driven DSSs with on- line analytical processing, provide the highest level of functionality and decision support that is linked to analysis of large collections of historical data (Department, 2008). They provide the opportunity to incorporate an enormous amount of data, and investigate underlying patterns, trends and make the data-driven learning possible.

III. Communications-driven DSSs use the network and communications technologies to ease and support collaboration in decision-making process and communication among stakeholders. In these systems, communication technologies are the dominant architectural component. Tools used include groupware, video conferencing and computer-based bulletin boards (Department, 2008), (Kumar, B, & Pragti, Decison Support System: An Overview, 2006).

IV. Document-Driven DSSs employ computer storage and technologies of processing to retrieve the document and related analysis. Database consisted of large documents, have normally the format of scanned documents, hypertext documents, images, sounds and video (Department, 2008). Product catalogues and specifications, procedures, policies and historical documents are examples of such systems.

Natural language and statistical tools for extracting , manipulating and summarization of (u)structured information are used in this type of DSS (Kumar, B, & Saxena, Decision Support System: An Overview, 2006).

V. ***Knowledge-Driven DSSs*** uses rule-based knowledge or expert knowledge in a specific discipline and based on certain facts, information ,performance, and procedure. They suggest a user in the specialized problem-solving domain, which contains information, knowledge and skills of problem-solving in a certain specialization. These type of DSS are also known as Expert Systems, as knowledge query and analysis is quite specialized.

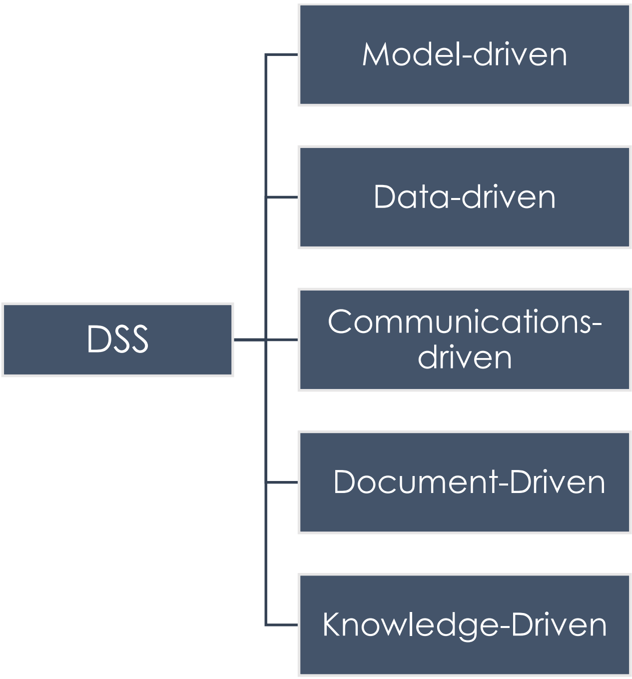


Figure 16: Decision Support System types

4.3.2. Generic components and Architecture

Components of each DSS is highly dependent on the application of DSS and also its context of use. But a typical DSS framework consists of two major systems (Kumar, B, & Saxena, Decision Support System: An Overview, 2006):

I. Humans decision maker, who are end users with various roles and functions,
II. Computer system, which consists of three main components:
   i. Database Management System (DBMS)
   ii. Model-base Management System(MBMS)
   iii. Dialogue Generation and Management System (DGMS)

DBMS is the collection of computer programs enabling the user to create, populate and manage database and control access to the data stored in it. DBMS can be either program running independently or embedded within a DSS generator (Kumar, B, & Saxena, Decision Support System: An Overview, 2006). DBMS provides knowledge about each database object from the entity, attributes, and types point of view. So DBMS components facilitate the collection, storage processing and managing of data (Kumar, B, & Pragti, Decison Support System: An Overview, 2006).

MBMS is the critical elements of DSSs, which defines meaning to data and consists of collected program embedded in the system generator and provide the possibility of model creation, edit, update and usually process. MBMS generic components are a model directory, model base, and a command processor. Model-base store models in it, which has the role of pulling data from the database and transforming it to the format of the required knowledge, by the decision maker.

DGMS acts as the user interface of DSS, which is the gateway to both DBMS and MBMS, allowing the user to query required information and receive them, processed by DSS.

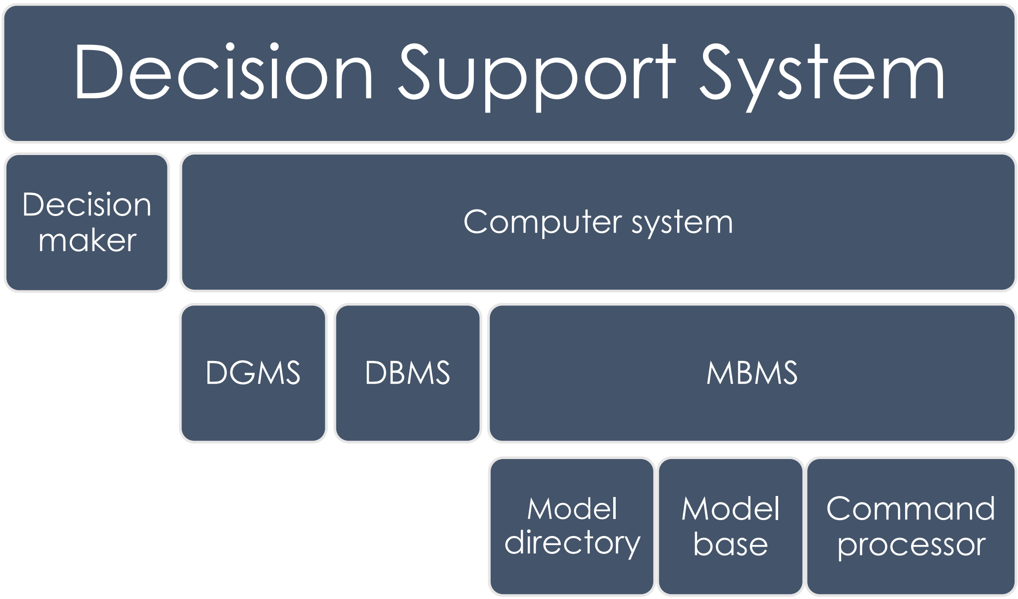


Figure 17: DSS generic components

The chapter of literature study gathered introductory information to the knowledge required to develop a Decision Support System for the 3D concrete printing process. Thorough investigations are conducted in next chapter, where the scope is narrowed down and specific DSS type, methodology, and 3D concrete printing key elements are recognized.

5. Developing 3D concrete printer Decision Support System

5.1. Introduction

Automation is a great necessity pushing construction industry toward investigating and implementing innovative construction techniques. 3D concrete printing is the technique which fills the gap between design and construction, brings up lots of advantages such as reduction in labor for safety reasons, reduction in construction time on site, reduction in production costs and an effort to increase architectural freedom. Moreover, quality, reliability, life cycle cost savings and the simplification of the workforce will be enhanced noticeably (Perkins & Skitmore, 2015).

In order to reach the mentioned targets, 3D concrete process should be fully understood, influential factors should be detected and clear relations between process products and process parameter should be drawn.

At this moment, the concrete printing process is not fully understood, as the effect of process parameters on each other and the product, characteristics are unknown. Moreover, material characteristics, process performances, and design platforms should be improved to satisfy defined requirements. of There have been clarifying efforts to understand and improve the concrete printing process, limitations and introduce its influential factors(Perkins & Skitmore, 2015), (Kumaraswamy & Dissanayaka, 2001)(S. Lim et al., 2012), (Feng, Meng, Chen, & Ye, 2015), (T. T. Le et al., 2012), (Thanh T. Le et al., 2012), (Perrot, Rangeard, & Pierre, 2015b), (Zhang & Khoshnevis, 2013), but none of them have looked at the **effect of related process parameters** on the defined product characteristics.

In this graduation project, in order to enhance the understanding of 3D concrete printing process, a decision support tool have been developed. This decision supports tool to support decisions in the printing process by showing the consequences of such decisions. The objective of such decision support tool is to show the effect of varying specific process parameters on the **dimension of a printed concrete layer**.

In the core of the decision support tool, there is a model, investigating the effect of relevant process parameter on the dimension of a printed concrete layer. Furthermore, the model will establish a relationship between process parameters and dimension of a layer.

Such a decision support tool will increase the understanding of the concrete printing process. More importantly , I will diminish the gap between design and realization phase.

5.2. Printed layer dimensional accuracy

5.2.1. Problem identification and importance

One of the main goals of adopting 3D concrete printing is to bridge the gap between design and realisation. In order to reach such an aim, discrepancies between as-designed and as-built product should be as minimal as is possible. There is always constraint of reality which imposes limitations over design, which result in considerable differences between what can be realised and what it has been designed.

One of the first *discrepancies between design and production* is the final designed height or length (dependent on the direction of the element print and usage). Due to the deformations of dimensions of printed layers, the final realised height will be less that the designed height (for the same number of layers). Deformations will occur in Height and width of a layer after a layer is printed.

Such a mismatch between design and realisation will affect the whole construction time and cost estimation in different phases of planning, design and construction. The actual time and cost needed to fulfil the designed requirement would be more since there will be more layers and material needed. So it is of importance to foresee the consequences of decisions in the printing process.

Other main pitfalls of concrete printing are to provide required provisions to print a manner which is stable enough to create as high as it is possible in a continuous printing toolpath. There are different ways to increase the stability of the printed layers, which may vary from improvements of material characteristics, elements' geometry and provision of supplementary material.

One of the approaches to eliminate such a problem is to focus on *micro instabilities* raised due to deformations in the width of a printed layer. Deformation in width will cause the cross section of a layer to have a trapezoidal shape, with different top and bottom width. Since there are errors in the placement of layers on each other, there will be eccentricity in introduced loads of upper layers. Because of the trapezoidal shape of the cross sections, this eccentricity will increase the chance of creating such a torque that may result in collapsing of the element.

As a result, by decreasing deformation in cross section width, the instability can be reduced. The first step should be investigating the effect of process parameter on layer deformation, establishing the proper relation and gaining insight over dimension variations by changing printing setting.

Each layer will deform, so the planned nozzle distance (z) from the layers below, should be updated, because, it will reduce the imprecisions of layer placement. And as a result, it will increase the stability of the printed element. The consequence is to link the constraints and realities in the printing process, in the design phase, when the G-code is being fed to the concrete printer. So, the printer will response automatically and dynamically during the process. Consequently, the gap between design and production would be diminished.

There are also other parameters especially material related properties, which can affect the deformation of a layer. Although they worth being investigated, they are excluded from this research, because:

the main aim of this research is to show the importance and effects of process parameters on deformation of a layer. So, the focus is investigating process parameters and propose a methodology to tackle properties of final printed product.

The objectives vary from situation to other situation, such mechanical properties or deformation of several layers. By proposed methodology in this graduation project, different properties of the concrete printing process can be enhanced.

This graduation project aims to find the effect of relevant process parameter on the deformation of a layer and derive an empirical model.

Figure 18: An example of a printed element surface

5.2.2. Deformation analysis: Important process parameters

3D concrete printing is a complex process, which the final process product, is affected considerably by parameters involved in the printing process. The properties of concrete printing process are a function of the different *process parameter.* Critical literature for various types of Rapid Prototyping (RP) or Additive Manufacturing (AM) have strongly suggested such a relation (Panda, 2009), (Li, Zheng, Nie, Zhao, & Huang, 2011), (Mohamed, Masood, & Bhowmik, 2015), (Garg, Siu, Lam, & Savalani, 2015). 3D concrete printing as a type of additive manufacturing has numerous influential process parameters which intervene in defining properties of final products. Adjusting relevant process parameters can improve products' properties.

By adjusting related process parameters dimensional accuracy of a printed layer can be improved. As it is mentioned, this research only focus on process parameters, which means that improving the dimensional accuracy by enhancing material characteristics, for instance, are excluded.

There is no literature about the influential process parameters on the dimensional accuracy of 3D concrete printing. So in order to find out relevant parameters, process observation and also literature study on other methods of 3D printing was conducted. The latter approach is used to give initial ideas, further investigations are done by observation because of inherent differences in different 3D printing processes and material.

The summary of contributions to improving dimensional accuracy and corresponding relevant process parameters are shown below (Sood, Ohdar, & Mahapatra, 2009).

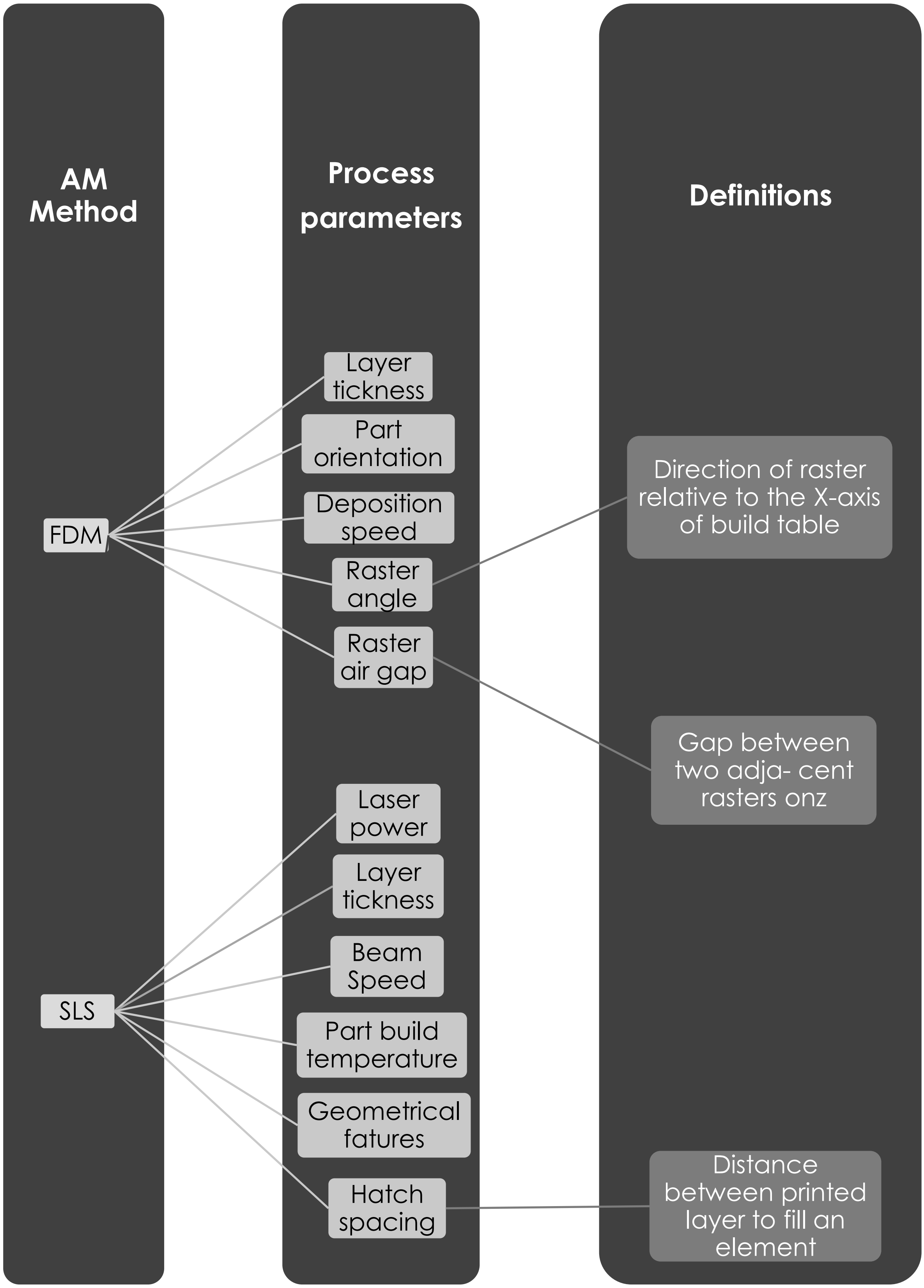


Figure 19: Additive Manufacturing dimensional accuracy

Although the behaviour of material, printing scale and method of FDM (Fused Deposition Modelling), SLS(Selective Laser Sintering) and concrete printing differ drastically, but it can be seen that some process parameters affect dimensions regardless of the mentioned differences: *speed of printing and Layer thickness*. It gives a clue in the case of 3D concrete printing which also should be approved by observations.

During the observations the following parameters turn out to be important:

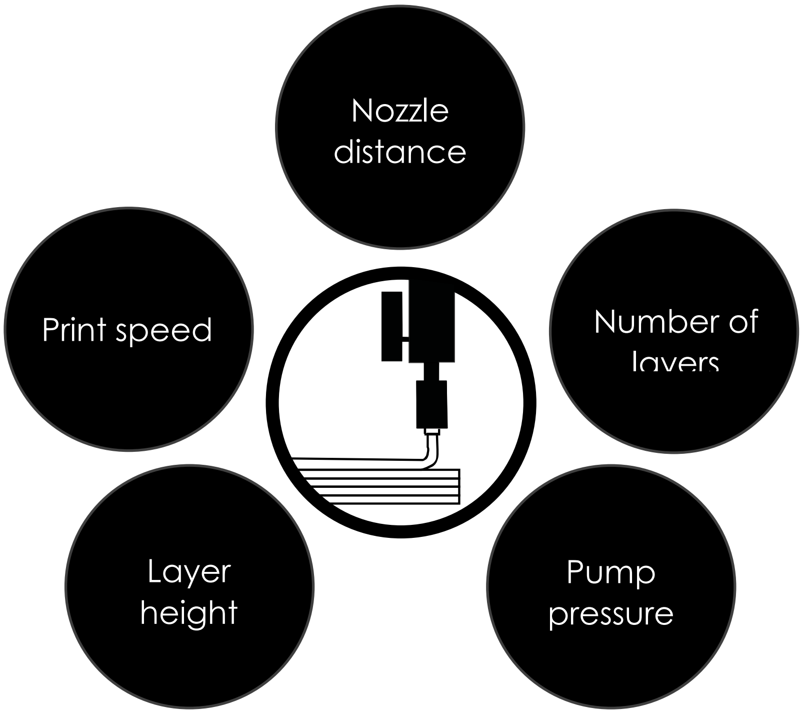


Figure 20:Observed influential Process parameters

Printing speed (mm/min) is the speed of the moving nozzle which defines how fast a certain tool path can be printed. As a result, it specifies the amount of material extruded in a certain time interval in a certain length of the tool path.

Observations have shown that higher the printing speed is, lesser the dimensional deformations are. The reasons are that the nozzle has less time to extrude material at a certain time in a certain location, hence there is less deformation due to its own weight for deformation.

Pumping degree(Hz) will specify the amount of material which is deposited by rotation of the printer pump, Higher the pumping degree is, higher the deformation is, as the higher amount of material result in higher deformation of a layer due the layer weight.

Nozzle dimensions which are the result of printer nozzle shape has a direct effect on dimensional deformations. By increasing the layer height, layer height deformation increases. The reason is the increase of the layer weight, which increases the layer deformation, due to the higher centre of mass. The resulted deformation is both in height and width direction. Change of nozzle width has not a significant influence on the layer deformation because in the same layer height the centre of layer mass does not change.

The increase of the number of layers increases the weight of the layers laying on first layers, which results in higher deformation of layers.

Nozzle distance from the surface on which concrete is going to be printed may show some influences on dimensional deformation, especially in interaction with other mentioned process parameters. How extruding material is pushing the deposited and how that can affect the deformations.

There are more factors may affecting dimensional accuracy, but the mentioned parameters are those which can be modified for the printing process, hence they are the first set of parameters to be investigated.

In order to investigate the effect of mentioned parameters, the possibility to change the parameters in different levels played an influential role in selecting the process parameter. At the time of starting the project, it was hard to change the nozzle dimensions to get different layer heights, so it was left aside. While fortunately now it is possible to 3D print different nozzles.

The number of layers got limited to a single layer because it was crucial to first find the most simple relation for one layer. So that the influences of the process parameters are understood on a single layer deformation and in the next steps, research will be developed and elaborated.

Another assumption has been taken in the combination of the included process parameters. For the same reason of limiting number of layers to one, the dual interaction of the process parameters is assumed as a base to form a relationship. By considering two process parameters, their effect and the level of influence will be more easily understood and a ground to further developments of the model will be founded. This issue is even more critical for technical researchers of the project and this decision has been reached to meet some levels of their concern.

The aim is to define a single layer deformation model, which include few parameters in order to create a basis to establish a relationship between process parameters and dimensional deformation.

As a result of the points mentioned above, two sets of process parameters has been assumed to investigate the influential process parameters on the dimensional deformation of a single printed layer.

Print speed (Pr) and Pump degree (Pu) and in another set of process parameters, *Printing speed (Pr) and Nozzle distance (Nd)* are coupled.

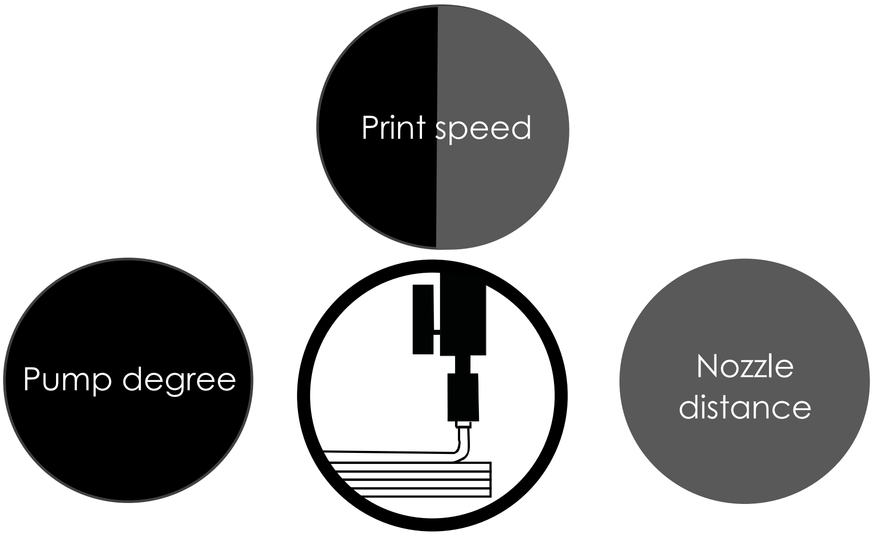


Figure 21: Focused process parameters

The effect of these two sets of process parameters has been checked on deformation of a layer. Deformation has been targeted in height, top width and a bottom width of a layer printed by a nozzle of *25mm×25mm*.

The selection of such a nozzle was due to the availability of this type of nozzle at the time of designing and performing the research.

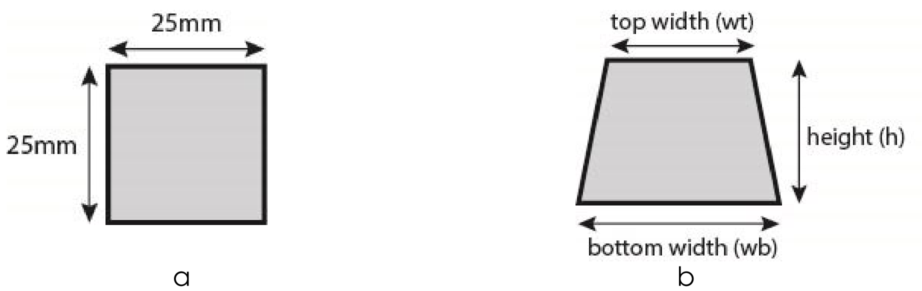


Figure 22: a) Nozzle dimensions, b)Printed layer cross section

By establishing an understanding of the introduced process parameters, *two models* is created *connecting mentioned process parameters to predictions of height, top width, and bottom width*.

Such models will be the core of a decision support tool, assisting designers and operator during the printing process to derive the most proper decisions to fulfil the requirements. Next section will elaborate on the models and their components.

5.3. Design of model-based Decision Support System

In chapter 3 different types of Decision Support Systems have been explained. Among them, *model-based Decision Support System* would be a suitable match for the case of dimensional deformation.

As described in section 5.3, at the core of the decision support model, there is a model created which relating influential process parameters to dimensional deformation. In the other words, there is a model built to predicts height, top width and bottom width in two models. These models are the means to increase the understanding of concrete printing process, which can assist the designer and operator with the proper decisions.

In this section, model-based Decision Support Systems are elaborated and required components for the case of dimensional Decision Support System has been mentioned.

5.3.1. Model-based Decision Support Systems

Model-based Decision Support Systems(DSS) are designed in order to help decision makers by employing models and data to communicate with the user via user interface. These models are mainly mathematical, which consists of (Burstein & Holsapple, 2008):

i. Decision variables as input, which are controlled by user;
ii. External variables as input, which are not controlled by user, and are under influence of environmental situations;
iii. Outcome variables as output used for measuring the consequences of implementation of input.

In the case of 3D concrete printed layer deformation, inputs are *Print speed & pump degree* in one model and *Print speed & Nozzle distance* on another model.

External variables are a number of layers and nozzle type which are *one* and *25mm×25mm*, due to mentioned reason in section 5.3.2. Output variables are dimensional prediction: height, top width, and bottom width.

Benefits of model-based Decision Support Systems are as follows (Turban, 2007):

i. Models allow easy manipulation of decision variables in order to track their influence on a system;
ii. Simulating scenarios of the decision process;
iii. Models enable the compression of time. Years of operations can be simulated in minutes or seconds of computer time;
iv. The cost of generating, error occurrence and risks associated with modelling analysis is much less than the cost of a similar experiment conducted on a real system;
v. Models enhance and reinforce learning and training.

From the above-mentioned advantages, another advantage of model-based DSS in the context of concrete printing is the fact that the level of process parameters effect on dimensional deformations is understood. Moreover, the result of the model will shed light on the behaviour of material in deformation during the concrete printing process.

5.3.2. Architecture

In this section, the architecture of the model-based dimensional Decision Support System will be elaborated. Moreover, components, their elements and design environment of the Decision Support System will be mentioned.

In section 3.3 main components of general Decision Support Systems have been mentioned. In order to shape the '*dimensional Decision Support System (dDSS)*', the main architecture of a DSS has been customized.

Moreover, dDSS is model-based DSS and its models play a centric role in defining relations, increasing the understanding and assisting the designer and operator with proper decisions. As a result, the architecture of dDSS is influenced by the architecture of model-based DSS.

'dimensional Decision Support System (dDSS)' contains 4 main components:

I. User Interface (UI):
   i. Language System (LS)
   ii. Presentation System (PS)
II. Model Management System (MMS)
III. Problem Processing System (PPS)
IV. Data-base

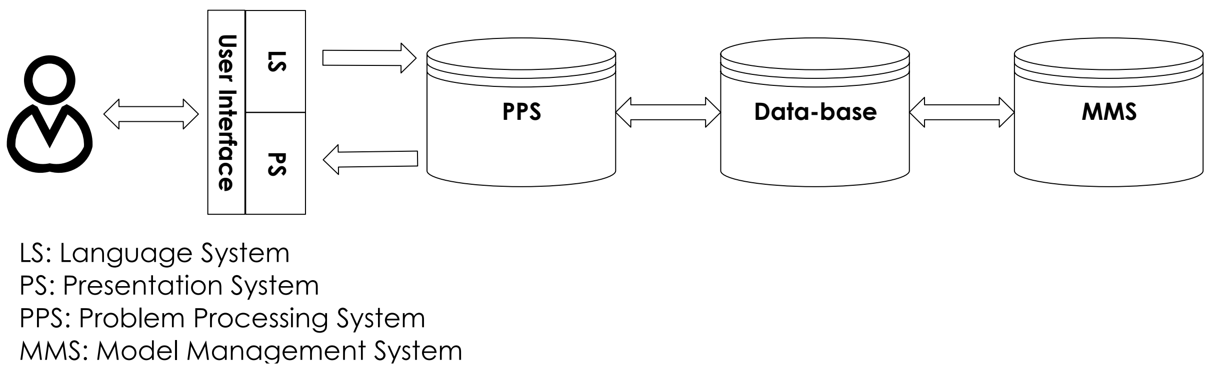


Figure 23: dDSS architecture

I. ***User Interface (UI)*** component is the gateway for the user to dDSS to *communicate, introduce specific levels of the process parameter and query required dimensional prediction. In the other words, UI performs as a link between user and DSS.*

Important issues taken into consideration while selecting the UI are screen design, choice of input and output devices, data and information representation format, use of different interface style (Kumar, B, & Saxena, Decision Support System: An Overview, 2006).

Language System (LS) is a part of UI which consists of all messages the DSS can accept. It clarifies the situation introduced to the system, accept knowledge, Recall or derive knowledge and govern coordination, control and measurement knowledge.

Presentation System (PS) presents all knowledge required through LS, seek knowledge for further clarification, and basically is the gateway of the DSS to communicate with the user (Holsapple, 2008).

MATLAB has been chosen to develop the UI because of its (T.Smith, 2006):

i. *Simplicity of its layout*: Graphical layout is *intuitive* for development and interaction

ii. *Automatic code generation*: MATLAB generate call-back function code and allows to *focus on the details* of the UI design.
iii. *Object property control:* Provides complete overview over available properties and hierarchy allowing the developer to modify UI components *efficiently*.

Through LS, the user can introduce Pump Degree(Pu) in *Hz* and Print Speed (Pr) in *mm/min* as process parameters, when the dimensional prediction is required by the user. Moreover, he/she can input desired layer dimensions in *mm,* in the case that proper process parameters are needed to reach desired dimensions. In both cases, inputs are in the format of the number.

The user can also select output representation, according to its needs which can be in the form of 3D or contour graphs. Also requirements, steps, and conditions of the interaction of user and UI.

Through PS, system provides knowledge in the form of:

i. Number (e.g. showing print speed, Height or etc.)
ii. Process parameter-dimension prediction graph: when one of the process parameters are given by the user. (e.g. Pu in known and the graph of Pr-H is required)
iii. *Contour graphs*: Querying detailed knowledge over the influence of Pr and Pu on layer dimensions.
iv. *3D response surface*: Showing the overall trend and relationship of Pr and Pu on layer dimensions.

II. Model Management System (MMS) is a software system that provides tools and environments to develop, store, and manipulate models, data, and solution methodologies associated with complex decision problems.

In dDSS, different elements of MMS mentioned in literature are customised and combined. Because this approach creates an *integrated MMS* which contains essential elements to access models and linkages with other components. In integrated MMS, linkages are established in the same environment which is built more efficient and shows smoother performance.

Components of MMS are:

i. Model base
ii. Model development environment (MDE)
iii. Model execution environment (MEE)

The environment which MMS has been established is an open-source statistical programming language of R. R is comprehensive statistical analysis package, with numerous libraries incorporating a vast range of data manipulation techniques.

Another positive feature of R is the fact that it is open source and free, allowing researchers, start-ups, and organizations to an extensive access to a powerful software, to perform statistical analysis. As a result, there would be no need for spending for licenced statistical software.

Integrated MMS is designed and developed in R and its components are elaborated in the following sentences.

Model-base is a collection of computer-based decision models. Its function is similar to a database, except that the stored objects are models. The models in the model base can be divided into different categories, such as strategic, tactical, operational, and analytical (Ting-Peng Liang, 2008).

In the case of dDSS, there are two models at the technical level, relating process parameters to a printed layer dimensions. Both models presented below can predict backward, in the sense of predicting proper process parameters, leading to desired layer dimension.

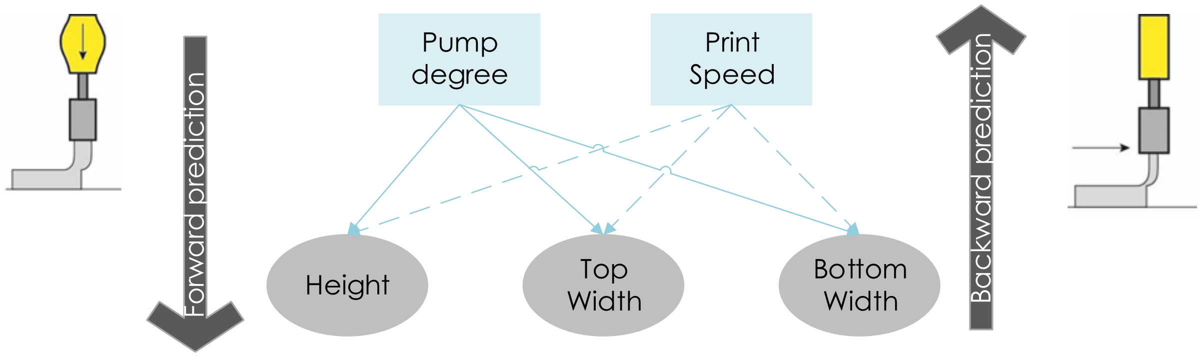


Figure 24: Pump degree-Print speed model (PuPr)

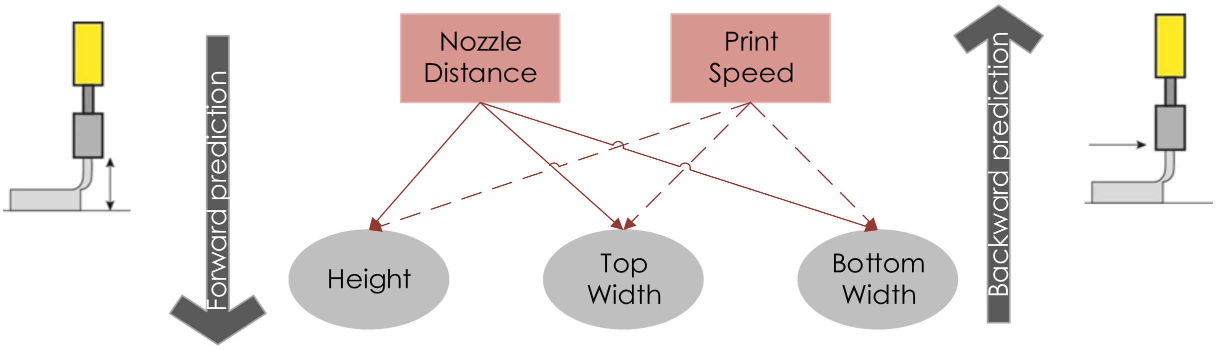


Figure 25: Nozzle distance- Print speed model (NdPr)

It is an important decision upon the experimenter to define a region of interest for each process parameter. Such a range specifies the fact that the parameters change. *Process knowledge* is needed to specify *design region*. This process knowledge is usually a combination of practical experience and theoretical understanding (Montgomery, 2012).

For dDSS, for each process parameter, the medium level is defined as a level which is used in the most cases. Such a level has been chosen as they are the levels which are used the most, while do not introduce excessive pressure on the printer, or affect the quality of the extruded material and printed element. For the same reason, the range for each process parameter has been exceeded.

For the case of ***PuPr*** model, Too much increase in Pump degree (Pu) results in the excessive rise of material temperature, and consequently changing the behaviour of material in a way that changes material characteristics in the design phase. Moreover, high Pump degree increases friction between extruding material and pump, which resulted in extra pressure on pump joints and splashed out the material. On the other hand, low levels of Pu results in stocking the pump, because it is not able to direct the material to a 5 to 10-meter hose responsible for depositing the material. As a result, Pu has been varied in a range ±10% from the medium (usual) pump level.

For the Print speed (Pr), the situation is less critical, because it has less effect on material characteristics and printer machinery. High levels of Pr result in discontinuity in print path, while low levels of Pr cause major deformations in the printed object, increase the time of construction, material use and cost of the concrete printing process. So the range of ±18% of the average level of Pr, define the range of print speed variation.

For ***NdPr*** model, the range for Pr is assumed to be as defined for PuPr model. Nozzle distance has a minimum equal to the height of the nozzle. And its maximum is the nozzle distance which in different values of Pr in a defined range, the material is still extruded continuously.

Ranges and levels of the variation for process parameters in experimentation are elaborated in sampling section.

Model Development Environment (MDE) is used to build the model. It also provides a platform on which models can be created, saved, integrated, selected, and maintained if necessary.

*Model Execution Environment (MEE)*executes the mentioned models and perform further manipulations on models (Ting-Peng Liang, 2008).

R has been chosen because it provides the environment to integrate different component mentioned above and realised mentioned components which are described in an abstract way. MMS and specifically model base are the *core* of the dDSS.

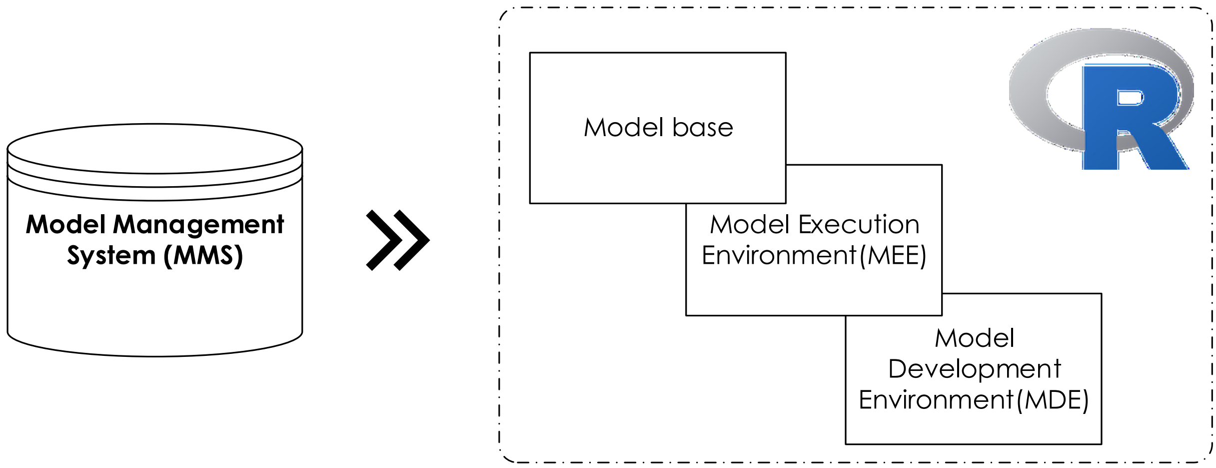


Figure 26: MMS components and environments

III. Problem Processing System (PPS) is the most active component of dDSS which is the software engine. PPS recognize the problem and solve it by providing required knowledge from MMS, according to user inputs and queries. In the other words, PPS links UI to the core of MMS, to provide input needed to derive required knowledge, and finally, represent them in the right format (and as is asked) to the used. As the MMS is the core of decision system, PPS acts like ***veins*** pumping data and knowledge through the whole body of the dDSS.

Some PPS behaviours are overt (witnessed by the user via PPS emission of PS elements) and others are covert (strictly internal, yielding assimilations of knowledge) (Ting-Peng Liang, 2008).

The *First-order abilities* of PPS are those which appear in front-line of dDSS and are on the basis of primary knowledge-manipulation activities within the MMS. These abilities are:

i. Knowledge acquisition
ii. Knowledge assimilation
iii. Knowledge selection
iv. Knowledge generation
v. Knowledge emission

Second-order abilities of PPS are concerned with over- sight and governance of first-order abilities within and/or across decision episodes. The abilities mentioned below have an important influence on arrangement and interplay of the first order abilities.

i. Coordination: ability to arrange knowledge-manipulation tasks
ii. Control: refers to the ability to ensure the quality and sufficiency of knowledge processing
iii. Measurement: the ability to track processing and outcomes within and across decision-making episodes in terms of desired criteria.

The environment of developing PPS is MATLAB, as it is a common approach to using it for a prototype of a computational system and conduct the further developments in a framework of programming language after approving the proof of concept.

The reasons are the extensive libraries and packages of MATLAB, its desktop environment allowing to work interactively with data, Suitable UI (for reasoning see above) and its strong built-in data representation.

In the case of dDSS, PPS has to communicate smoothly with other components of the system. UI is one of the components by which both first and second order abilities of PPS is closely represented. It is more efficient to develop both environments in the same environment.

On the basis of the points mentioned in the UI and PPS part, MATLAB found to be a proper choice.

IV. ***Database*** plays a centric part in dDSS, which is a container of designs and generated experiments' data. Those data lead to deriving required knowledge in MMS, controlled, measured, coordinated by PPS, represented by UI .

In the database, specifications of the model base are stored to be accessed by PPS in order to perform second order functions on the knowledge, for further processing. Moreover, in a database designed experiment configurations has been stored, by which the model is initially built. Above mentioned data are stored in the format of CSV.

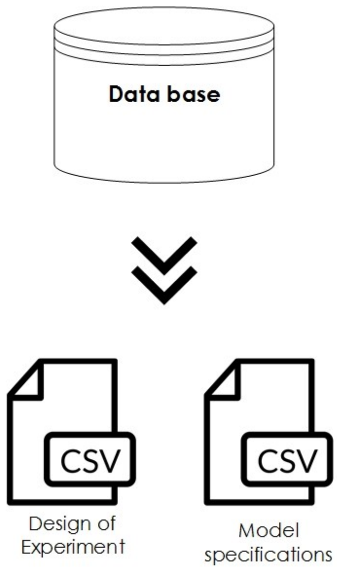
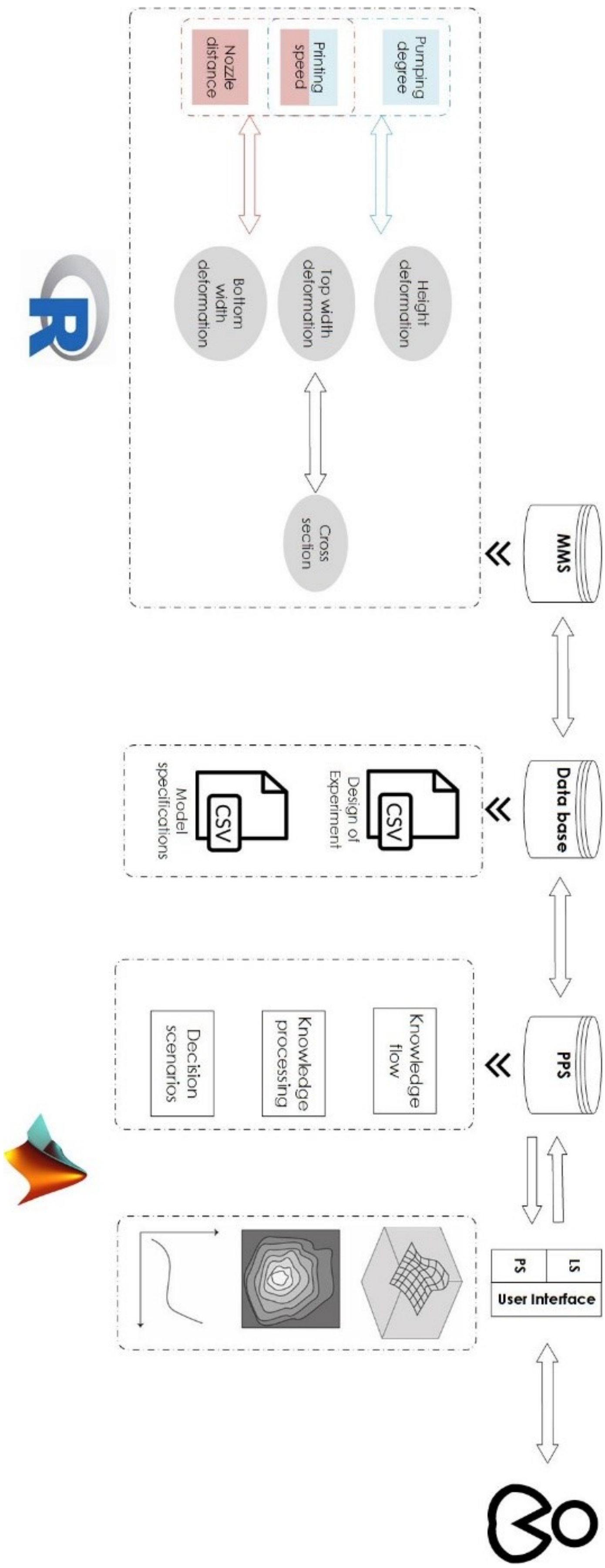


Figure 27: Database components and format

Below, in an integrated diagram, dDSS has been presented.

Figure 28: Extensive overview on dDSS



In the next section, the elements will be elaborated by explaining underlying methods and details in dDSS components. As a result, the theoretical abilities and functionalities of MMS, PPS and database mentioned above will be realized.

5.4. Methodology

As it can be seen in Figure previous section, Model Management System (MMS) is the core of dimensional Decision Support System (dDSS), containing the models producing the enquired knowledge. As a result, in this section, the methodology of constructing models in MMS has been elaborated.

In order to construct underlying models, according to the described method, data generated, to provide enough observation for explaining the relations between process parameters and single layer dimensions. Data settings, generated and implemented are explained in this section.

5.4.1. Design of Experiment (DoE)

In order to increase the understanding of the behaviour of layer dimensional deformation, ***data-driven approach*** has been selected. The required behaviour shed light on the effects of influential process parameters on layer deformation. These effects are complex and can be hardly explained by mechanistic models, which try to investigate via mechanistic and physical rules.

As a result, data-driven approach creates an opportunity to observe, approximate and explain the relationship among process parameters of 3D concrete printing and dimensional deformations. Hence, experiments are needed to be designed in order to provide sufficient data with right setting to realize dimensional predictions.

In order to understand what happens to concrete printing process, process parameters under investigation, deliberately varied in certain levels, and outputs (layer dimensions) have been observed. In the other words, ***experiments*** should be conducted in order to understand the cause-and-effect relationship.

Moreover, it is important to determine how process parameters are responsible for the observed changes in layer dimensions, develop models relating process and response parameters, using the models for process improvement and facilitate decision –making. Experiments should be planned and designed to provide required data, that the observations can reach the abovementioned goals.

Well-designed experiments can often lead to a model of system performance; such experimentally determined models are called empirical models. A well-designed experiment is important because the results and conclusions that can be drawn from the experiment depend on to a large extent on the manner in which the data were collected (Montgomery, 2012).

There are different experiment strategies:

The best-guess approach, which starts with an arbitrary combination of the parameters, observe the outputs, switching the levels of one or two parameters, to improve the response parameters. This approach is not suitable for the 3D concrete printing process, as the technique requires a great deal of theoretical and practical knowledge under study. Moreover, suppose the initial best-guess does not produce the desired results. Now the experimenter has to take another guess at the correct combination of factor levels. This could continue for a long time, without any guarantee of success.

To understand another drawback, suppose the initial best-guess produces an accept- able result. Now the experimenter is tempted to stop testing, although there is no guarantee that the best solution has been found (Montgomery, 2012).

One-factor-at-a-time (OFAT) starts with a baseline set of levels selection, and by considering all parameters except one which is varied in the considered range. This parameter varying will be repeated to represent the behaviour of response parameters against each of the input parameters. The main disadvantage of such a method is the fact that it is not possible to show the effect of parameters' **interaction**. The one-factor-at-a-time strategy will usually produce poor results and the method is less efficient than other statistical methods.

Design of experiment (DoE) or experimental design, is the name given to the techniques used for guiding the choice of the experiments to be performed in an ***efficient way*** (Ralston, 2003). Three main principles of statistical DoE are *replication*, *Blocking*, *randomization*.

Replication is repeating the experimentation in order to obtain more precise model and estimation of errors in experiments.

Randomization refers to the order of experiments run, and by including such a principle the experiments are not under the influence of previous or subsequent runs.

Blocking is employed to improve the precision of targets and response parameters. For instance, in the concrete printing process, each bag of printable concrete may vary in quality and they perform different characteristics. So, this accounted as nuisance factor, which can be eliminated by blocking. Each block forms homogenous experimental conditions, in terms of batches of concrete. Then the analysis will be done within and between blocks to show the dependency of the experiment to the blocking factor and eliminate that.

Figure 29: DoE steps

In the context of 3D concrete printing, DoE provides the possibility of efficiently directing the resources toward the response parameters, while considering interactions. As a result, the such a strategy for experiment design fits the purpose of making a model to achieve dimensional prediction and facilitate the process of decision-making in process parameter setting selection.

5.4.1.1. DoE types

In this section, the most common types of DoE have been explained, then the criteria to choose a method used to create Model Management System (MMS) in dDSS has been explained.

Randomized Complete Block Design (RCBD) is a DOE technique based on blocking, mentioned in the previous section. There are always uncontrollable parameters (nuisance factor) which affect the dimensions of a layer, in addition to process parameters under investigations (*primary parameters*). Thus, experiments should be randomized while data generation, so averagely, their effect will hopefully be negligible. RCBD is useful when the interest is focusing on one particular primary parameter whose influence on the response variable is supposed to be more relevant (Ralston, 2003). Hence, blocking technique on the other factors is used , to keep the values of the nuisance factors constant. So a batch of experiments is performed where the primary factor assumes all its possible values, while possible combinations of the nuisance factors are provided, to realise randomized blocking. Number of experiments is shown as follows:

$$N(L_i) = \prod_{i=1}^{k} L_i$$

Equation 1

Where L is levels of k parameters involved in the experimental investigation.

Here the aim is to focus on the primary factor, but in the case of dDSS, the effect of all considered process parameters are important to be clear, and they have all the same priority of investigation.

Factorial experiment is a strategy of experimentation allowing the variation of parameters together and is an important concept in designing experimentations for engineering disciplines. The method can be in two manners, full or fractional.

In full factorial, L^n experiments are planned to be performed, where n is the number of parameters, and L is the levels of investigating parameters. Full factorial is probably the most common and intuitive strategy of experimental design (Ralston, 2003).

In fractional factorial, the number of planned experiment have been reduced to combining k parameters out of n number of parameters (L^k), to reduce the cost and time needed to data generation. The idea of the fractional factorial design is to run only a subset of the full factorial experiments. Doing so, it is still possible to provide quite good information on the main effects and some information about interaction effects. The fractional factorial samples must be properly chosen, in particular, they have to be balanced and orthogonal. By balanced, we mean that the sample space is made in such a manner so that each factor has the same number of samples for each of its levels (Ralston, 2003).

Plackett-Burman is very economical, two-levels, resolution III designs, which its relation is I = ABD = ACE = BCDE (A, B, … are parameters under study), estimating the main effects, while might be confounded with two-factor interactions. Resolution is an important property and ability to separate main effects and low-order interactions from one another. Formally, the resolution of the design is the minimum word length in the defining relation excluding which its defining relation (Box, Hunter, & Gord, 2005). The method is suitable for making rough estimations of the main effects, which makes it a bit unsuitable for dDSS, as interactions are not considered.

Plackett-Burman designs are helpful only for screening the design space to detect the large main effects and the sample size must be a multiple of four up to thirty-six (Ralston, 2003).

The ***Taguchi*** method is focusing on finding the best values of the process parameters (controllable factors) to decrease the sensitivity of the changes in nuisance factors. As a result, the method is also called Taguchi robust parameter design. Taguchi gives information about the interaction between the controllable process parameter and the noise parameters, which are important for a robust solution. This method does not handle non-linear dynamics and a mathematical model is not derivable from the technique. Moreover, the prediction preciseness of the method is not high.

Response surface Methodology (RSM) consists of a group of mathematical and statistical techniques used in the development of an adequate functional relationship between responses of interest (dimensional prediction of a printed layer, and a number of associated process (or input) parameters. In general, such a relationship is unknown but can be approximated by a low-degree polynomial model(Khuri & Mukhopadhyay, 2010). Two important models are commonly used in RSM which is first order and second order model.

The aim of conducting such a technique is:

I. Establishing a relationship which is able to predict response variables,
II. Through hypothesises, the level of significance of parameters will be tested,

III. To determine the optimum setting of process parameters on the region of interest.

After this short elaboration on a different type of DoE, next section states the selected method to construct the Model Management System (MMS) of the Decision Support System of a concrete printed layer.

5.4.1.2. Selection of DoE method

As it is mentioned in the previous section, there is a number of DoE techniques order to be implemented for constructing dimensional Decision Support System (dDSS). On the basis of the criteria mentioned below, the ***RSM*** technique has been selected.

The ***number of levels L*** for each process parameter is an influencing factor in choosing RSM method because L provides the possibility to investigate the relationships by considering the possible non-linearity. For dDSS, it is important to implement the technique which incorporates such a possibilities, as the relationships are not known. As a result, the L bigger than 2 will be more suitable to construct MMS models.

The choice of a suitable DOE technique depends also on ***the aim of the experimentation***. Here the aim is:

to screen the level of significance of process parameters against layer dimensions, developing an empirical model and establish a framework to perform further optimizations regarding minimizing dimensional inaccuracy.

As a result, the method should be able to provide good precision in prediction, allowing investigating the interaction among process parameters, and providing the possibility of incorporating non-linearity of the relation among layer dimensions and process parameters.

RSM is strong in identifying the critical parameters, the main and interaction effects of parameters which provide enough information for experimental studies(Montgomery, 2012). Furthermore, the significance of interactions and square terms of variables are more clearly predicted in RSM(Mohamed et al., 2015). Also, the prediction accuracy is high, a provide a graphical representation of responses and parameters and their interaction. It can be noted that RSM is a powerful optimization design allowing multi-objective optimization in cases that are required to optimize more than one response.

In the case of dDSS, the number of parameters k under investigation is minimum (2 parameters in two parallel models, see section 5.4.2), thus the N number of experimentations would not be an important limiting criterion to select DoE technique. But for the cases with k more than 2, it is important to take into account N. Because it is directly affecting the resources and time needed to generate and analyse experiments. The graph below shows required number of an experiment by a specific technique.

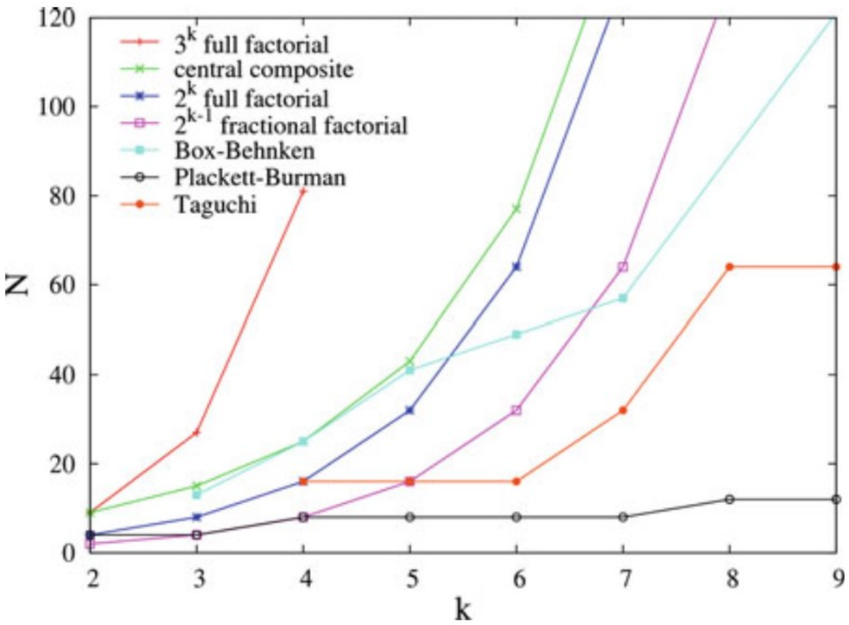


Figure 30: Required number of experiments for different DoE methods (Ralston, 2003)

It can be seen that by increasing k, required N is exponentially growing in most cases. Note that central composite and Box-Behnken mentioned in the graph, are two design in RSM method which will be elaborated in the next chapter.

5.4.2. Response Surface Methodology (RSM)

Response surface methodology(RSM), is a collection of methods in mathematics and statistics, contributing to the modelling and analysis of problems. The target or response variable is dependent on numbers of variable and the ultimate goal of RSM is to optimize the response and find the best combination of parameters' settings to achieve such an optimum.

For the case of dimensional Decision Support System (dDSS) it is important to draw a relationship between process parameters in two models, to predict the single layer dimensions.

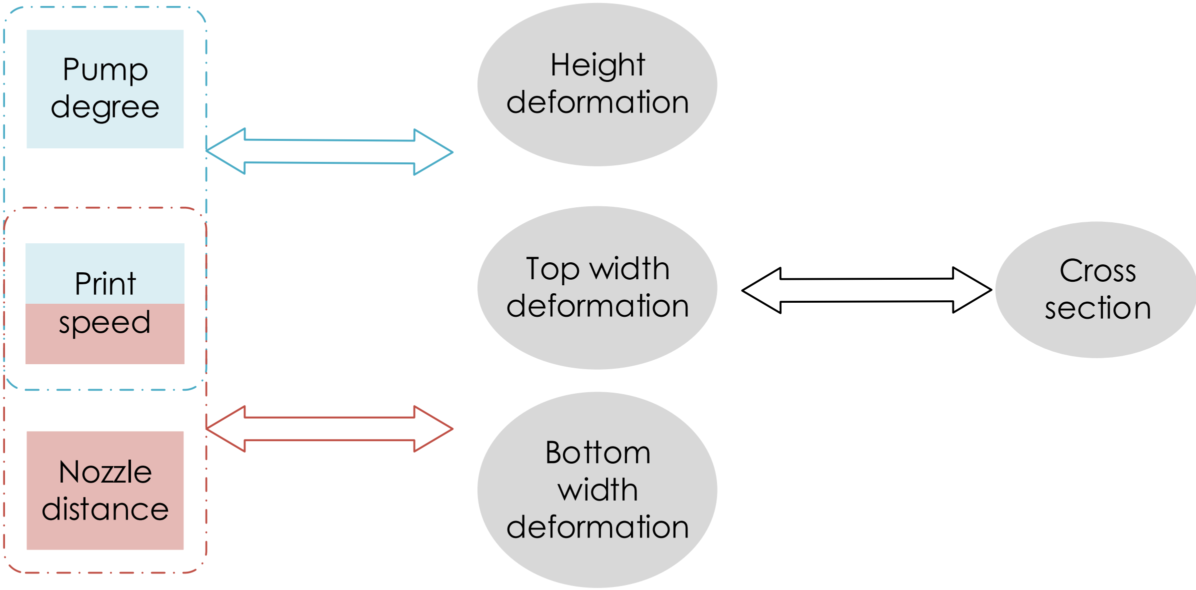


Figure 31: dDSS models

As a result, here there are three models, creating functions to link *Print speed (Pr)* and *Pump degree(Pu) to layer height(h), top width(t) and bottom width(b)*. The dimensions are functions of Pr and Pu:

$$height\ (h) = f(Pr, Pu) + \varepsilon$$

$$top\ width\ (t) = g(Pr, Pu) + \varepsilon$$

$$bottom\ width\ (b) = q(Pr, Pu) + \varepsilon$$

Where ε represent the noise or observed error in the response variables (*h*, *t,* and *b*).

RSM is used to represent the expected response for h, t and b, which is called **response surface**:

Expected response of height (h)	E(h)= $f(Pr, Pu)$
Expected response of top width (t)	E(t)= $f(Pr, Pu)$
Expected response of bottom width (b)	E(b)= $g(Pr, Pu)$

In addition to deriving expected responses via RSM, such response surfaces are represented graphically in 3D versus the levels of Pr and Pu, for a better visualisation and understanding their shapes. In addition to 3D response surface graphs, the contours of such graphs are plotted, in which lines of constant response are drawn in Pr and Pu plane. Each contour corresponds to a particular expected values.

Such response surfaces of E(h), E(t) and E(b) are unknown, Thus, the first step in RSM is to find a proper model for the relationship between response variables and the set of independent variables. Here, response variables are *height (h), top width(t) and bottom width (b),* and independent variables are process parameters of Print speed (Pr) and Pump degree(Pu).

RSM is a stepwise approach, tries to find the relationships from the simplest explanation and enhance the model if needed by adding more terms to explain the relationships.

Usually, a low-order polynomial in some region of the independent variables is employed. If the response is well modelled by a linear function of the independent variables, then the approximating function is the ***first-order model*** (Montgomery, 2012)***:***

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \varepsilon$$

Where x_i are independent variables (*i=1,2,…k*) involved in modelling response variable of y. This model is also called pure linear function, as the interaction among the independent variables are not considered. In such a model investigates the **main effects** of independent variable or process parameters in the case of dDSS.

Two variables have ***interaction*** on response variable y when the effect of each variable on y is not the same, for different values of the other variable. Another step in RSM is to incorporate the effect of interaction between process parameters under investigation. This step helps to shed light on the manner which parameters are interacting to influence on response variables which are layer dimensions in dDSS.

This effect is studied by adding the term of cross-product x_1x_2 representing the two-factor interaction between the design factors. Because interactions between factors is relatively common, the first order model with interaction is widely used (Montgomery, 2012). Higher-order interactions can also be included which is not the case for dDSS, as there are only two process parameters under study. Such a model is called linear interactive model in this research, as it contains the interaction effect, in a linear relationship.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i<j} \beta_{ij} x_i x_j + \varepsilon$$

The next step seeks to explain the possible curvatures in the system by polynomial higher degree. RSM conduct such an investigation by fitting the model with *full quadratic model*, a ***second-order*** function for response variable y:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i<j} \beta_{ij} x_i x_j + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \varepsilon$$

Usually by couscous implementation of tools and techniques (transformations of responses and factors, for example) in fitting processes, finding an industrial process that requires a third-order model is highly unusual. Therefore, the focus is on designs that are useful for fitting quadratic models. As we will see, these designs often provide a lack of fit detection that will help determine when a higher-order model is needed (Croarkin & Tobias, 2003).

Obviously, it is probable that a polynomial model will not be a reasonable approximation of the true functional relationship over the entire space of the independent variables, while for the limited region of interest they usually work quite well.

The method of *least squares* is used to estimate the parameters in the polynomials approximation. The response surface analysis is then performed using the fitted surface. in the case that the fitted surface is an adequate approximation of the actual response, then analysis of the fitted surface will be approximately equivalent to analysis of the actual system. The model parameters can be estimated most effectively if proper experimental designs are used to collect the data. Designs for fitting response surfaces are called response surface designs (Montgomery, 2012).

By the ***sequential procedure***, after suggesting the proper approximation of response variable, RSM follows the objective of finding **the optimum response**, by lead the experimenter in an efficient manner toward the general vicinity of the optimum.

This sequential procedure also starts to form the first order model, if there are small curvature in the model. Once the region of optimum was detected, an elaborated model such as linear interactive or second order model is needed, because usually lack fit of a first-order model is indicated (Montgomery, 2012). At that time, additional experiments are conducted to obtain a more precise analysis, and thus, reach the location of the optimum.

The ultimate goal of the RSM is to determine the optimum value of response variable, which in the scope of dDSS is not the objective. In addition to the time limitations due to the scope of graduation projects, there is a main practical reason, skipping the optimization step.

It is preferable to minimize dimensional deformations, in order to reach the expected final height and increase dimensional accuracy. There are more several parameters affecting dimensional deformation which are not considered in the models created as the core of dDSS. Hence, optimizing the dimensional accuracy of these models will not lead us to the optimum responses for dimensions. Moreover, since there is limited control over the process itself, the concrete printer operator (researcher) should be in full control of the process. He or she control process parameters including Print speed and Pump degree, in relation to several factors which dimensional accuracy is one. So optimizing the dimensional deformation and derive proper setting will not necessarily lead us using derived process parameters.

For the sake of providing a framework suitable for further developments, to create DSS which contains optimizations, RSM is proposed. The method is also able to handle ***multiple response optimizations*** which give more strength to DSS, as multiple important response variables are considered.

RSM may seem to be a like a regression problem, however, there are several intricacies in this analysis and in how it is commonly used that are enough different from routine regression problems. These intricacies include the common use (and importance) of coded predictor variables; the assessment of the fit; the different follow-up analyses that are used depending on what type of model is fitted, as well as the outcome of the analysis; and the importance of visualisation (Lenth, 2009).

According to the need of designer and the expected preciseness of the model, RSM provides piece-by-piece, iterative experimentation that evolves the model.

In the next section, steps used of modelling according to RSM is explained.

5.4.2.1. RSM design assumptions

In order to properly fit and analyse response surfaces, certain aspects should be considered to come up with the suitable experimental design. Features which are essential for a proper experimental design of RSM are set as criteria to choose the experimental setting and design, which will be mentioned in this section.

the ***Central Composite Design (CCD)*** is selected as response surface design**,** which generally, contains 2^k *factorial* (or fractional factorial of resolution V) with n_F *factorial runs, 2k axial or star runs*, and n_C *centre runs* (Montgomery, 2012). In the case of dimensional Decision Support System (dDSS), 4 factorial, 4 axial and 5 centre runs have been assumed. For factorial and axial runs the replications are not considered. The figure below shows a design for factorial, axial and centre points when k=2.

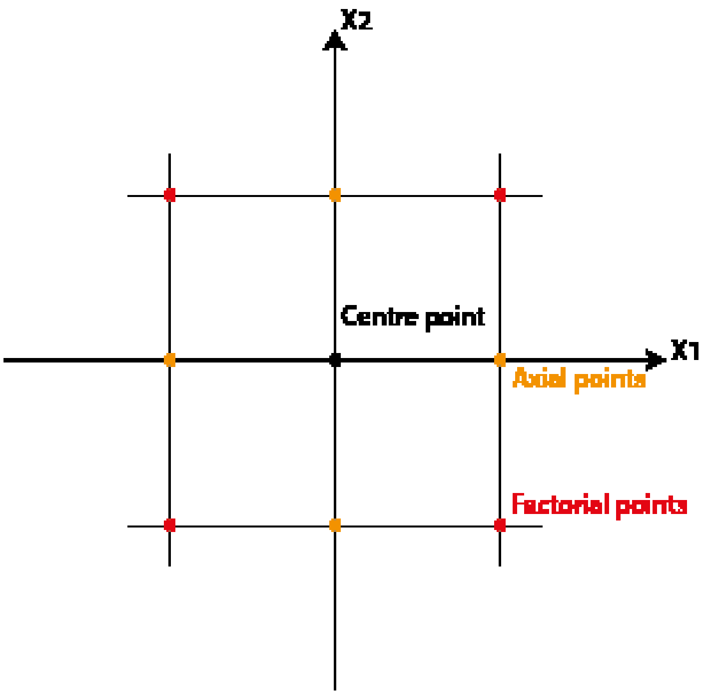


Figure 32: CCD design points

CCD is a popular class of experimentation design as it is an efficient approach allowing **sequential experimentation**:

I. *First*, a *block* of designed experiments with the combination of 2^k has been used to fit a first-order model. Pure linear model is constructed, if the design does not show adequate fitness, cross-production of the independent variables will be incorporated to seek the effect of parameters interaction on response variables and the fitness of such model against the linear interactive model.

II. *The second* step is to add axial runs (*2k*), allowing for a second-order approximation, which will be followed by model adequacy check.

So in order to perform required experimentation step by step, when is needed, they are designed in blocks. Blocks control the certain experiments in each block, to be performed in a homogeneous situation. Thus the variation between experimentation conditions minimized.

However, in response surface, the estimation of the polynomial effects are often influenced by the block effect. The desired blocking strategy is to minimize the blocking effect on the model coefficients. Orthogonal blocking provides the same estimate of the model coefficients as would have been obtained by ignoring the blocks (Wang, Kowalski, & Vining, 2009). It is preferable to design orthogonal blocks, as it eliminates the effect of blocking on the nature of the response surfaces.

Now, **foundations of CCD** design is described. The fundaments of CCD design to determine the level of preciseness of prediction in the design region. This is of importance, as the behaviour of the region is unknown to us.

An important aspect of response surface analysis is using an appropriate ***coding transformation of the data***. The way the data are coded affects the results of finding the path toward the optimum responses in design region. In the other words, it affects the results of canonical analysis and steepest-ascent analysis . As optimization is not in the scope of this research, for more information about the mentioned analyses, see *Montgomery, 2012*. Using a coding method that makes all coded variables in the experiment vary over the same range is a way of giving each predictor an equal share in potentially determining the path, leading to the general vicinity of the optimum. Thus, coding is an important step in response surface analysis(Lenth, 2009).

Coding implemented here when there are two natural variables of Ƞ and ɵ. Functions shown below transforms the data to ranges [-1, +1] for all variables and creates a coded design region.

$$x_1 = \frac{\eta - (\frac{\eta_{max} - \eta_{min}}{2})}{(\frac{\eta_{max} - \eta_{min}}{2})}$$

$$x_2 = \frac{\theta - (\frac{\theta_{max} - \theta_{min}}{2})}{(\frac{\theta_{max} - \theta_{min}}{2})}$$

As it has been mentioned before, ***Randomization*** is an important concept in DoE methods, as well as RSM. *Randomization* makes sure that the experiments are not under the influence of previous or subsequent runs. So, the order and settings of parameters n experiments are designed randomly.

Another basis for CCD design is rotatability. A design is ***Rotatable*** when the variance of the predicted values of y is a function of the distance of a point from the centre of the design. Before a study begins, little or no knowledge may exist about the region that contains the optimum response. Therefore, the experimental design matrix should not bias an investigation in any direction (Croarkin & Tobias, 2003). As a result, rotatability is a reasonable assumption to base the design.

On the other hand, the prediction preciseness of response variable y can be a function of distance and direction from the centre point. Such a design which defines ***Cuboidal Region of Interest***, locates the axial points on the centres of the faces of the cube, as it is shown for a design with 3 factors x_1, x_2, and x_3 (k=3). This variation of the central composite design is also sometimes used *because it requires only three levels of each factor, and in practice, it is frequently* difficult to change factor levels. However, note that face-centered central composite designs are not rotatable (Montgomery, 2012).

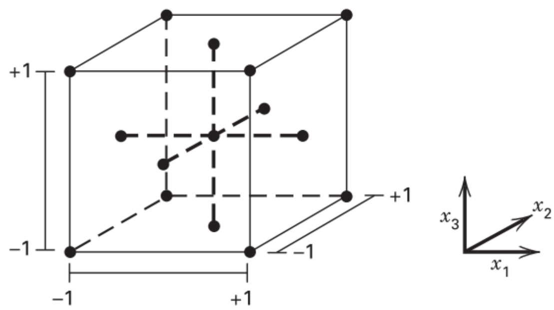


Figure 33: Cuboidal Region of Interest (Montgomery, 2012)

There are **two parameters** in the design that must be specified: the ***distance α*** of the axial runs from the design centre and the number of centre points $\boldsymbol{n_C}$**:**

I. Runs on centre points are conducted in order to check the curvature of the design region. As a result, it is used to check the fitness of both *first and second-order*. Moreover, centre runs are chosen to be used as the estimate of the experimental error. n_C between 3 and 5 within each block (mentioned in sequential experimentation description) would provide sufficient runs to investigate the error.

II. Distance from centre α defines the rotatability of design region. For $\alpha=(n_F)^{1/4}$, *rotatable* CCD will be achieved, where n_F is the number of points used in the factorial portion of the design. By defining α = 1, *Cuboidal Region of Interest* will be defined.

There are three **types of CCD** designs, which are defined by the place of star points and distance from design centre α.

I. Circumscribed Central Composite (CCC) designs are the original form of the CCD, in which *axial points are at some distance α from the centre* based on the properties desired for the design and the number of factors in the design. The star points to establish new extremes for the low and high settings for all factors. These designs are *rotatable* and *require 5* levels for each factor. CCC provide high-quality prediction over the whole design region (Croarkin &

Tobias, 2003). In CCC design, orthogonal blocking is possible by selecting the proper α in order to set (as traditionally is discussed in literature for a rotatable design) (Wang et al., 2009):

i. all the sums of products of the independent variables within each block are zero,
ii. the fraction of the total sum of squares for each variable contributed by each block must be proportional to the number of observations in each block.

Figure below shows CCC design for k=2, which results in $\alpha = \sqrt{2}$, the radius of the circle, showing the rotatability of design region .

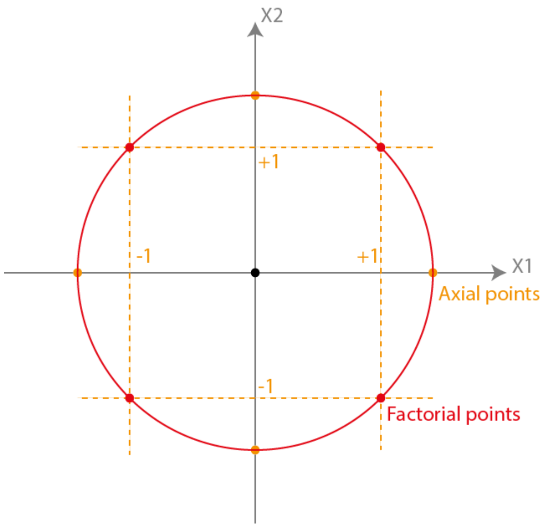


Figure 34: CCC design region

II. Inscribed Central Composite (CCI) suites for those situations in which the limits specified for design region are limited. The CCI design assumes the range of axial points as the boundary and defines a factorial or fractional factorial design within the boundary. CCI design is a scaled down version of CCC design with 5 levels required for each factor. CCI is rotatable, while its quality o prediction is less accurate for the entire design region, compared to CCC (Croarkin & Tobias, 2003). CCI provides the possibility of orthogonal blocking, which is beneficial to eliminate the blocking effect in modelling. The figure below shows CCI design for k=2.

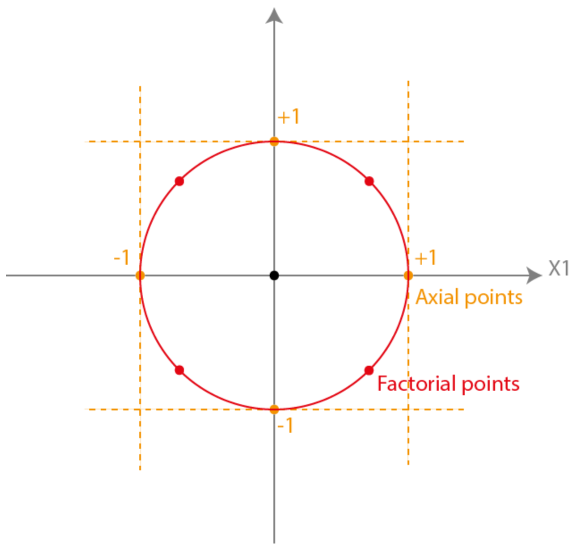


Figure 35: CCI design region

III. Face centred Central Composite (CCF) In this design α = ± 1 which indicates that, the axial points are at the centre of each face of the factorial space. CCF requires 3 levels of each factor. In CCF, it is not possible to design orthogonal blocks, but it is possible to track the blocking effect of gathered data, which will be elaborated on the method analysis section. The figure below shows CCF design for k=2.

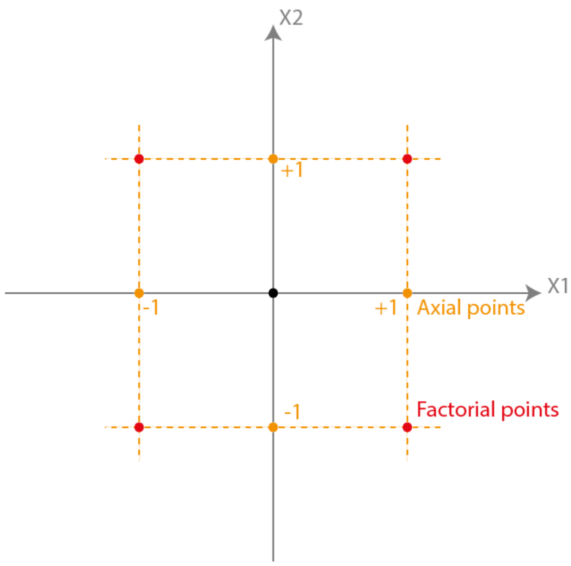


Figure 36: CCF design region

After elaborating on the assumptions of design experiments, the next section describes the analysis details in RSM.

5.4.2.2. RSM analysis steps and details

In this section, first steps of RSM design and analysis is elaborated and then details each step analysis is described. The first step is ***DoE*** (Design of Experiment) which design required experimentation as described in the previous section, followed by stepwise data generation in order to fit models, relating response variables (printed layer dimensions) and independent variables (process parameters of Pr and Pu).

Model fitting starts with the simplest relation among response and independent variables and moves toward higher orders of approximation in loops, including analysis and adequacy check steps. In the following figure, RSM design and analysis are shown.

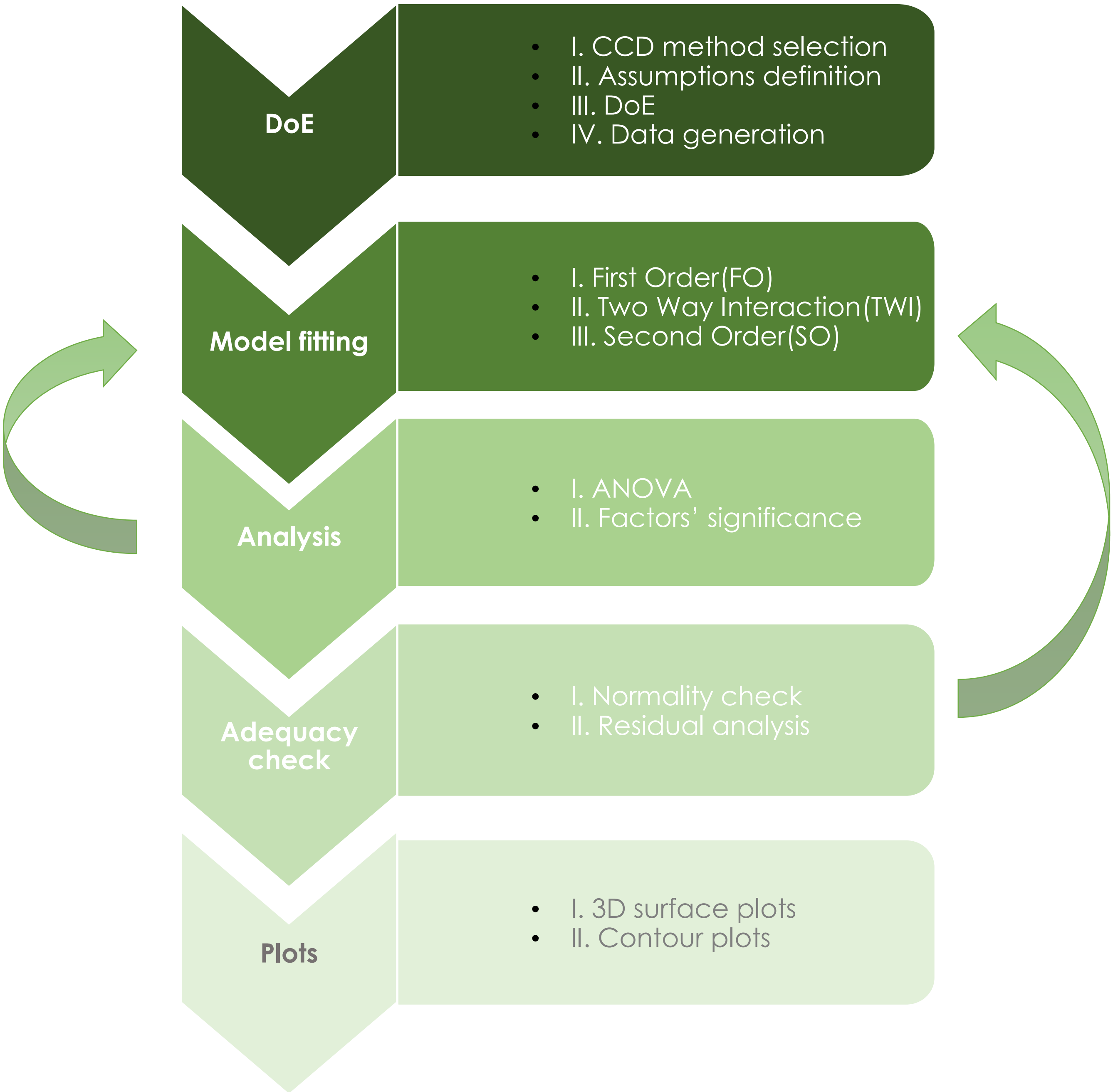


Figure 37: RSM steps

If the analysis does not satisfy certain expectations, higher order model will be

constructed. On the other hand, if analysis shows sufficient performance, adequacy check will be performed. In the same scenario, If the model showed adequate performance, the model would be considered as acceptable, otherwise, higher order model will be constructed and the same process will be repeated again.

If SO model does not perform adequately in either step of analysis or adequacy check, experimentation should be redesigned. Modifying initial assumptions such as selection of process parameters, ranges or levels, will probably lead the experimenter to achieve proper model.

Model is tested to be fitted to data by least squares***.*** Replications on centre point are used to calculate the experimental error of the model. Through the ***Analysis of Variance (ANOVA)*** table, the influences of independent variable through their coefficient and significance level is tested. The level of significance is shown by P-value and is tested against confidence interval (which is usually 95%).

Another information which can be derived from ANOVA is a lack of fit of FO, TWI, and Pure quadratic models. It states the extent which a model is fitted to data according to the assumed order of approximation. Its calculation is based on the single-degree-of-freedom sum of squares. Using lack of fit and significance of models, significant variables and suitable order of a model can be understood.

R-squared is another useful information which can be derived from ANOVA and it measures the proportion of total variability explained by the model. A potential problem with this statistic is that it always increases as factors are added to the model, even if these factors are not significant. The adjusted R-square is adjusted for the "size" of the model, that is, the number of factors. The adjusted R- square can actually decrease if nonsignificant terms are added to a model. It is a measure of how well the model will predict new data (Montgomery, 2012).

Adequacy check consists of two tests of assumptions, *Normality assumption,* and *residual analysis*.

I. An extremely useful procedure is to construct a normal probability plot of the residuals. A normal probability plot of the raw data is used to check the assumption of normality when using the t-test. In the analysis of variance, it is usually more effective (and straightforward) to do this with the residuals. If the underlying error distribution is normal, this plot will resemble a straight line. In visualizing the straight line, place more emphasis on the central values of the plot than on the extremes (Montgomery, 2012).

In general, moderate departures from normality are of little concern, while, an error distribution that has considerably thicker or thinner tails than the normal is of more concern than a skewed distribution.

II. Residual analysis is performed by plotting residuals versus fitted values. If the model and assumptions are correct, the residuals should be structureless, and a systematic trend could not be found in residual versus fitted plot.

Finally after constructing the mode and conducting required analysis and tests, response surfaces is visualised to lead the experimenter and decision maker toward the desired response.

Usually, computer programs and soft wares are used to proceed RSM design and analysis as thy increase the speed and visualisation of the results. Moreover, they contain elements of sequential steps all in a package. By such integration, performing RSM design and analysis has been improved.

As it is explained in section 5.4.2, *R* programming language has been employed in order to conduct RSM design and analysis.

5.5. Sampling Procedures

In this section the data used, RSM assumptions and details used to build models in the MMS of dDSS are elaborated:

I. ***"PuPr":*** considering Print speed (Pr) and Pump degree (Pu) as process parameters to affect layer dimensions.

II. ***"NdPr":*** considering Print speed (Pr) and Pump degree (Pu) as process parameters to affect layer dimensions.

In this section, assumptions and details are described for the both models.

Design region for two process parameters of Print speed and Pump degree is shown in the figure below (see 4.4.2 for elaboration).

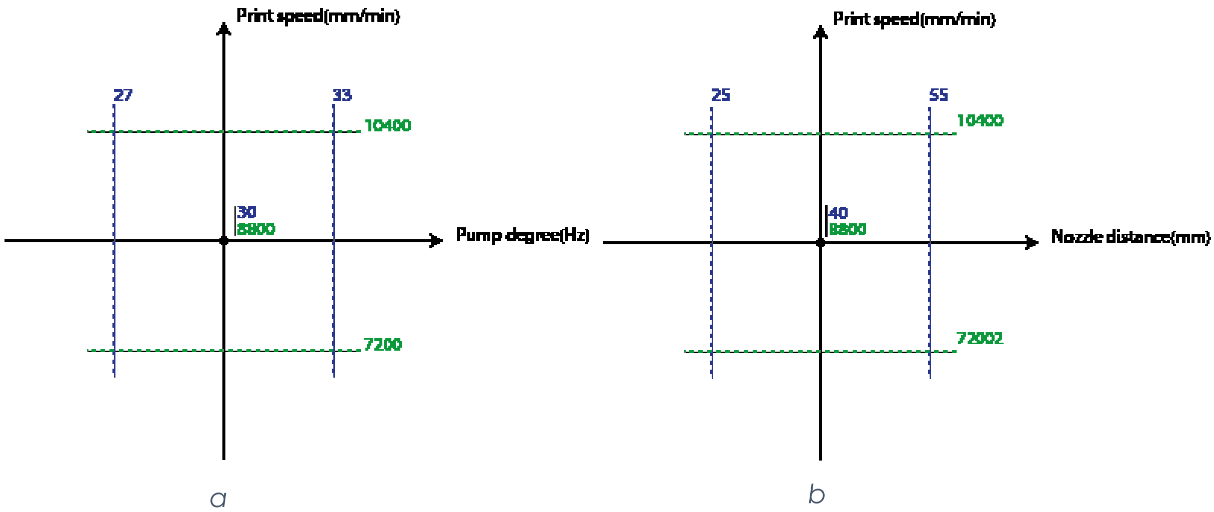


Figure 38: Design regions, a) PuPr, b)NdPr

For ***PuPr*** model, transformed variables of Pr and Pu are needed in order to be used in RSM design and analysis. Functions below transform Print speed and Pump degree, where min and max values of them represent the lower and higher values of the range mentioned above the result of such transformations are coded in the range of [-1,+1].

$$Pr = \frac{\text{Print speed} - (\frac{\text{Print speed}_{max} - \text{Print speed}_{min}}{2})}{(\frac{\text{Print speed}_{max} - \text{Print speed}_{min}}{2})}$$

$$Pu = \frac{\text{Pump degree} - (\frac{\text{Pump degree}_{max} - \text{Pump degree}_{min}}{2})}{(\frac{\text{Pump degree}_{max} - \text{Pump degree}_{min}}{2})}$$

In order to perform RSM design of the experiment, data which was produced previously and covers the design range of the current graduation research and development project. Print speed(mm/min) in the data set is in the range of *[7200,10400],* where the common speed is 8800 mm/min (mid-level)and Pump degree (Hz) *[27,33]* with the common pump of 30 Hz (mid-level). Both process parameters were varied in three levels of min, mid and max.

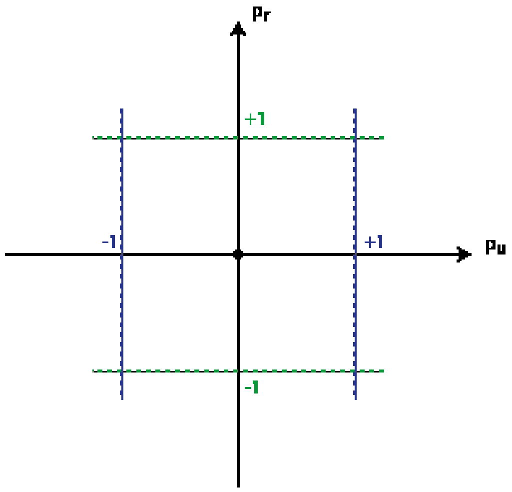
For ***NdPr*** model, transformed variables of Nd and Pr are defined as follows:

$$Nd = \frac{\text{Nozzle distance} - (\frac{\text{Nozzle distance}_{max} - \text{Nozzle distance}_{min}}{2})}{(\frac{\text{Nozzle distance}_{max} - \text{Nozzle distance}_{min}}{2})}$$

$$Pu = \frac{\text{Pump degree} - (\frac{\text{Pump degree}_{max} - \text{Pump degree}_{min}}{2})}{(\frac{\text{Pump degree}_{max} - \text{Pump degree}_{min}}{2})}$$

The range of Nozzle distance(mm) is defined [25,55] when its mid-level is 40 mm, and the range for Print speed is the same with PuPr model.

Below the transformed design region of the data is illustrated.



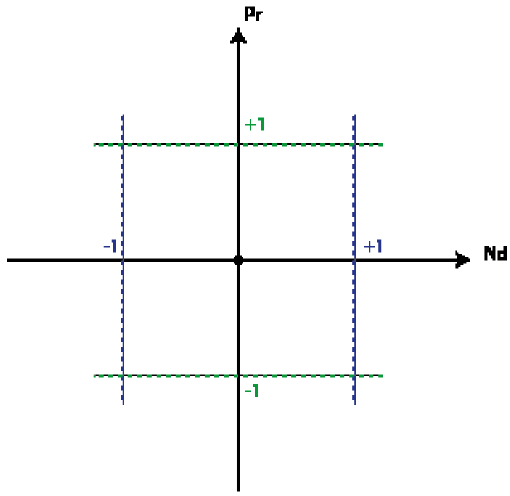


Figure 39: Coded design regions, a)PuPr , b)NdPr

Previously printed data in the database was used for RSM models. In Appendix 1 the printed setup for previous data generation is shown. As there are 3 levels of variation for process parameters, the ***CCI design*** described in 5.4.2.1 was chosen. As a result 2^k factorial, 2×k axial point runs is needed without considering the replications. Moreover for model error estimation, 3 to 5 runs are needed on centre points. Factorial points are those with all combinations on min and max level of variables. Axial points are a combination of mid for one variable and min and max for the other variable.

The following assumptions have been considered for RSM design and analysis, match the requirements of CCF design and available data.

Table 3: PuPr design specifications

Model	PuPr
Number of process parameters	2
Process parameters	Pu*, Pr*
Number of factorial points (k)	4
Number of axial points	4
Number centre points	5
Replications of factorial point	2
Replications of axial point	2
Replications on centre points	1
Number of blocks	2

* Pu and Pr stand for Pump degree and Print speed

Table 4: NdPr design specifications

Model	NdPr
Number of process parameters	2
Process parameters	Nd*, Pr
Number of factorial points (k)	4
Number of axial points	4
Number centre points	3
Replications of factorial point	1
Replications of axial point	1
Replications on centre points	1
Number of blocks	2

* Nd stands for Nozzle distance

Dataset used to build the stepwise approximation is shown in Appendix 2, which is printed prepared and measured as following.

Figure 40: Printing tool path

Figure 43: Overall Printing line numbering

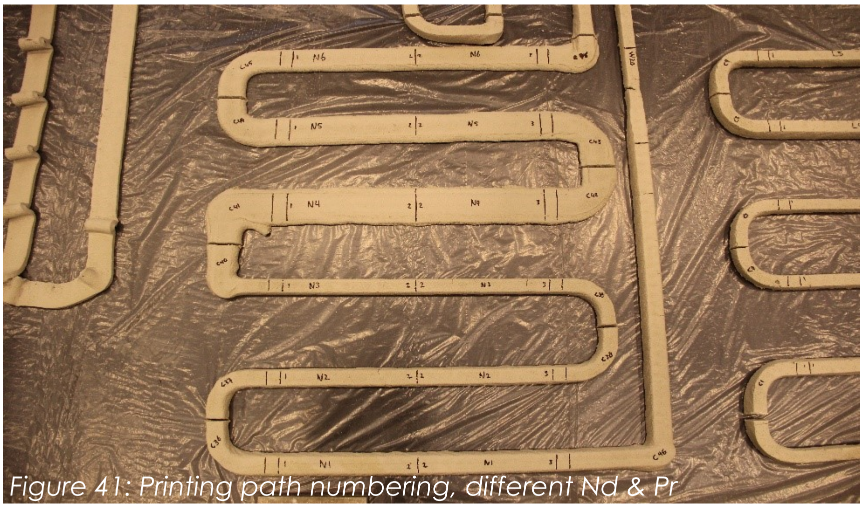


Figure 41: Printing path numbering, different Nd & Pr

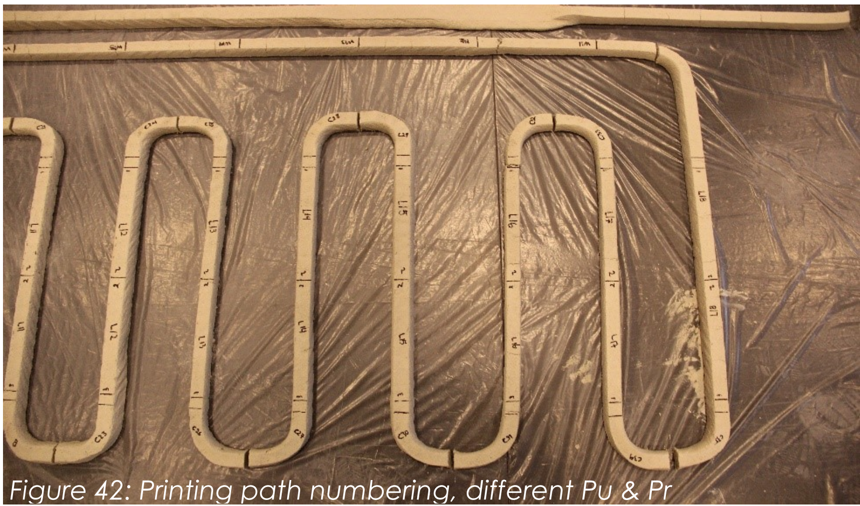


Figure 42: Printing path numbering, different Pu & Pr


Figure 46: Preparing samples to be cut


Figure 44: Overview of samples with same Pu


Figure 45: Cutting samples


Figure 47: Samples to be measured

5.6. Data pre-processing

Before conducting the main analysis according to the design proposed in section 5.5, it is important to perform pre-processing.

For models under investigation, data measured for each setting of process parameters in two models of ***PuPr***(considering *Print speed* and *Pump degree* as process parameters-see 5.4.2) and ***NdPr*** (considering *Nozzle distance* and *Print speed* as process parameters-see 5.4.2), has been plotted to check the extent which measurements of layer dimension (height, top and bottom width) are scattered comparing to each other, in a specific setting.

As a result, an initial idea of data fluctuations would be derived. Data were generated in replications, and under fixed process conditions(when process parameters kept constant). They have been produced under constant process parameters, which were assumed in this research, but there may be more variables which are out of the boundary of investigation and have an influential impact on layer dimensions(response variables of this research). As a result, by initial pre-processing, a better idea about the possibility of missing variable(s) is reached.

5.6.1. *PuPr* model

Results of comparing data between each replication of a specific process setting showed that the noise can be ignored. Hence, the effect of unconsidered process variables (parameters) is neglected able.

As a result, the range of dimension variation is clarified and a reasonable tolerance of ***1 mm (4%) for height and top width***, and ***2 mm for bottom width(8%)*** has been shown to be reasonable. So values in the range of the tolerance are assumed to be acceptable both for prediction derived and measurements performed.

In the pre-processing, for each setting(with specific *Pu* and *Pr*), outliers which do not lay in the range of tolerance have been ignored. In most cases, there were no outliers, while in some cases there was maximum of 3 points out of the tolerance, between 10 measured point for each setting. Then the representative point is the average, for each printing setting, with specific levels of process parameters. Representative point is used for RSM design and analysis of *PuPr* model.

In Appendix 3 pre-processing done for ***PuPr*** has been shown, in which data are processed in the same sequences as they were printed. Graphs show the fluctuations of the points in a setting with specific pump degree and print speed.

Another pre-processing analysis studied the correlation between response variables of layer Height, Top width, and Bottom width. The correlation between layer dimensional deformations has been investigated, As it is presented for some analysing three printed lines with specific settings for process parameter in Appendix 4, there seems to be not noticeable correlation among layer dimensional deformation.

As a result, the assumption of independent response variables, used for RSM design and analysis of experimental design seems to be reasonable. However, more investigations should be performed to investigate the correlation, as physical law suggest such correlations, especially between top width and bottom with, as decreasing in one, results increasing in another.

Moreover, in the case of sequential estimation of layer dimensions, in a research done by the author before, it can be seen that after estimation of Height in the first step, the Top bottom is estimated using Height estimated in the first step of the approximations. Both Height and Top with shown to be significant in determining the bottom width of a printed layer.

5.6.2. *NdPr* model

Data available for *NdPr*, which enables different variation of *Nd* (Nozzle distance) and *Pr* (Print speed), contains 1 replication of a specific process setting, except for the case mentioned below. A number of replications are 2 and details are shown in Appendix 5.

I. *Nd=25 mm* (min level in design range) and *Pr=7200 mm/min* (min level in design range),samples 1 and 5

II. *Nd=25 mm* and *Pr= 8800 mm/min*, samples 2 and 9.

Hence, These 2 process setting were analysed to track the effect of the possible missing variable(s).

As it can be seen In data presented at Appendix 5, the deviation between two sets of each process setting is noticeable. Tolerance of 1mm to 1.5 mm for Height and Top width, and 2 mm to 2.5 mm seems to be reasonable, but as it can be seen in graphs bellow, the deviations are more than the tolerance. Graphs below show only one comparison for each setting, and the other layer dimensions show the same behaviour.

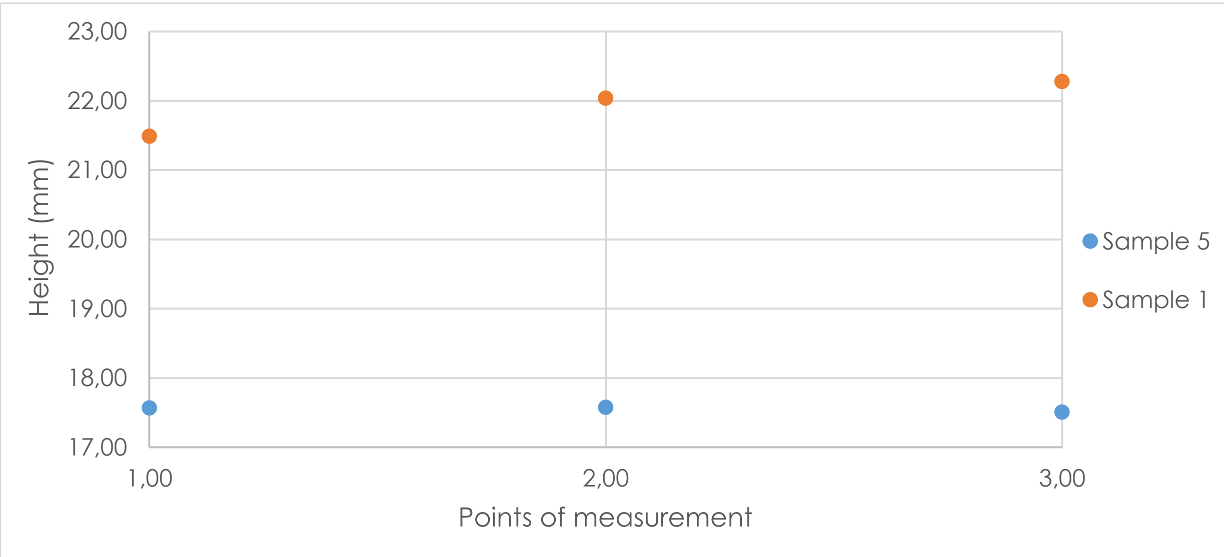


Figure 48: Output discrepency in two replications of a single setting

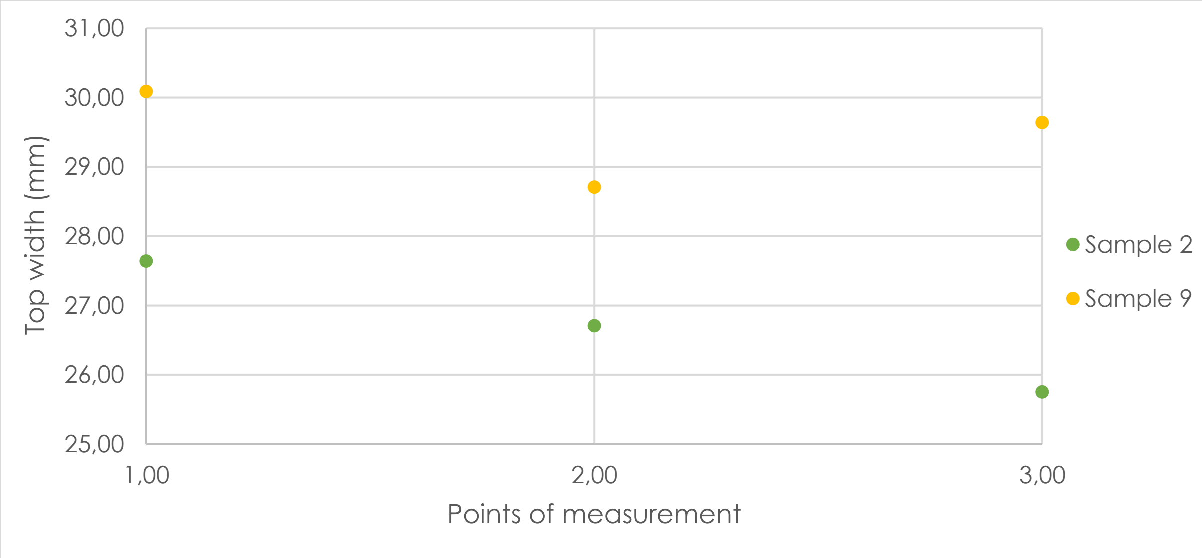


Figure 49: Output discrepancy in two replications of a single setting

One of the possibilities is the presence of ***"lurking" nuisance factor(s),*** which are unknown and uncontrollable.

Another possibility is that the source of nuisance is a factor(s) is known but uncontrollable. Such a factor, in this case, may be temperature fluctuations of material which is influenced by the constant pump operation. The pump was kept at a constant level (mid-level), and pump usually shows oscillations in its temperature and pressure, affecting material characteristics. Such effects on material characteristics can result in showing different viscose behaviour under constant process setting of this research.

Another reason may be because of the levelling imperfection in the print surface, which results in variation of Nozzle distance, in addition to what it has been planned and assumed. Hence, at a certain Nozzle distance, actual Nozzle distance is different as printing tool path is not levelled perfectly.

Because of such a fluctuation between two replications of the same process setting, it is more logical to focus on repeating the data generation, by trying to put control as much as it is possible on levelling of the printing tool path, or making the design of experiment robust against lurking variable.

Because of the scope of this research, new design for ***NdPr*** is skipped and the focus is laid on ***PuPr*** model.

In the following section, RSM analysis is performed and elaborated.

5.7. Results and adequacy check

AS it is mentioned in section 5.5, RSM analysis is a stepwise approximation, which requires validations and adequacy

RSM analysis is performed in R statistics, according to CCI design of the experiment, with the data shown in Appendix 2. ***PuPr*** model is approximated stepwise as follows:

I. First order approximation for ***Height, Top and Bottom width***, only main effects
II. First order approximation Height, Top and Bottom width, main effects and interactions
III. Full second order approximation Height, Top and Bottom width

In the same manner, the analysis is performed stepwise, reviewing the following elements within each model (approximation):

I. Lack of fit
II. Factor significance
III. Adjusted R-squared

After studying the abovementioned elements, adequacy checking containing the following analysis have been tested:

I. Normality check: to test the normality assumption
II. Residuals analysis: to examine the deviation of predicted data from the actual measured values, implemented in RSM model approximation.

The analysis and adequacy check steps are done in a loop, for each type of approximations mention above. When the criteria are met, the effort of design and analysis of the higher order approximation is stopped, and model derived should be verified by generating verification data and analysis (section 5.8).

In this research and development project of dDSS, previous data is used, hence, the benefits of stepwise data generation and analysis are not applicable. On the other hand, there is the opportunity to ***construct all types of approximations, compare them and reach the most suitable model according to the data in hand.***

As data used for the approximations are limited in numbers, more reliable conclusions are made in the validation phase, where more data points are used to test the adequacy and the precision of models' predictions.

5.7.1. First order, main effects approximation

Factorial points along with centre points, as the initial block is used to fit the first order model, investigating the influence of main effects on response variables in *PuPr* model. Linear model fit is done in *R statistics* and the first table as an output is ANOVA table, showing the least squares estimate of the coefficients of coded factors described in the previous section, along with their errors, t-values, and P-values (Lawson, 2015). From this table, significant terms of the models are clarified.

The second table shows the ANOVA table from the fit, for the first order main effects model. F-test is performed to check the adequacy of the approximation and "Lack of fit". If there is a significant lack of fit (P-value< 0.05), it will be inferred that the model is not adequate for prediction.

I. Below output for Height is shown:

```
            Estimate Std. Error  t value  Pr(>|t|)    
(Intercept) 24.05538    0.10039 239.6227 < 2.2e-16 ***
Pu           0.45500    0.12797   3.5555   0.00522 ** 
Pr          -1.65000    0.12797 -12.8936 1.483e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Multiple R-squared:  0.9471,    Adjusted R-squared:  0.9365 
F-statistic: 89.44 on 2 and 10 DF,  p-value: 4.159e-07

Analysis of Variance Table

Response: Height
            Df  Sum Sq Mean Sq F value    Pr(>F)
FO(Pu, Pr)   2 23.4362 11.7181 89.4427 4.159e-07
Residuals   10  1.3101  0.1310                  
Lack of fit  2  0.2581  0.1291  0.9815    0.4157
Pure error   8  1.0520  0.1315                  
```

* Pu and Pr stand for Pump degree and Print speed

Figure 50: First order approximation ANOVA

From the first ANOVA table, I can be seen that both Pr and Pu which indicate the main effects of the process parameters are significant, as P-value is smaller than 0.05. This can also be confirmed through the second ANOVA table where first order model is showed to be significant (FO(Pu,Pr)).

F-test for model fit indicates that the model has not significant lack of fit (P-value>0.05) which means that the model has shown enough adequacy. Hence, the prediction from the model can be considered as accurate as running additional experiments, as long as no lurking variables or process parameters change before additional experiments can be run (Lawson, 2015). Adjusted R-squared is close to 1which show the high precision in the approximation.

Adequacy checks step (see section 5.5) is elaborated by conducting normality check and residual analysis. As shown below, data approximately lay on the straight line indicating the acceptable level of normality. So the assumption of the normality is approved.

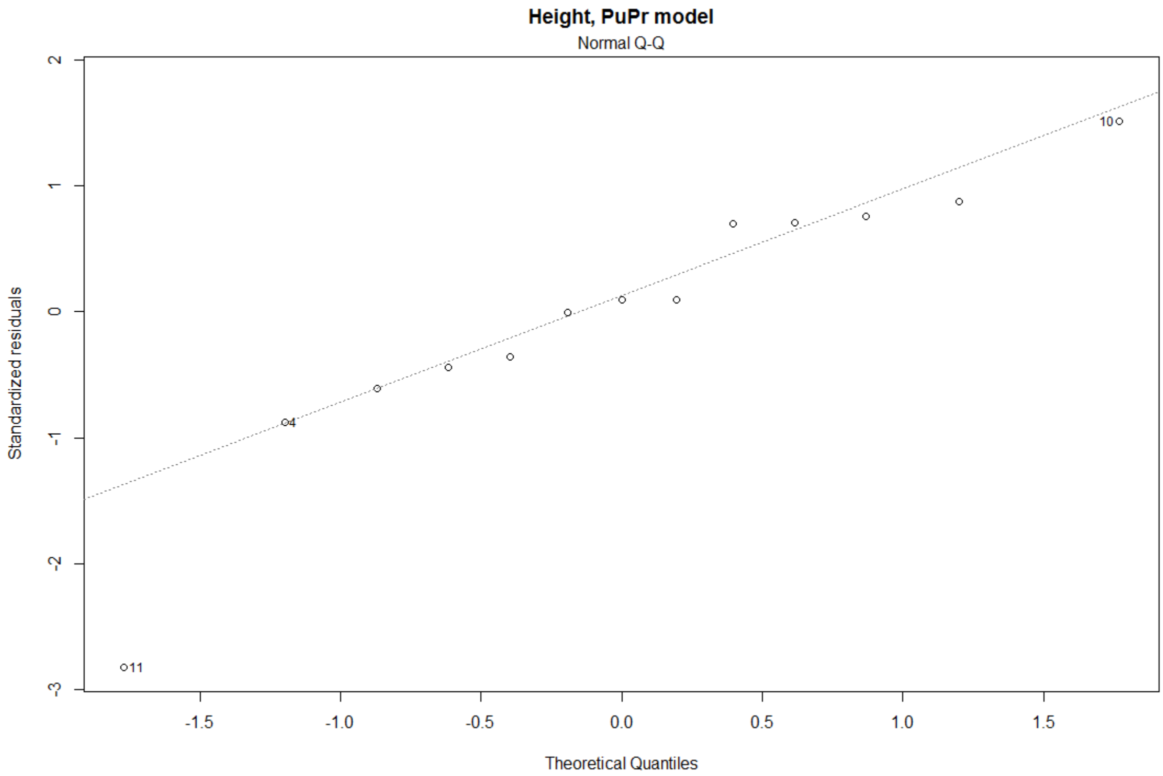


Figure 51: First order Q-Q plot

Quantiles are cut points dividing the range of a probability distribution (here normal distribution) into contiguous intervals with equal probabilities, or dividing the observations in a sample in the same way.

The graph below shows residual; analysis of residuals (mm) versus fitted values (mm). As it can be seen in the plot below, the min and max range of residuals are ***0.5 mm (2%)*** which is under the tolerance rate derived in pre-processing phase mentioned in section 5.6.

On the other hand, it can be seen that there is a systematic trend in scattered residuals, indicating the need of higher order approximation for the model. Although the imprecision is neglect able (2%), more terms are added to an approximation to reach the most suitable model.

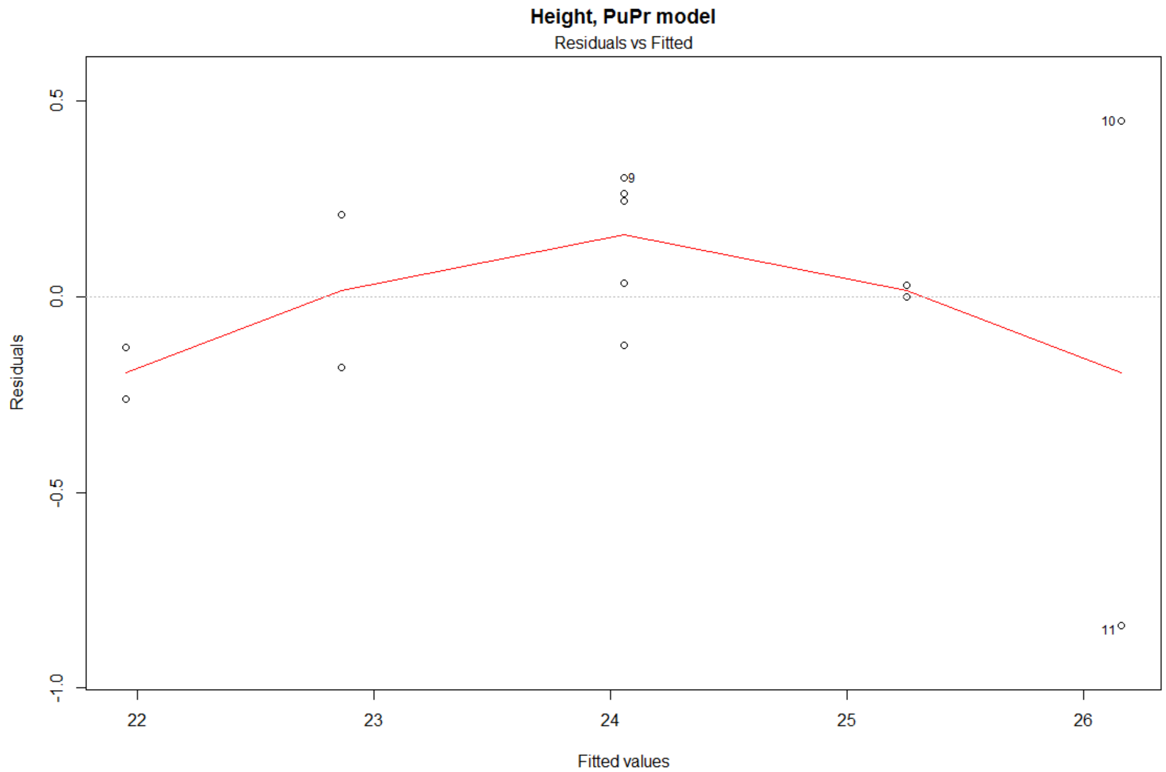


Figure 52: First order residual plot

II. Top width approximation results in the following output:

```
             Estimate Std. Error  t value  Pr(>|t|)    
(Intercept) 21.94000    0.10975 199.9126 < 2.2e-16 ***
Pu           0.60500    0.13990   4.3245  0.001503 ** 
Pr          -1.62500    0.13990 -11.6153 3.967e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Multiple R-squared:  0.9389,    Adjusted R-squared:  0.9267 
F-statistic: 76.81 on 2 and 10 DF,  p-value: 8.528e-07

Analysis of Variance Table

Response: TopWidth
            Df  Sum Sq Mean Sq F value    Pr(>F)
FO(Pu, Pr)   2 24.0532 12.0266 76.8080 8.528e-07
Residuals   10  1.5658  0.1566                  
Lack of fit  2  0.8565  0.4283  4.8304    0.0421
Pure error   8  0.7093  0.0887                  

Direction of steepest ascent (at radius 1):
        Pu         Pr 
 0.3489104 -0.9371561 

Corresponding increment in original units:
        Pu         Pr 
 0.3489104 -0.9371561 
```

Figure 53: First order approximation ANOVA

All main effects are shown to be significant, with considerably good prediction precision (adjusted R-squared), while there is a slightly significant lack of fit for the proposed model, as it is 0.0421, close to the limit of 0.05. It can be suggested that such lack of fit be considered as neglectable, after performing residual analysis and seek to possibility and the extent of systematic higher order trend.

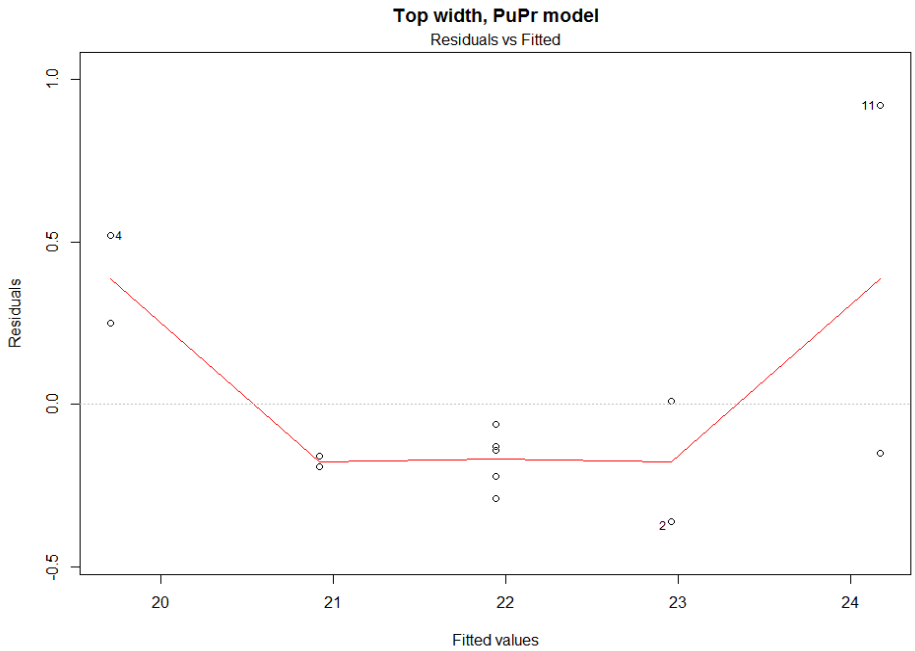


Figure 54: First order residual plot

Moreover, according to the plot presented below,

Although the deviations of the residuals are within the defined tolerance of ***1 mm (4%),*** but the second order trend can be seen in the analysis. Hence, the approximation continues to incorporate additional terms of process parameters.

Normality check seems to be violated especially as it may have a systematic trend showed below, which probably indicates the skewness of data to the right of the normal distribution bell shape curve.

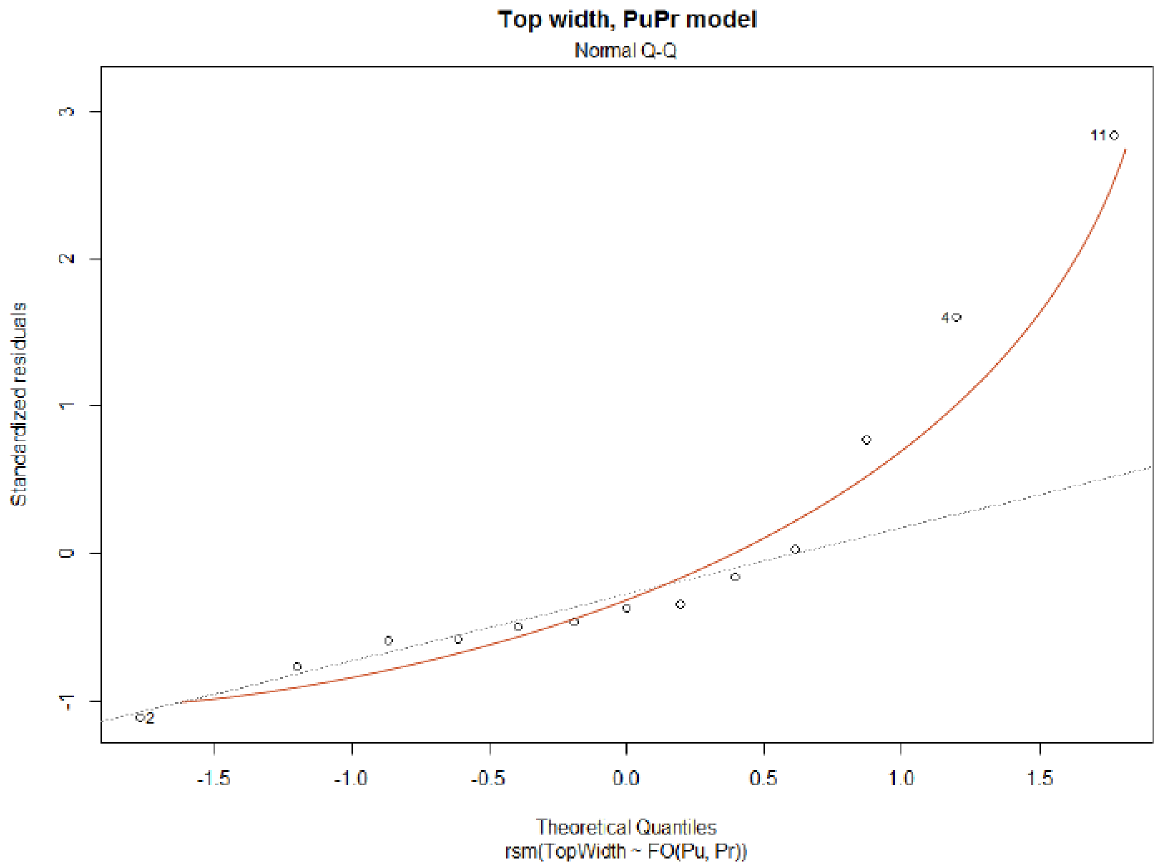


Figure 55: First order Q-Q plot

III. Bottom width showed the following behaviour in analysis:

```
            Estimate Std. Error  t value  Pr(>|t|)
(Intercept) 24.05538    0.10039 239.6227 < 2.2e-16 ***
Pu           0.45500    0.12797   3.5555   0.00522 **
Pr          -1.65000    0.12797 -12.8936 1.483e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Multiple R-squared:  0.9471,    Adjusted R-squared:  0.9365
F-statistic: 89.44 on 2 and 10 DF,  p-value: 4.159e-07

Analysis of Variance Table

Response: Height
            Df  Sum Sq Mean Sq F value    Pr(>F)
FO(Pu, Pr)   2 23.4362 11.7181 89.4427 4.159e-07
Residuals   10  1.3101  0.1310
Lack of fit  2  0.2581  0.1291  0.9815    0.4157
Pure error   8  1.0520  0.1315

Direction of steepest ascent (at radius 1):
        Pu         Pr
 0.2658354 -0.9640184

Corresponding increment in original units:
        Pu         Pr
 0.2658354  0.9640184
```

Figure 56: First order approximation ANOVA

First order showed a significant level of process parameters, preciseness and insignificant lack of fit. TH analysis is followed by adequacy check.

In the normality plot, it can be seen that the data seems to violate the normality assumption, as , in the tales of data, deviations become considerably bigger. This effect is known as fat tale effect. One remedy is transforming the data, but first, here higher order approximately will be performed, by adding extra terms of a process parameter in approximation model.

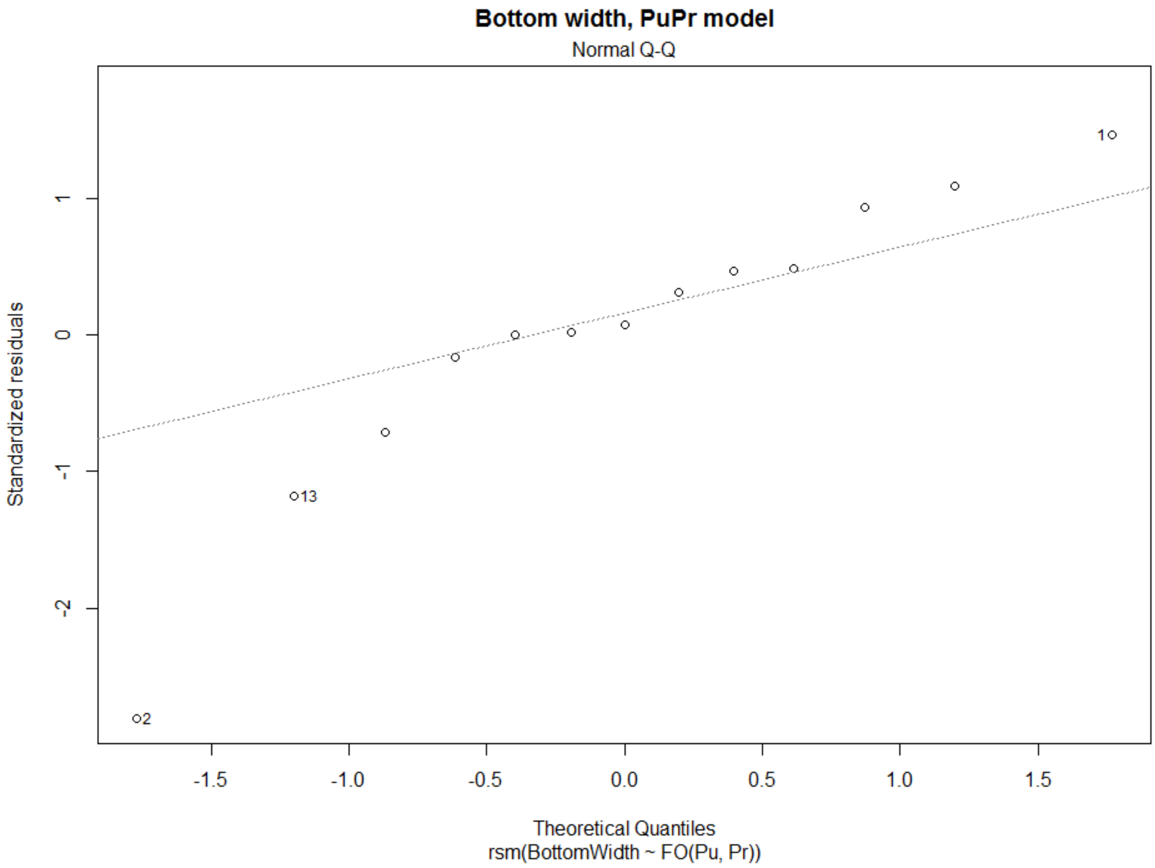


Figure 57: First order Q-Q plot

The residual analysis shown below, however, seems to be randomly scattered around the baseline, which is preferable as it is trendless. All residual points are scattered in the defined range of tolerance which is ***2 mm (8%).***

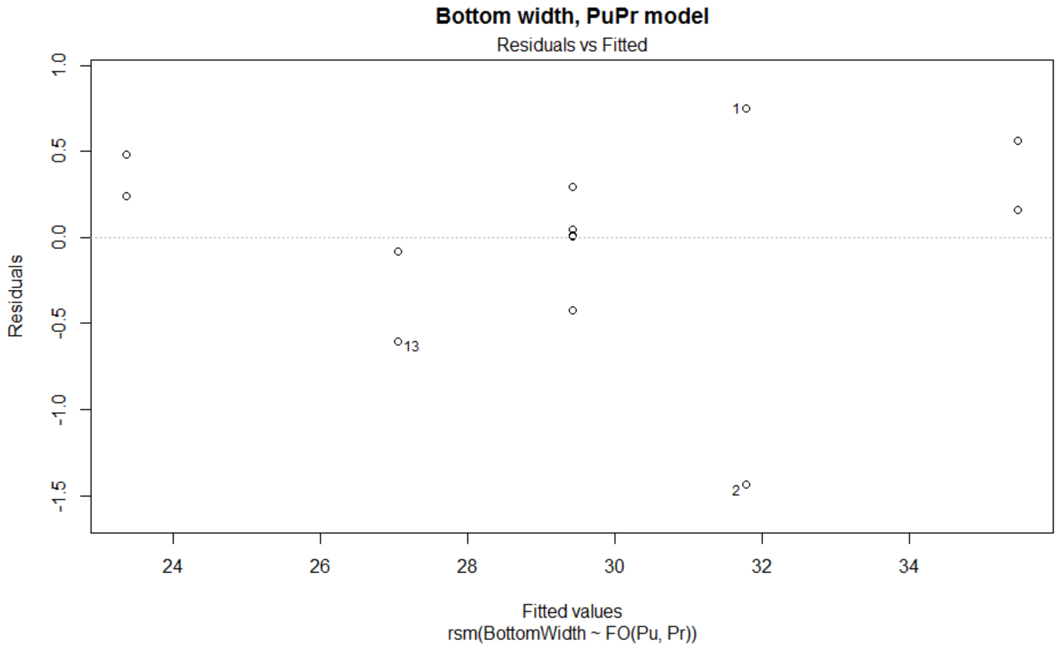


Figure 58: First order residual plot

5.7.2. First order approximation, main and interaction effects

I. Approximation output shown below states the fact that interaction of Pu and Pr, is not statistically significant in approximation. It can be approved by P-value for two-way interaction as well.

```
             Estimate Std. Error  t value  Pr(>|t|)
(Intercept) 24.05538    0.10219 235.3874 < 2.2e-16 ***
Pu           0.45500    0.13027   3.4927  0.006802 **
Pr          -1.65000    0.13027 -12.6657 4.855e-07 ***
Pu:Pr        0.10500    0.13027   0.8060  0.441020
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Multiple R-squared:  0.9506,    Adjusted R-squared:  0.9342
F-statistic: 57.76 on 3 and 9 DF,  p-value: 3.348e-06

Analysis of Variance Table

Response: Height
            Df  Sum Sq Mean Sq F value    Pr(>F)
FO(Pu, Pr)   2 23.4362 11.7181 86.3090 1.342e-06
TWI(Pu, Pr)  1  0.0882  0.0882  0.6496    0.4410
Residuals    9  1.2219  0.1358
Lack of fit  1  0.1699  0.1699  1.2922    0.2885
Pure error   8  1.0520  0.1315
```

Figure 59: First order approximation with interaction ANOVA

By including the interaction factor, the model still shows an insignificant lack of fit, however, the prediction precision has been decreased as R-squared dropped from 0.97 in the first order main effect model to 0.934 in this model.

Main and more important improvement has been seen in adequacy check. While the normality check is passed, as shown in the Q-Q plot below, the systematic trend observed in the first order main effect, has been smoothened. Although there is still slightly systematic trend. Such a trend should be tried to get eliminated in full quadratic approximation.

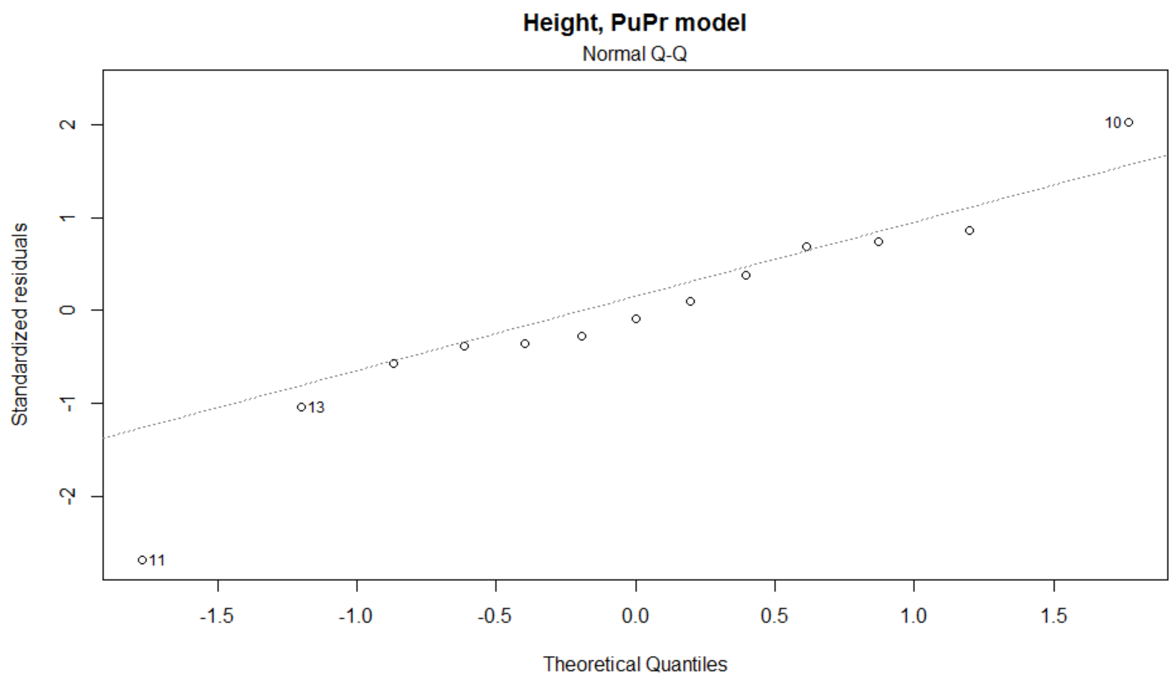


Figure 60: First order approximation with interaction Q-Q plot

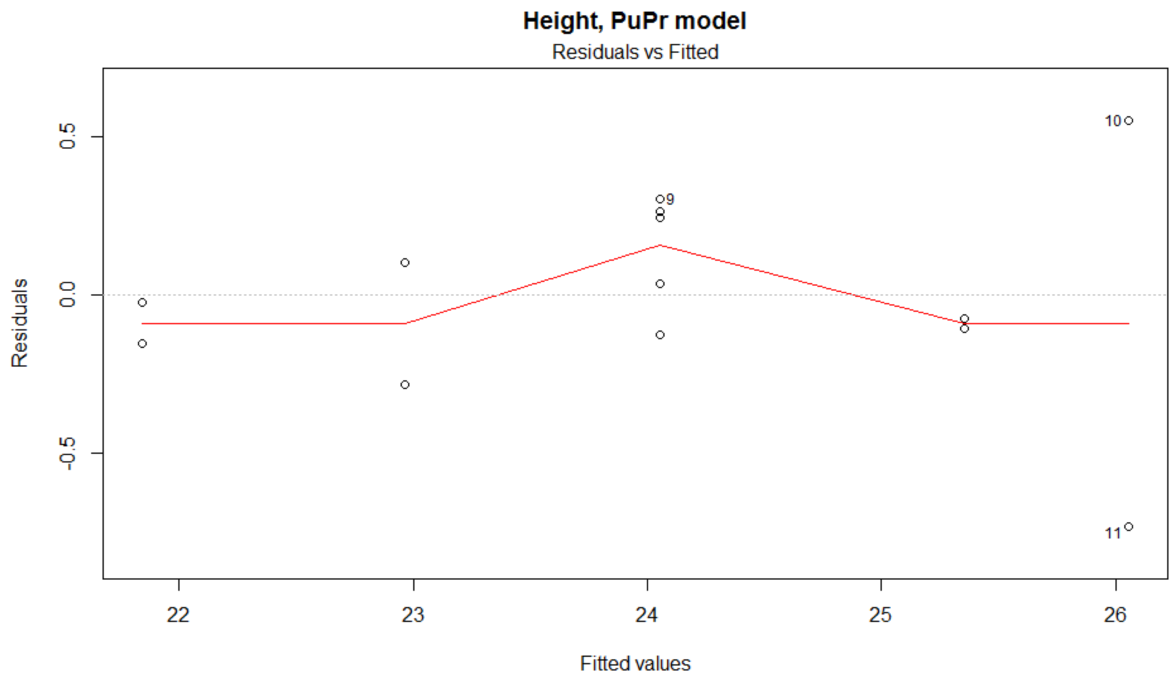


Figure 61: First order approximation with interaction residual plot

II. For Top width approximation, from both ANOVA tables, a fact can be inferred that the interaction between Pu and Pr is statistically significant. In the other words, in print speed and pump degree has a different effect on the value of the Top width of a printed layer, when one variable is constant and the other variable is being changed.

```
              Estimate Std. Error  t value  Pr(>|t|)    
(Intercept) 21.940000   0.089567 244.9567 < 2.2e-16 ***
Pu           0.605000   0.114176   5.2988 0.0004946 ***
Pr          -1.625000   0.114176 -14.2324 1.779e-07 ***
Pu:Pr       -0.280000   0.114176  -2.4524 0.0366148 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Multiple R-squared:  0.9634,    Adjusted R-squared:  0.9512 
F-statistic: 78.88 on 3 and 9 DF,  p-value: 8.786e-07

Analysis of Variance Table

Response: TopWidth
            Df  Sum Sq Mean Sq  F value    Pr(>F)
FO(Pu, Pr)   2 24.0532 12.0266 115.3201 3.855e-07
TWI(Pu, Pr)  1  0.6272  0.6272   6.0141   0.03661
Residuals    9  0.9386  0.1043                   
Lack of fit  1  0.2293  0.2293   2.5865   0.14644
Pure error   8  0.7093  0.0887                   
```

Figure 62: First order approximation with interaction ANOVA

There is of lack of fit, indicating that the prediction is almost as precise as generating more data and perform prediction. Moreover, the precision of Top width prediction has been improved as adjusted R-squared is improved from 0.96 in the first order main effect model to 0.95.

Normality check is approved as the scattered data in Q-Q model, almost lays on a straight line of normality.

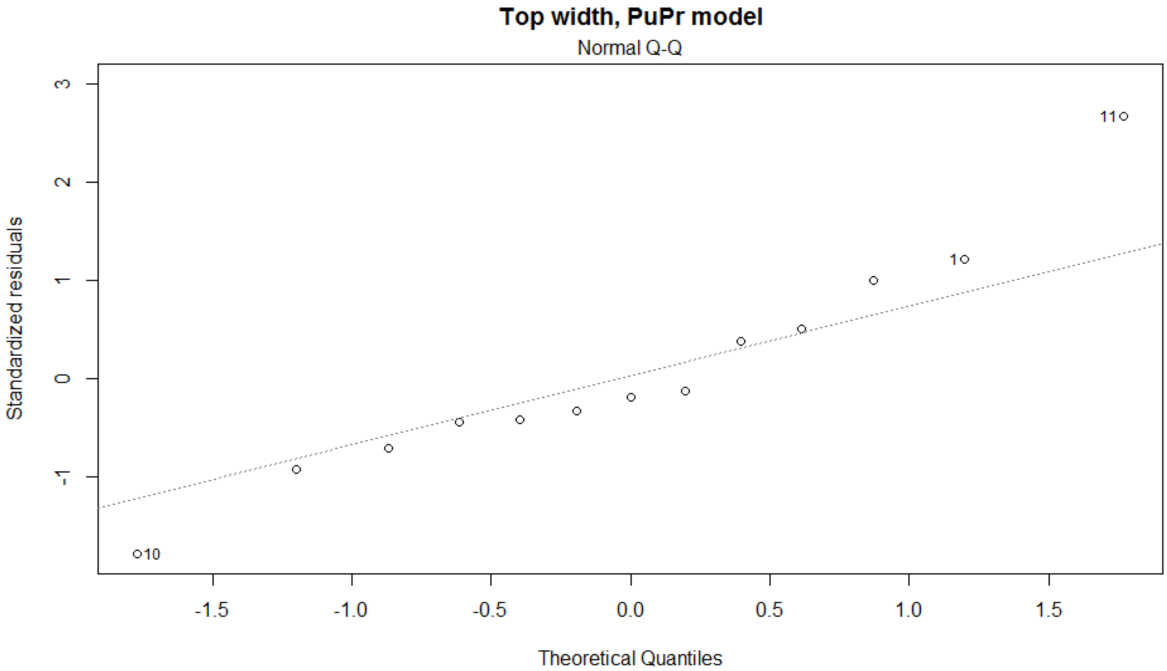


Figure 63: First order approximation with interaction Q-Q plot

It seems that the curvature suggested to response surface of Top width prediction, smoothened the systematic trend of the linear main effect model. Residuals are scattered almost symmetric relative to the baseline.

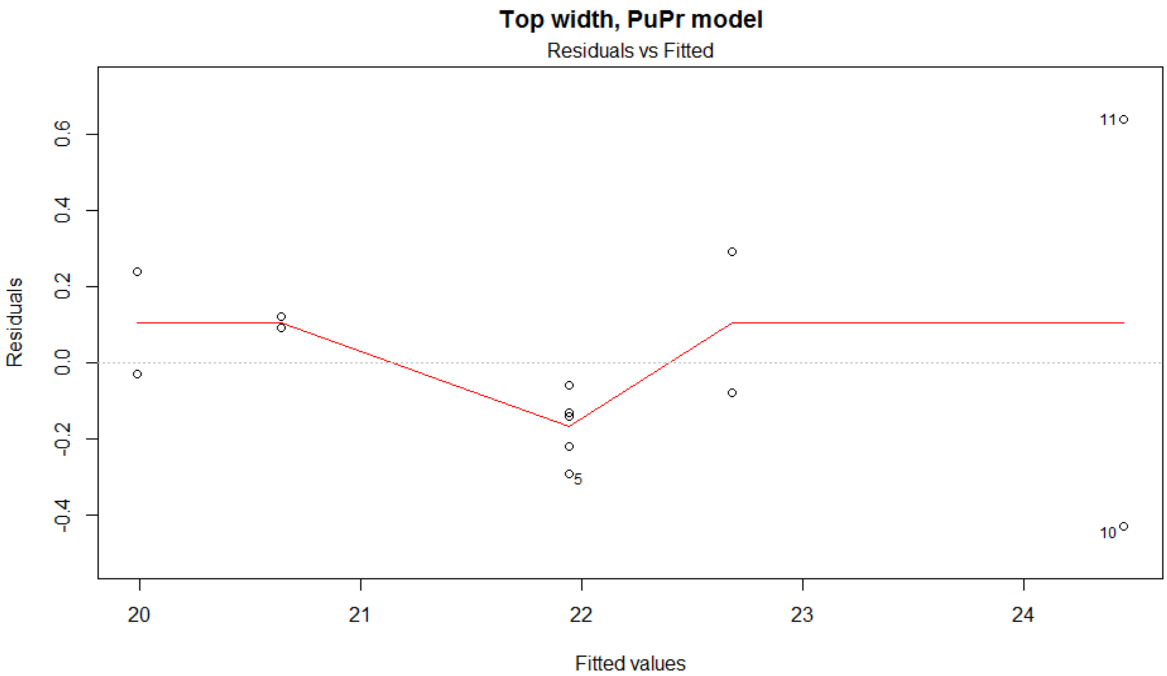


Figure 64: First order approximation with interaction residual plot

Although this model seems to show reasonable performance, while its adequacy has been met, but since there is data available to perform the second order approximation, a full quadratic model is constructed. Moreover, as it is mentioned at the beginning of the section, final judgment is made after validation phase, as makes more data available to judge the fitness and adequacy of the prediction.

III. Adding interaction effect of pump degree and print speed is shown to not be significant, while the prediction precision has been dropped slightly around 0.02 of adjusted R-squared.

```
             Estimate Std. Error  t value  Pr(>|t|)
(Intercept) 29.42538    0.15778 186.4987 < 2.2e-16 ***
Pu           1.84625    0.20113   9.1795 7.263e-06 ***
Pr          -4.20875    0.20113 -20.9257 6.090e-09 ***
Pu:Pr       -0.35125    0.20113  -1.7464    0.1147
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Multiple R-squared:  0.9832,	Adjusted R-squared:  0.9775
F-statistic: 175.1 on 3 and 9 DF,  p-value: 2.687e-08

Analysis of Variance Table

Response: BottomWidth
            Df  Sum Sq Mean Sq  F value    Pr(>F)
FO(Pu, Pr)   2 168.978  84.489 261.0738 1.073e-08
TWI(Pu, Pr)  1   0.987   0.987   3.0499    0.1147
Residuals    9   2.913   0.324
Lack of fit  1   0.001   0.001   0.0040    0.9511
Pure error   8   2.911   0.364
```

Figure 65: First order approximation with interaction ANOVA

Normality check has been improved as there is no trace of fat tale effect comparing to linear main effect model.

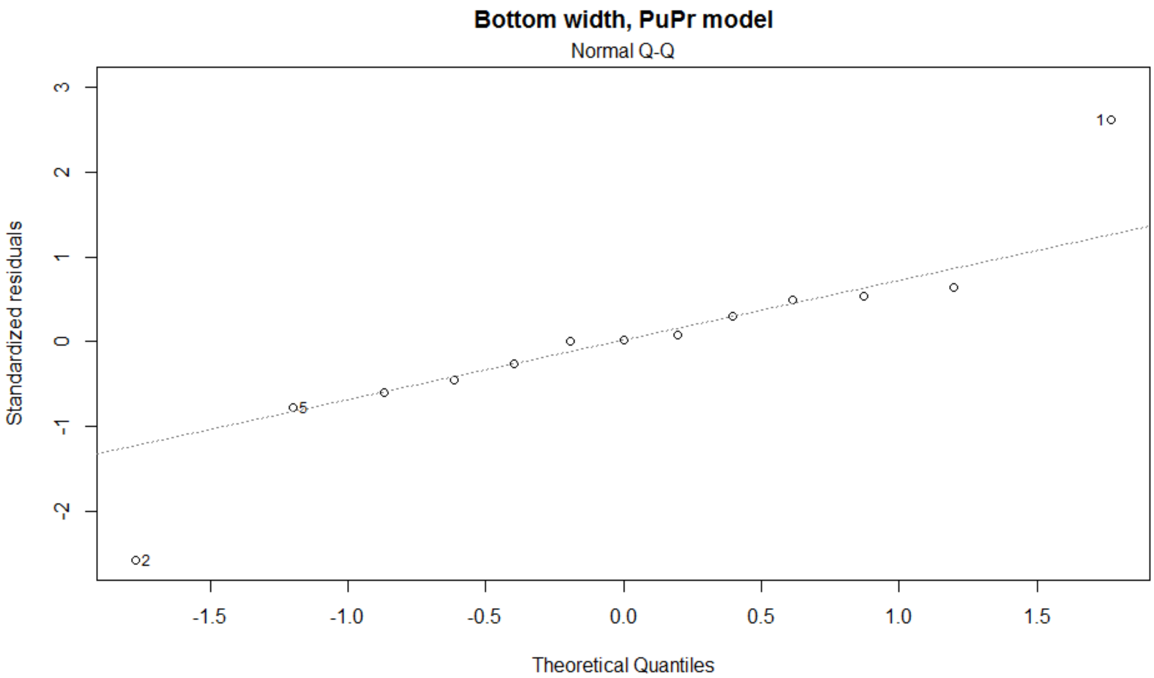


Figure 66: First order approximation with interaction Q-Q plot

Prediction performed by first order model with interaction is reasonably adequate, as residual analysis shows the random scattering of data around baseline.

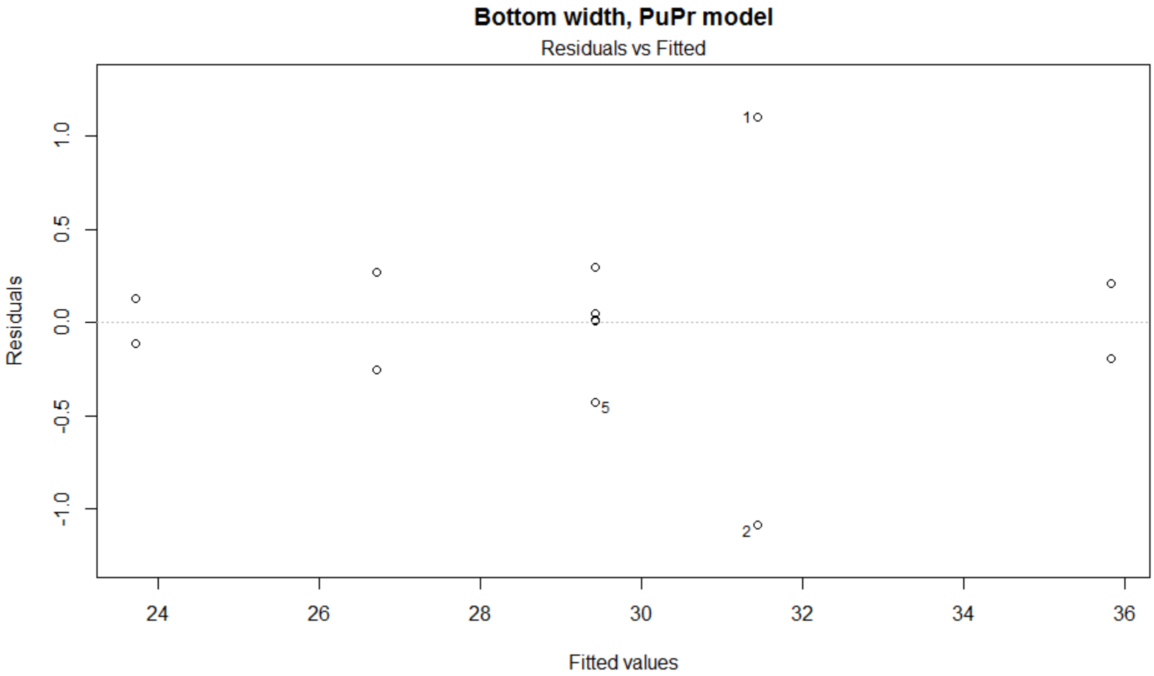


Figure 67: First order approximation with interaction residual plot

On the basis of the same reasoning mentioned for linear interaction model of Top width, higher order approximation is performed and final judgement is awaiting the validation section.

5.7.3. Second order approximation, *PuPr* model

I. Second order approximation is performed by adding the quadratic main effects of variable which are print speed and pump degree.

From the second table of ANOVA it can be concluded that Pure quadratic (PQ) terms of Pu and Pr, have not significant effect of model precision, because the P0-value is calculated 0.1548, which is far bigger than the limit of 0.05. But closer look through the first ANOVA table, it seems that the quadratic main effect of pump degree has slightly significant effect on Height prediction of a printed layer, as P-value is close of 0.05, while showing insignificant lack of fit.

```
              Estimate Std. Error  t value  Pr(>|t|)    
(Intercept) 24.151138   0.117469 205.5966 < 2.2e-16 ***
BlockB2     -0.169415   0.118495  -1.4297   0.16903    
Pu           0.525000   0.080972   6.4837 3.264e-06 ***
Pr          -1.656667   0.080972 -20.4597 2.106e-14 ***
Pu:Pr        0.105000   0.099170   1.0588   0.30297    
Pu^2        -0.247800   0.122265  -2.0267   0.05696 .  
Pr^2         0.092200   0.122265   0.7541   0.46003    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Multiple R-squared:  0.9609,    Adjusted R-squared:  0.9486 
F-statistic: 77.85 on 6 and 19 DF,  p-value: 2.365e-12

Analysis of Variance Table

Response: Height
            Df Sum Sq Mean Sq  F value   Pr(>F)
Block        1  0.096  0.0960   1.2204   0.2831
FO(Pu, Pr)   2 36.242 18.1210 230.3195 4.78e-14
TWI(Pu, Pr)  1  0.088  0.0882   1.1210   0.3030
PQ(Pu, Pr)   2  0.324  0.1622   2.0611   0.1548
Residuals   19  1.495  0.0787                  
Lack of fit  3  0.216  0.0719   0.8991   0.4632
Pure error  16  1.279  0.0800                  
```

Figure 68: Second order approximation ANOVA

Deviations from the normal straight line can be acceptable from the range close to than ±2. But normality assumption seems to be violated as there is the effect of fat tails, in the range quintile range close to the mean 0 (w axis of Q-Q plot).

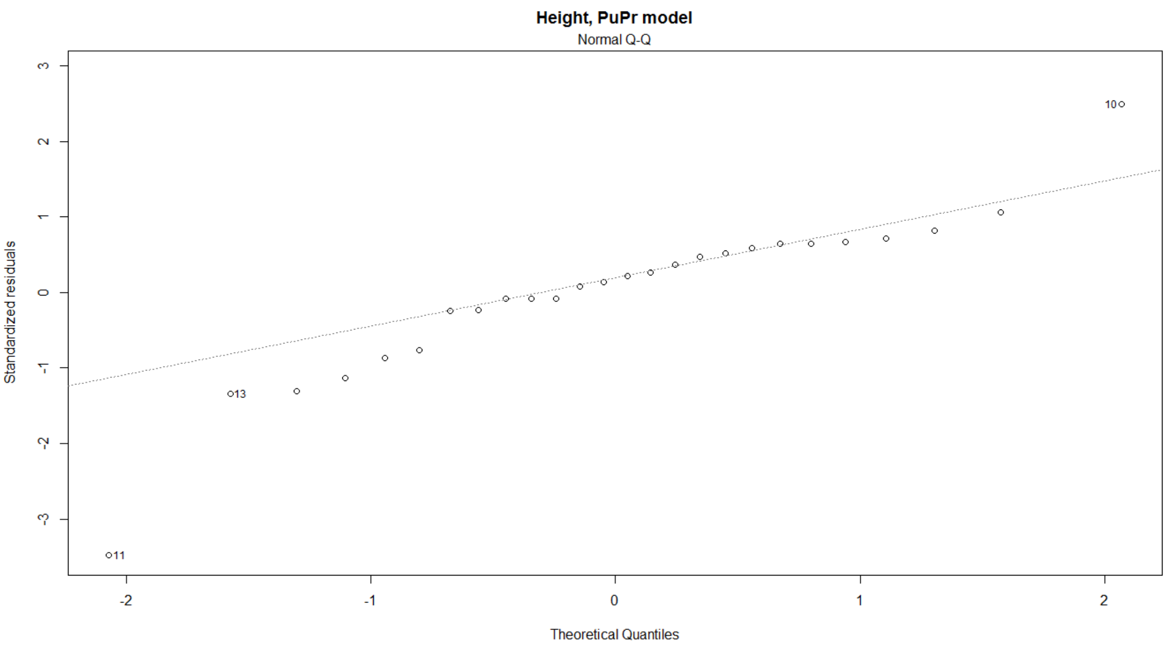


Figure 69: Second order approximation Q-Q plot

On the other hand, residual analysis shows random scatterings of data around baseline, which indicates that the second order approximation is an adequate estimation. Such an approximation cannot be reliable as the normality check has been rejected. Further discussions on the most suitable approximation on Height is elaborated in discussion, according to the results shown in this section and validation phase.

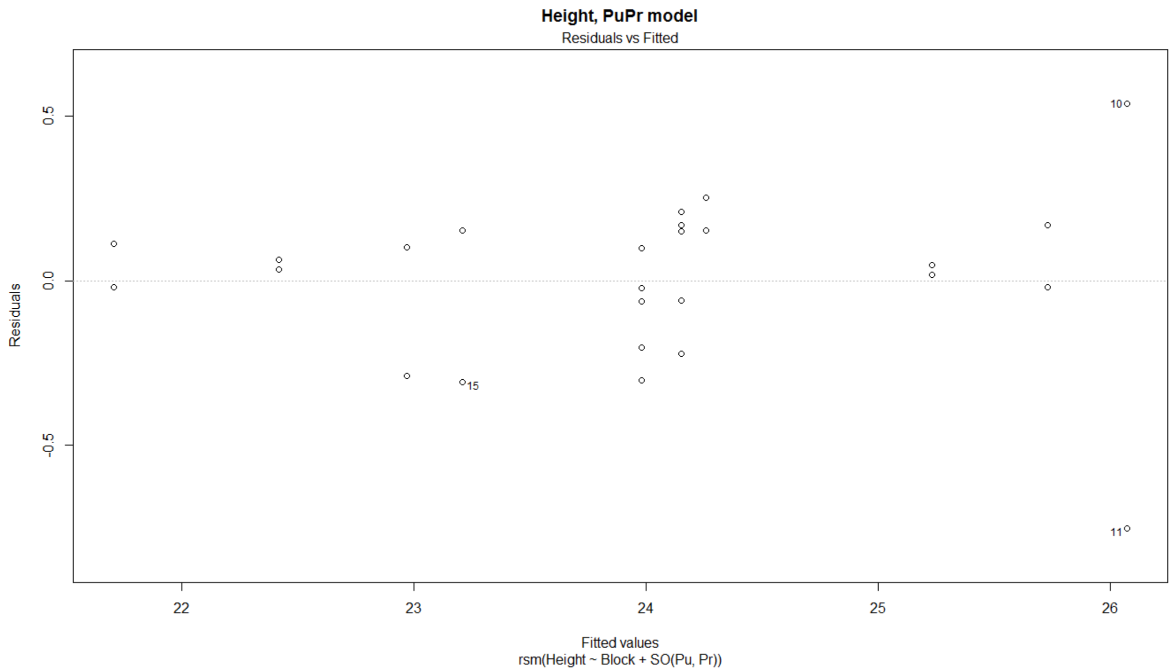


Figure 70: Second order approximation residual plot

II. For Top width prediction adding quadratic main effects has shown the point that Top width prediction is significantly influenced by the quadratic effect of print speed. There is no lack of fit in second order model, while showing precise prediction as adjusted R-squared suggests.

```
             Estimate Std. Error  t value  Pr(>|t|)
(Intercept) 21.824123   0.147070 148.3928 < 2.2e-16 ***
BlockB2      0.075631   0.148354   0.5098   0.61606
Pu           0.590833   0.101377   5.8281 1.296e-05 ***
Pr          -1.598333   0.101377 -15.7663 2.284e-12 ***
Pu:Pr       -0.280000   0.124160  -2.2551   0.03611 *
Pu^2        -0.197100   0.153075  -1.2876   0.21335
Pr^2         0.385400   0.153075   2.5177   0.02094 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Multiple R-squared:  0.9393,    Adjusted R-squared:  0.9202
F-statistic: 49.04 on 6 and 19 DF,  p-value: 1.476e-10

Analysis of Variance Table

Response: TopWidth
            Df Sum Sq Mean Sq  F value    Pr(>F)
Block        1  0.002  0.0020   0.0165  0.89915
FO(Pu, Pr)   2 34.845 17.4225 141.2715 3.93e-12
TWI(Pu, Pr)  1  0.627  0.6272   5.0857  0.03611
PQ(Pu, Pr)   2  0.815  0.4075   3.3042  0.05869
Residuals   19  2.343  0.1233
Lack of fit  3  0.132  0.0441   0.3190  0.81148
Pure error  16  2.211  0.1382
```

Figure 71: Second order approximation ANOVA

Normality check is shown that the data can be assumed to be distributed normally distributed. The data showed to be plotted on the straight line of normality, with a better preciseness, comparing to first order interaction model of Top width.

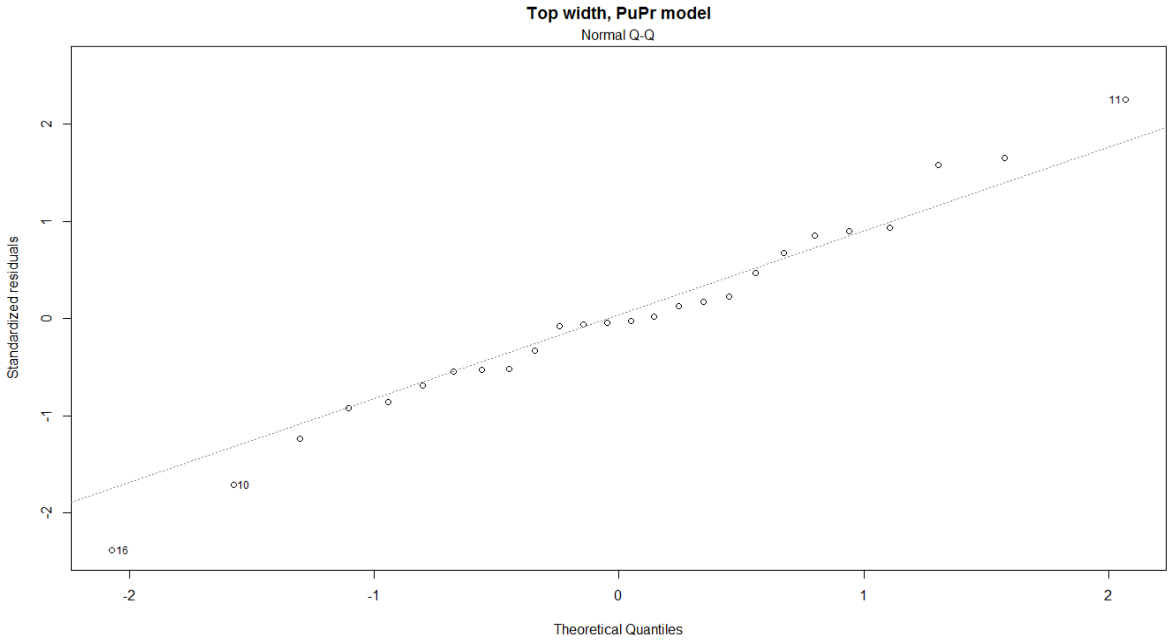


Figure 72: Second order approximation Q-Q plot

Residual analysis shows improvement in adequacy of the prediction, as there is no more systematic trend and data seems to be scattered more randomly around the baseline.

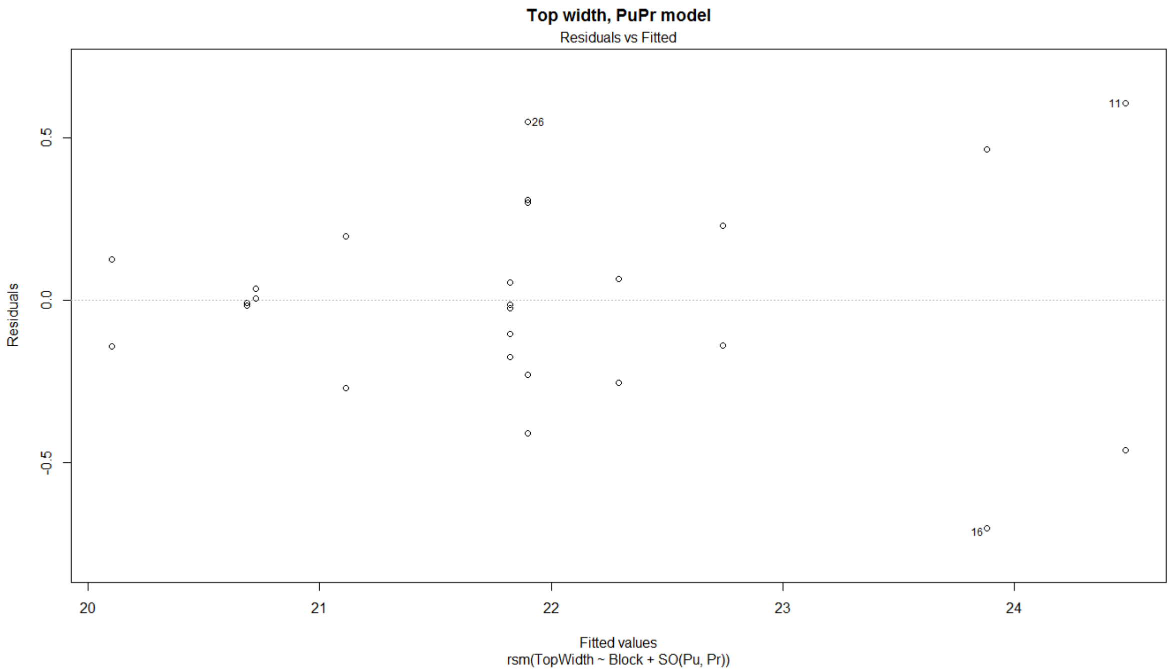


Figure 73: Second order approximation residual plot

III. Approximation output for Bottom width prediction has shown that adding quadratic effect of pump degree has not significant influence on value of Bottom width. On the other hand, quadratic term of print speed has significant effect on the model, suggesting the pretty much reasonable prediction precision of adjusted R-squared of 0.975 and not suggesting any lack of fit.

```
            Estimate Std. Error  t value  Pr(>|t|)    
(Intercept) 29.30538    0.21246 137.9348 < 2.2e-16 ***
BlockB2     -0.47615    0.21431  -2.2218   0.03864 *  
Pu           1.96750    0.14645  13.4347 3.761e-11 ***
Pr          -4.19250    0.14645 -28.6277 < 2.2e-16 ***
Pu:Pr       -0.35125    0.17936  -1.9583   0.06504 .  
Pu^2        -0.29250    0.22113  -1.3227   0.20163    
Pr^2         0.48750    0.22113   2.2046   0.04001 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Multiple R-squared:  0.9817,	Adjusted R-squared:  0.9759 
F-statistic: 169.4 on 6 and 19 DF,  p-value: 1.866e-15

Analysis of Variance Table

Response: BottomWidth
            Df  Sum Sq Mean Sq  F value   Pr(>F)
Block        1   1.868   1.868   7.2600 0.01436
FO(Pu, Pr)   2 257.377 128.689 500.0171 < 2e-16
TWI(Pu, Pr)  1   0.987   0.987   3.8350 0.06504
PQ(Pu, Pr)   2   1.363   0.682   2.6481 0.09673
Residuals   19   4.890   0.257                 
Lack of fit  3   0.821   0.274   1.0760 0.38722
Pure error  16   4.069   0.254                 
```

Figure 74: Second order approximation ANOVA

Normality check however, shows some deviation from +1 quantile of the mean value 0, with normal distribution, containing the standard deviation of 1. This deviation seems to be increase in quantiles closer to +2.

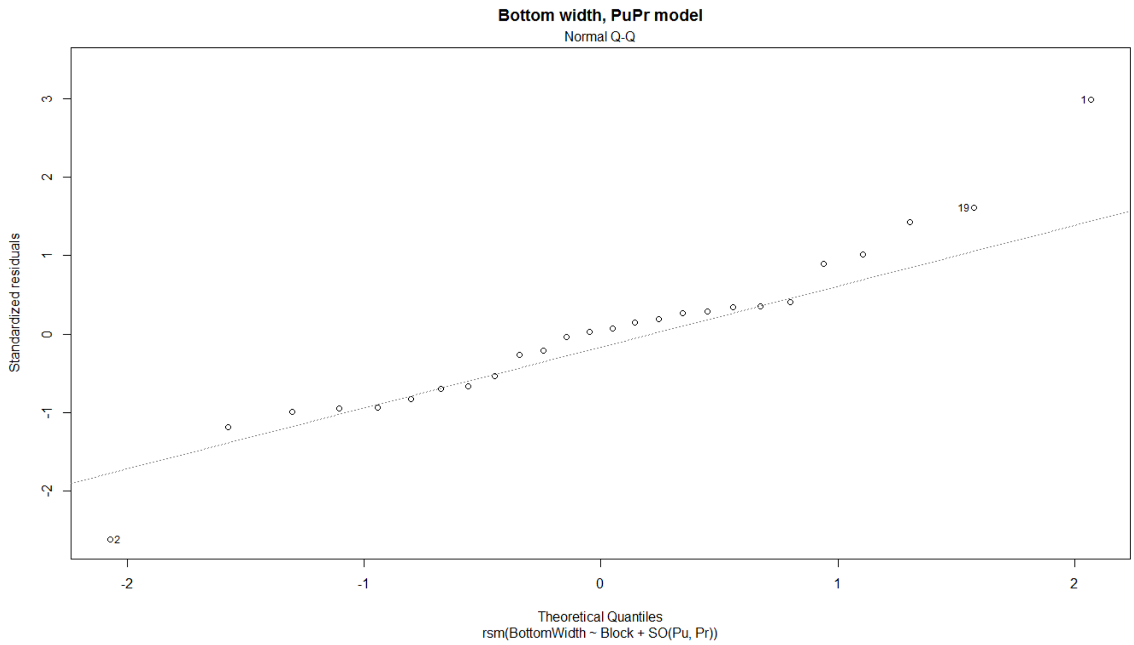


Figure 75: Second order approximation Q-Q plot

Residual analysis however, shows randomness adequacy of the prediction, but since the normality assumption seems to be violated, this model is not the adequate representative of an approximation.

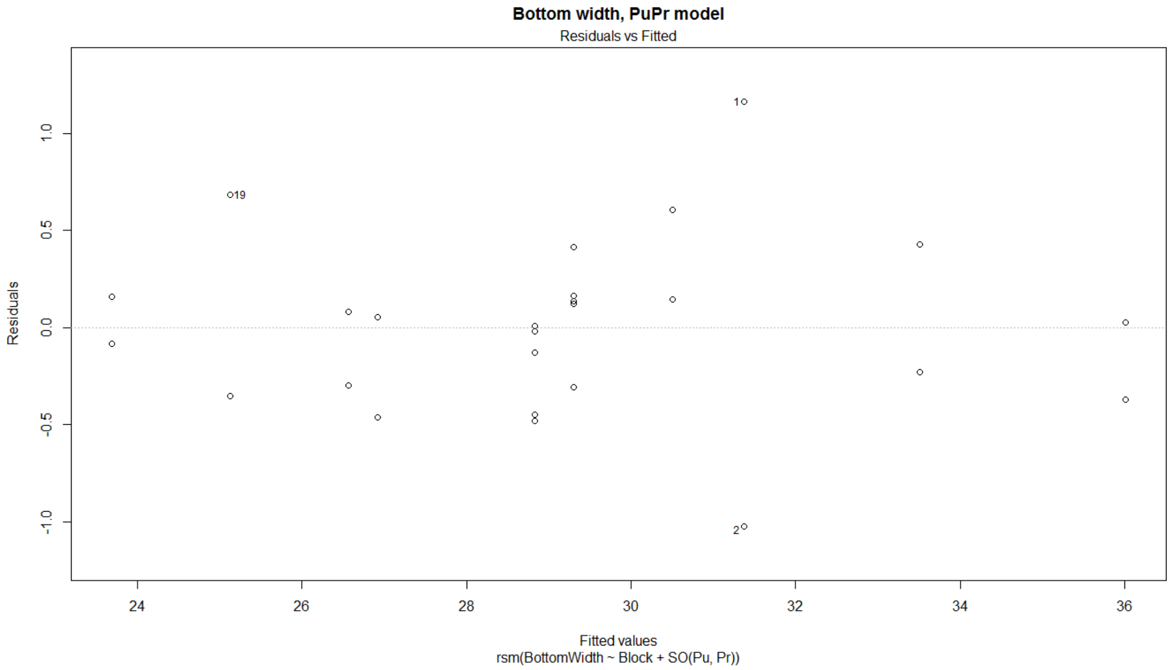


Figure 76: Second order approximation residual plot

5.8. Validation

5.8.1. Initial validation

The validation phase is important as it finalized the model selection, by examining proposed models in previous chapter. In this section, residual analysis has been performed for models which showed good performance, adequacy, and while do not violating the normality assumption.

Dataset shown in Appendix 6, which was previously produced has been used for validation response surfaces proposed for *PuPr* model, as the core of dDSS, linking single printed layer dimensions to process parameters of *Pump degree (Pu)* and *Print speed(Pr)*.

50% of the total data is used for validation, in which there are three ranges of data, for process parameters settings. *"Inside the range"* contains data which their level of Pr (range of [7200,10400] mm/min) and Pu(range of [27, 33] Hz) are varied in the design region (see section 5.4.2). "*Pr outside the range"* is consisted of data which value of print speed has been exceeded (range of [10800,11600] mm/min), to check the extendibility of models. For the same reason *"Pu outside the range"* seeks the preciseness and adequacy of the models by investigating pump degree values out of the design region (range of [24,39] Hz).

According to the output analysis and adequacy checks performed in section 5.8, Following models were able to pass tests and have been chosen for further analysis by performing residual analysis of the validation data shown in Appendix 6.:

I. Height approximation:

i. First order, main effects
ii. First order , main effects and interaction

II. Top width approximation:
i. First order , main effects and interaction
ii. Quadratic

III. Bottom width approximation:
i. First order , main effects and interaction

I. For layer height approximation, adding interaction term do not improve the residual analysis (See Appendix 6). It can be inferred that the interaction between print speed and pump degree has not significant effect on layer height. In the other word, by varying one variable of Pr or Pu, layer height is not affected, while the other variable is kept constant.

For data inside the range, the range of variation in ±1.5 mm (6%), which is exceeding the tolerance is assumed. Looking more closely to data deviations reveals that *90%* of the validation data used in the range is deviating *±4%,* which is the assumed tolerance. For the other 10% of validation data, such a deviation from initial tolerance is neglectable (± 0.5), hence the deviation from the baseline of residual analysis is acceptable.

However, it can be seen for the data inside the range, that there is a slightly systematic trend in data deviation, which seems to suggest higher order approximation. With the current data, the quadratic model estimated in section 5.8.3 is violating normality assumption, hence, if a higher order approximation is needed, data should be transformed to meet the normality assumption. Since the deviation from the baseline is acceptable*, First order approximation* is assumed to be a reliable model.

First order approximation of layer height, also shows reasonable estimation for print speed and pump degree outside the design region. Outside the range, estimations are in the reasonable variation of 6%. It means that such a model can be used to give a fair idea about layer height in the mentioned range.

By closely observing the trend, it can be inferred that for the data set of Pr outside the range, the *"heteroscedasticity"* is exhibited meaning that the residuals get larger as the prediction moves from small to large, which inherently create no problem, but it's suggested to be an indicator of model improvement.

II. In Appendix 6 residual analysis of first order approximation with interaction and quadratic approximation of a layer bottom width is shown. The quadratic model seems to improve the *interaction model*, as it eliminates the systematic trend which can be noticed in interaction model.

For *data inside the range*, *82%* of the data is deviating from an actual measured value within the assumed tolerance of *±1mm (4%),* and 95% *of the data is in the acceptable deviation range from the actual top width of ±1.5 mm (6%).* For the data inside the range, the quadratic model in most cases, slightly improved the approximation, while the difference is not noticeable.

Most improvement occurs in estimating data when *Pr is outside the range of the RSM design*. For this data set, points are scattered better on two sides of the baseline, showing the fact that the model performs a better approximation. In interaction model, 40% of the data lay in the *deviation range of 4%(tolerance)*, from the actual value, while such deviation has been improved to *84% by quadratic model.* Moreover, 90% of the data lay in the acceptable deviation range of 6%, from the actual top width.

Both models show same performance for Top width estimation when pump degrees are outside the design region. *70%* of data are in the *deviation range of 4%(tolerance)*, from the actual value. But the range of deviation for the quadratic model is smaller, and data is scattered closer to the baseline, indicating the better prediction.

III. In Appendix 6 residual analysis of the *first order approximation with interaction*, for a layer Bottom width is shown. Data is scattered is to a reasonable extent, on both sides of the baseline, while there is almost no systematic trend noticeable in the residual plot.

For Bottom width, the *tolerance of ±2mm or 8%* (deviation from the actual value)was assumed, according to the distribution of data in a certain setting of process parameters. According to the validation data inside the design range, *98% of data* lay inside the tolerance range.

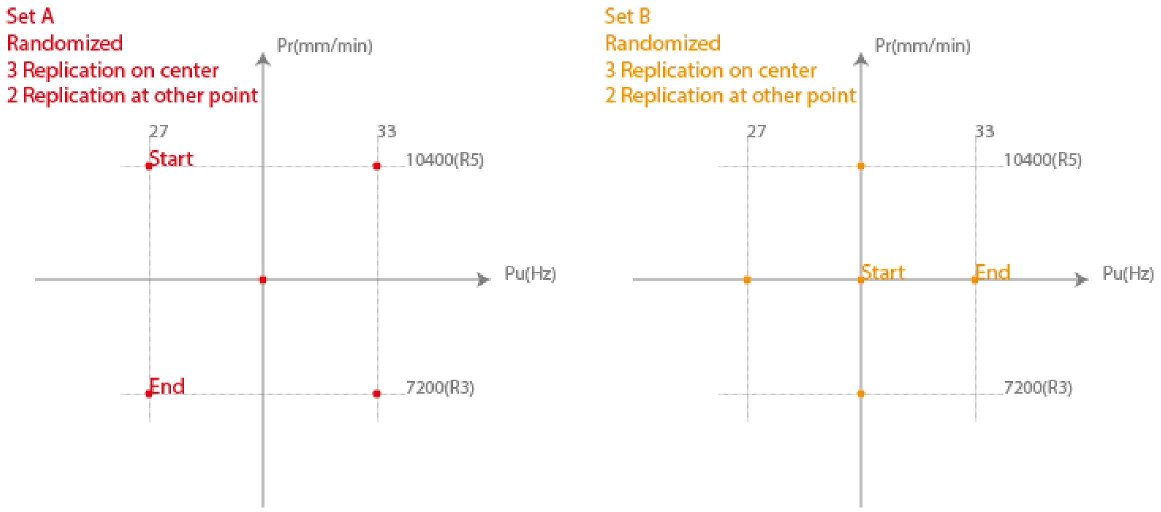
For the data set with the levels of print speed outside the design range, *70% of the data* lays in the *8% tolerance* range, while because of them the *heteroscedasticity* effect can be noticed, indicating the possibility that the model can be improved for that range. It also can suggest a higher order approximation considering the full range [7200, 11600] mm/min, as there can be seen a second order systematic trend in the residual plot.

On the other hand, when pump degree is out of the design range, the model do not perform acceptable, as only 13% of the data fall within the tolerance range.

5.8.2. Supplementary validation

Initial validation performed in the previous section, used same data set, 3D printed in the same condition in terms of laboratory temperature, humidity, and homogeneity of material batches. As a result, results of suggested model were tested against homogeneous conditions of data generation. It is important to test the generality of the suggested models, against defined tolerances. So supplementary validation is important to test the models for a different set of printing, especially when different batches of material will be used. Hence, the extent which model can tolerate different printing settings, which are not considered in design and analysis are tested.

In designed setting for validation data, new CCI design is considered (sets A and B), to incorporate design and centre points replication and randomness in data generation sequences, in order to construct new PuPr model. As a result, the effect of randomness and more dataset replications can be compared with the current model, with fewer replications and not considering randomness. RSM design of experiment has been conducted in R statistics. In graph bellow, Start and End refer to the starting point and ending point of the nozzle head, stating the sequence of printing.



Moreover, it is necessary to check the response of a printed layer dimensional approximation in the design region, as the initial validation covers data inside the region which are located on the boundaries and on axes of design region (see 4.5.2.2 for more information on design region of PuPr model). As a result, the following data setting has been proposed to generate new data for ***Supplementary validation of inner design region.*** These points are shown in set C and D.

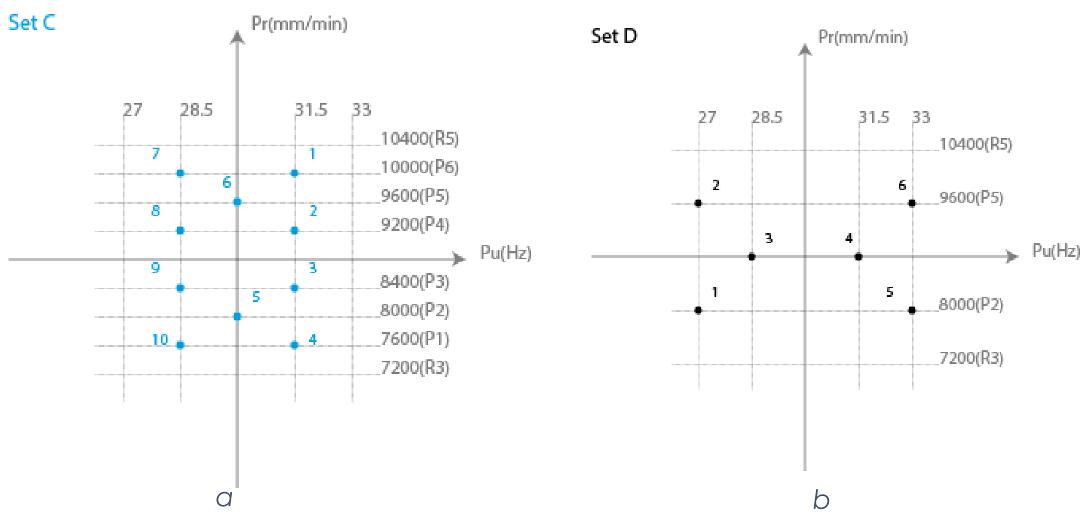


Figure 78: Supplementary validation inside the design region

Set E investigates the extendibility of the model in the range out of the design region, when print speed is exceeding from 10400 mm/min to 11200 mm/min and decreased from 7200 mm/min to 6400 mm/min.

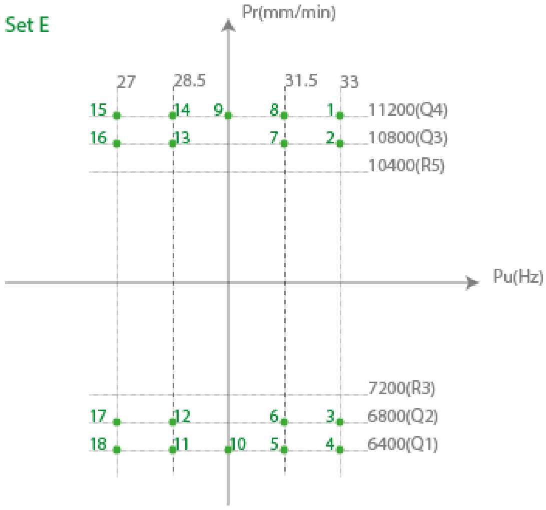


Figure 79: Extending the design region

Pump degree is not exceeded the design region, as it imposes extra pressure on 3D printer when exceeding the pressure from 33 Hz. Moreover, it increases the chance for material to get stocked in the mixer and 3D printer hose. On top of that, pump degree is not varied in practice beyond the defined design region.

The following graph shows the integrated design boundary for supplementary design and validation.

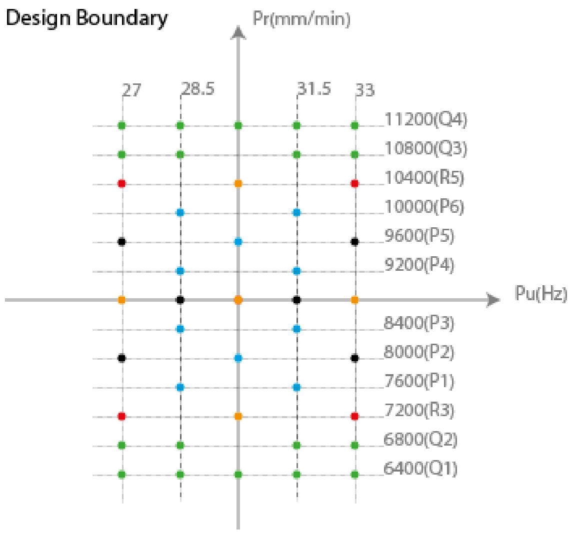


Figure 80: Overall supplementary validation points

In Appendix 7, printing tool path for the proposed design of validation data is presented.

Although supplementary validation was planned, it has not been conducted due to unforeseen situations occurred for the quality of the material and performance of the pump. Due to time limitations of the graduation project, there were not enough time to conduct the supplementary validation, after fixing the problem. As a result, this supplementary step is suggested to be done to have a better overview on the generality of the models, and also their tolerance against variation in material properties and process settings.

5.9. Discussion

At the core of the dimensional Decision Support System(dDSS), and in the Model Management System (MMS), models has been created to link printed layer dimensions and *Print speed (Pr), Pump degree (Pu) and Nozzle distance(Nd)* as process parameters. Response Surface Methodology (RSM) has been conducted to map the relationship among layer dimensions (response variable) and process parameters and derive empirical models. As a result, the path to maximizing dimensional accuracy and minimizing layer deformation is paved. This is the final goal of RSM method. At this step, optimization step seems to be not necessary, because there are numerous factors and parameters which affect the printing process. So choosing process setting requires considering numerous criteria and satisfy dependencies which also needs the experience of the researcher and operator. By optimizing mentioned process parameters, the focus will be narrowed down to satisfy dimensional constraints, and other important process targets may be ignored.

In the following sub-chapters, For two models of ***PuPr*** and ***NdPr***, RSM design and analysis, empirical models and influences of process parameters have been discussed.

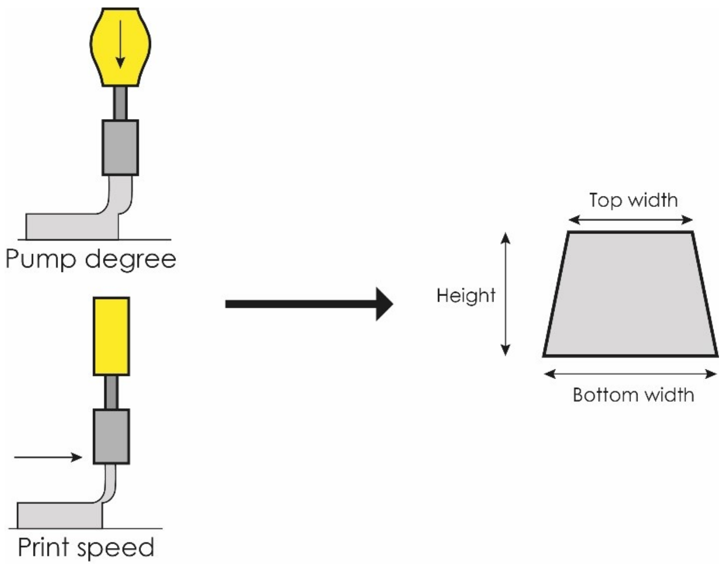


Figure 81: Pump degree-Print speed RSM model

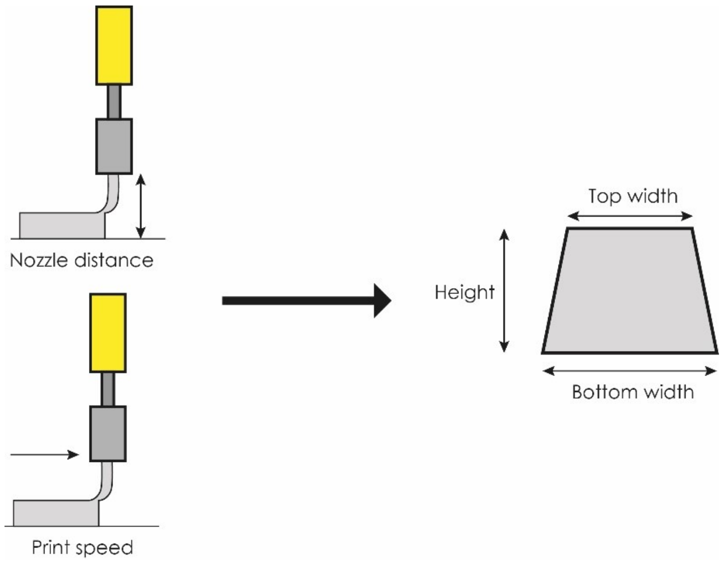


Figure 82: Nozzle distance-Print speed RSM model

5.9.1. *NdPr* model

In the data pre-processing phase, three aims were followed, (i) test the variation of data within a certain setting of process parameters, (ii) test the variation of data among replications of certain setting of process parameters, and if the other two tests response reasonable, (iii) test the correlation of layer dimensions.

For *NdPr* model, data variation among two replications with the same setting was noticeably high, indicating the point that there may be other variables influencing layer dimensions, which is not considered.

One reason may be the existence of the variables which are known and uncontrollable. Fluctuations of pump pressure and temperature when is set at a certain level, affect the viscosity of concrete. Hence, concrete layer deforms differently when time is passed, as the temperature of the pump keeps increasing.

Another possible reason is because of the fact that the printing area is not levelled perfectly. Hence, there are differences in the height of the printing surface, affecting the actual Nozzle distance. Such fluctuations in Nozzle distances place concrete layer differently on the surface, results in different layer deformation.

In order to eliminate such natural variations and increase the sensitivity of experiment, it is suggested to employ experiments units for a study to be as homogenous as it is possible. As a result, variance σ^2 of experimental error . Moreover, by using heterogeneous groups of experimental, generalization of conclusions will be derived. These heterogenous experimental units are grouped into homogenous sub-grouping. *Randomized Blocking* is a useful method to minimize the uncontrollable factors in the experiments (Lawson, 2015).

A method should provide the experimenter the possibility to determine levels of process parameters (Nozzle distance and Print speed) to reach the desired response variables(layer dimensions), and more simultaneously minimize the variations of response variables. *Taguchi* Method developed in by a Japanese engineer, employing quality control concepts in the design phase. It is also referred as the off-line quality control and aims to utilize experimental design techniques to find nominal settings of system parameters that will make the products robust to noise encountered in the system operation process and the use environment. This method, however, is criticized for being inefficient and suggestions have been made for simpler, more efficient alternatives to implement some Taguchi ideas (Lawson, 2015).

5.9.2. *PuPr* model

Pre-processing phase reveals that both variations in a printed layer dimensions are reasonable both for a certain setting of parameters and among replications of a certain parameter setting. The variation for Height and Top width is ±1mm (4%) and for Bottom width is ±2mm (8%). These are assumed as tolerances acceptable for the precision of the empirical models.

Another suggestion to define the tolerance is to consider the size of fine aggregates in the concrete mix which is *2mm or 8%*. Because of the random placement of the aggregates in the layers, one aggregate can be missed in a measuring point while at the other measurement point the presence of an aggregate increases the measurement.

RSM design and analysis have been performed and followed by adequacy check, testing the preciseness, fitness, and adequacy of stepwise created models. For each layer dimension, three models were created and tested to derive the best model, depicting the relation between layer dimensions and process parameters. These three models are (i) Firs order, with main effects, (ii) First order, with main effects and their interaction, and (iii) quadratic model.

For printed layer *Height, First order approximation with main effects* performed adequately, while passing normality check and residual analysis:

$$Height = 24.06 + 0.46 \times Pu - 1.65 \times Pr$$

Here Height is in mm and Pu and Pr coded variables, while the units of the coefficients are mm. The relationship between natural (without coding) variables and Height can be derived by decoding variables as mentioned in section 5.5.2.1. Here, in order to provide the possibility to compare the effect of process parameters, the only coded relationship is considered. Design region is bounded to the range of [-1, 1]. So the proposed model should be as precise as it is possible for this range.

It can be noticed that the constant coefficient, has the biggest value among other coefficients, stating the fact that initial conditions of the process have the biggest influence. Initial condition refers to nozzle type, which is square with the dimensions of 25mm×25mm. *Pu* has a direct effect on the height of a layer, because in the higher values for pump degree, the amount of the material which is extruded is higher, resulting in the higher number of height values. On the other hand, print speed has the reverse effect on height, as an increase in print speed results in a decrease of height. The reason is that the printer has less time to deposited material at a certain point when print speed is increased. Moreover, the interaction between print speed and pump degree has no effect on the height of a layer. It means that in a constant level of one variable, changing the value of the other variable has no effect on layer height.

It can be noticed that the absolute effect of print speed is almost more than three times bigger than the effect of pump degree. IT is because of the fact that print speed is easily changed by G-code, and there is no mediator physical component, which affects the Print speed variation. On the other hand, by changing pump degree there are several obstacles decreasing the pump pressure on its way to the head of the nozzle. The flow of material to be extruded from the nozzle is reduced because of friction, turns, and corners of the connection between pump and hose and also the length of the hose. As a result, one unit change in print speed and pump degree has no the same effect on Height of a layer.

This model performed quite acceptable for the validation data inside the design region. In such a way that 90% of data fell in the range of 4% tolerance.

For print speed varied between 10400 and 11600 mm/min, 87% data fall into the 4% tolerance which provides the ability to get a good idea about the variation of data outside the range which the model is designed for.

On the other hand, when pump degree is decreased to the levels below 27 Hz to 24 Hz and increased to 39 Hz, only 60 % of the data were validated and placed in the range of 4% tolerance. From the practical point of view, pump degree is hardly varied above the defined range, hence it is not suggested to perform extra design of experiment for to extend the pump degree range, as it imposes pressure to 3D printer in higher pump degrees, and increase the chance of blockage at lower pump degrees.

For the data set of print seed outside the range, the “heteroscedasticity” is exhibited meaning that the model can be improved. The most common way of improvement is data transformation, and here it is suggested to define separate design range for print speed bigger than 10400 mm/min (the maximum value of the design range of this research). As a result, the region beyond the region used here would be studied more thoroughly.

Moreover, there are trends in data deviation from the baseline of residual analysis, suggesting the suitability of higher order model approximation. That can also be investigated in a separate design region, for a better approximation.

Top width of a printed layer is estimated by *quadratic approximation*, which the coded relationship is shown as follows:

$$Top\ width = 21.82 + 0.59 \times Pu - 1.6 \times Pr - 0.28 \times Pr \times Pu - 0.2 \times Pu^2 + 0.39 \times Pr^2$$

Here Top width is in mm and Pu and Pr coded variables, while the units of the coefficients are mm.

Same as Height, it can be seen from constant coefficient, nozzle dimensions have the biggest effect. Because of the reasons mentioned for Height estimation, first order print speed has the highest effect on estimation, in a reverse manner. Pump degree has also a significant influence on top width estimation. By increasing pumping degree, the material can flow in width as the layer is confined in height. Hence pumping degree should affect top width influentially, which is proved by showing to be statistically significant in the analysis.

Quadratic term of print speed has a significant influence on Top width estimation , in a way that its effect is direct, meanings that with increasing speed, the top with will decrease in total. But the rate of decrease is less than the rate of top width decrease in the case of the linear model.

The interaction of print speed and pump degree also has a significant reverse effect on Top width estimation. Assume that first the print speed in kept constant, by increasing Pump degree, in total, the top layer is increased because more material is deposited (effect of Pu main effect). On the other hand, deposited material deforms due to its own weight. Hence, in a certain speed, more pump degree results in more material placement, which increases the deformation of layer top width because of its own weight. Such a situation decreases the top width, the material is not zero slump and shows deformation due to its own weight. Such deformation is occurred by sliding the material on the edges of the cross section, resulting in decreasing the Top width.

So in constant print speed, by increasing the pump degree, the rate of increase in top width is decreased, as the effect of deformation due to more material deposition increases. Such an effect implies the significance of the interaction between print speed and pump degree.

Quadratic model for Top width estimation, response quite good when print speed varies in design range and 84% of data are placed in 4% tolerance. While 70% of data placed in 4% tolerance range, when Print speed exceed the range. If 8% tolerance *(set aggregate size as tolerance)* more than 92% of the whole data both for inside and outside of the range lays in the tolerance rate. So quadratic model gives precise responses, to an acceptable extent., while covers a large region of data both for print speed and pump degree.

For the case of Bottom width approximation, the model proposed to relate print speed and pump degree is first order model, with main effects and their interaction:

$$Bottom\ width = 29.43 + 1.85 \times Pu - 4.21 \times Pr - 0.35 \times Pr \times Pu$$

Here Bottom width is in mm and Pu and Pr coded variables, while the units of the coefficients are mm.

constant coefficient, nozzle dimensions has the biggest effect, as it can be traced by its value. First order main effect of print speed has the highest effect on estimation, in a reverse manner, as it defines the amount of material deposited at a specific point in the specific time span. So by increasing the speed, in constant pump degree, there is less time to place material at the certain printing path. There is less material, and hence less bottom width. Deformation in layer dimensions results in an increase of the bottom width, because of the flow of material. The flow of material is in the width direction and toward the bottom of the layer. This is because of the reason that printed layer is confined in height.

Another reason that increasing print speed decreases dimensions of the layer, especially in bottom width, is because the increase in print speed, increase the tendency of extruded material to flow in length (print path) direction, and the flow of material toward the bottom is decreased.

Pump degree has also a significant influence on bottom width. By increasing pumping degree, more material can flow in width, and toward the bottom. Hence, pump degree has an effect on Bottom width approximation.

On the other hand, at the certain print speed, by increasing the pump degree, the dimension of Bottom width is increased because: (i) more material is deposited. (ii) At the same time, deformation of the layer in its cross section is increased because more material is deposited, and this deformation slides the material toward bottom width. So Bottom width is increased.

But the rate of the increase is not constant, and it decreases. Because the rate of deformation occurred due to layer weight decreases. This is because of the elastic behaviour of the material. So, the increase rate of width decreases when print speed kept constant. Such an effect implies the existence of interaction effect on Bottom width estimation.

The model showed very precise estimation as 98% of the validation data fall inside the 8% tolerance (assumed for Bottom width by two different approaches).

For exceeded print speed, 70% of data lay in the tolerance. The model can be used to give an initial idea about the Bottom width value, but since the heteroscedasticity effect can be seen, the model should be improved to incorporate a bigger design range.

Only 13% of the validation data lays in the tolerance range when pump degree is extended, which suggests a separate design of experiment for such a range. But because of the practical reasons mentioned above, such experiment seems to be excessive.

6. dimensional Decision Support System Employment

In this chapter, applications of developed dimensional Decision Support System (dDSS) is explained. dDSS is developed to be employed in two different stages of 3D concrete printing: (i) Design-Production (DP) intersection, (ii) Post-Processing. In this sense, dDSS is categorised as *"*FIRST GENERATION OF DECISION SUPPORT SYSTEM(DSS)*"*.

As the first generation of DSS, the model-based system consists of an *offline* models, which are developed by stored data. Model is not developed further when receiving new data during the process. In the other word, dDSS does not contain a self-learning model, which is used during the printing process, is being fed by process data, and develop itself during the printing process. Asa result dDSS is used in the scope of the process parameters defined, giving both overall and specific overview of relations between process parameters and layer dimensions of a printed layer. Moreover, first generations of DSS, are not designed to directly a response to dynamics of the process, in the sense that the be used to derive decision to leverage process parameters to cope with process situation in time, and level the response variable to the what is assumed desire.

dDSS provide the possibility to step further toward the "SECOND GENERATION OF DSS", in which the system consists of an offline core model, but is used in the process dynamically to responses during concrete printing, leveraging process parameters, to obtain desired layer dimensions. This type of DSS is elaborated in chapter 7, section 6.In the following sections, employments of dDSS is explained.

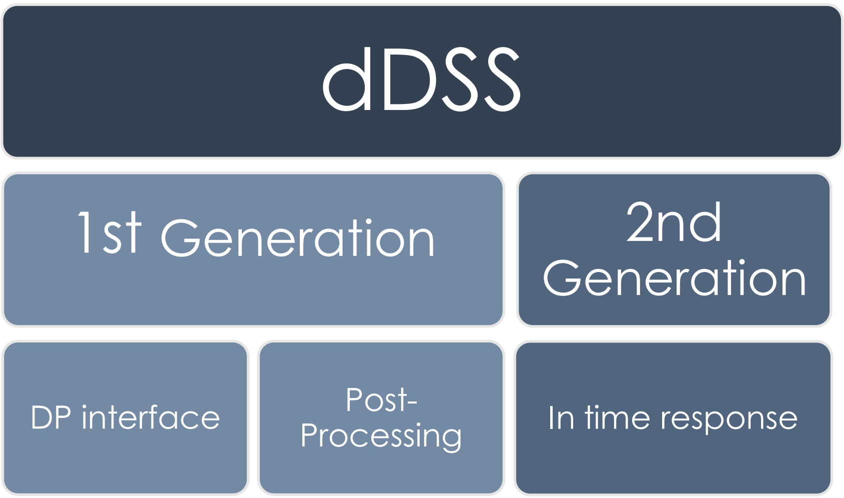


Figure 83: dDSS employments overview

6.1. dDSS: First generation of Decision Support Systems

dDSS is used to derive the following knowledge and be used in different stages of design and production of 3D concrete printing.

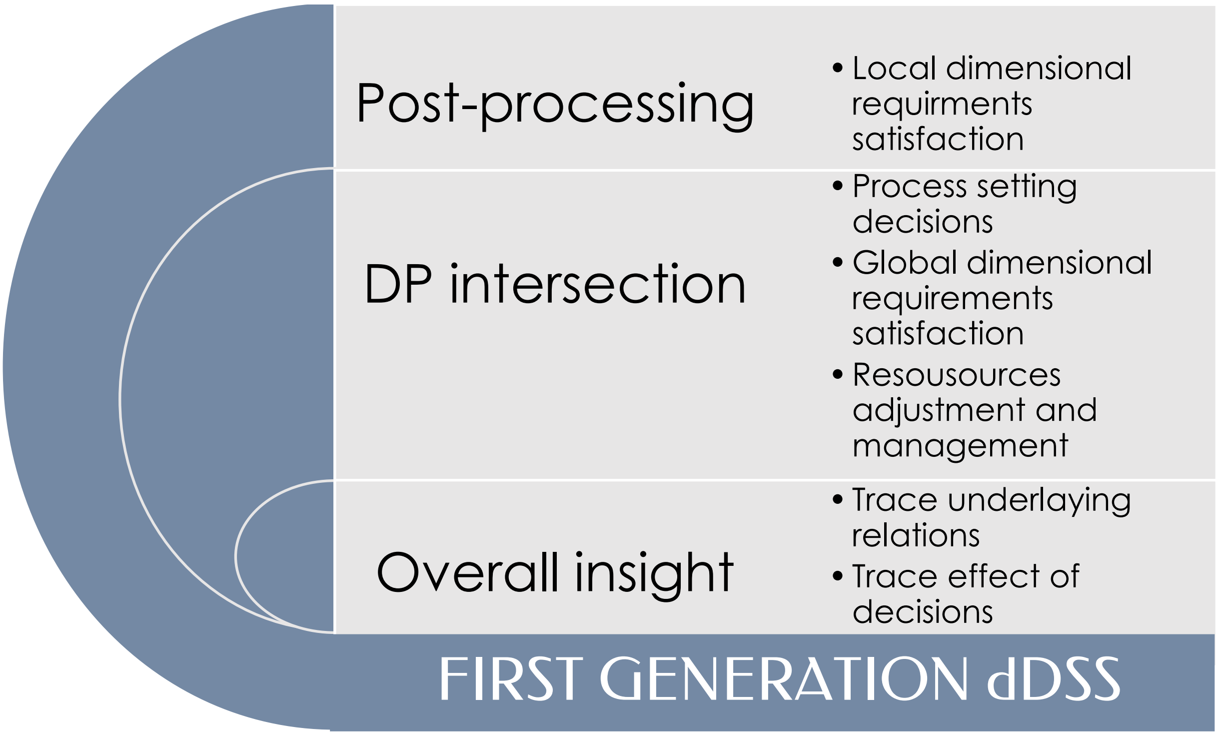


Figure 84: First generation dDSS employments

6.1.1. Overall insight

6.1.1.1. Case 0: Zero input

One of the main current problem in concrete printing process is the unknown relationship among process parameters and printed layer dimensions. dDSS established a relationship among print speed, pump degree and layer dimensions. As a result, the influence of process parameters can be tracked on dimensions, printed under different process settings. Moreover, *3d response surfaces* gives overall insight about the decision parameters and final dimensions of a layer. As a result, the user has a better understanding of the effects of different process parameters.

Contour graphs, adds more elaborated details about reachable maximum and a minimum of height, top and bottom width of a layer. Moreover, the desired range of process setting can be derived in more details, as contour graphs present process parameters and one of the layer dimensions, in addition to representing values. In contour and 3D response plots, coded Pump degree and Print speed are considered and presented, while the unit for height, top width and bottom width is mm.

Through the user interface shown in figure 85 user can interact with the system to gain preferred knowledge. In order to gain overall insights, 3D response surfaces and contour graphs should be generated. In “Plot Output” checkbox, by selecting “3D Response Surface” or “Contour plot”, the user can derive preferred output.

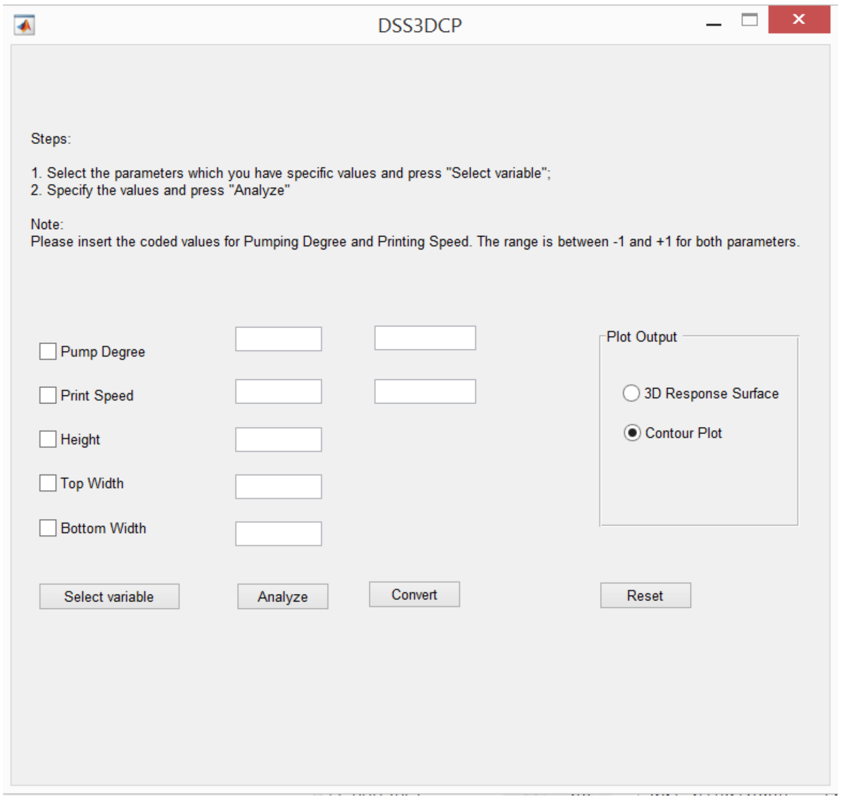


Figure 85: User interface

Blow response surfaces for Height, top, and Bottom width is presented. In figure 86 first order response surface is shown for height. With increasing pump degree, height is increased, while decreasing print speed have the same effect.

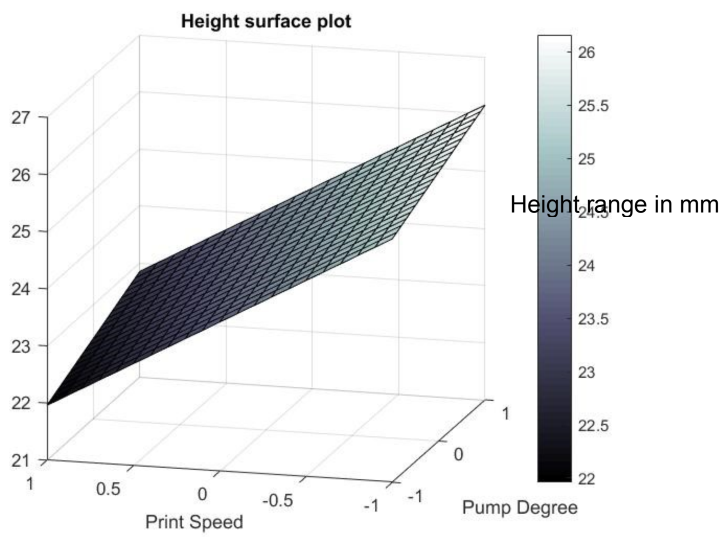


Figure 86: 3D response surface for Height

In figure 87, second order response surface is shown for To width of a printed layer. Print speed and Pump degree are shown as coded, to derive the actual values, coded values can be converted by dDSS. As it can be seen, by differing the values of process parameters, while other is constant, height is affected in the same manner. In Top width response surface shown in figure 87, Print speed and Pump degree show quadratic effect.

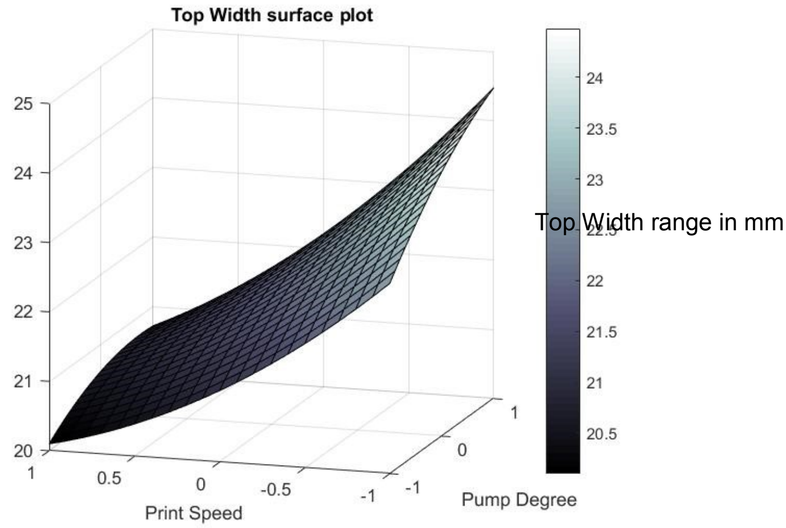


Figure 87: 3D response surface for Top Width

In the Bottom width response surface, the slight curve is noticeable, which is because of the fact that there is an interaction between Print speed and Pump degree, while their main effects are related to bottom with linearly.

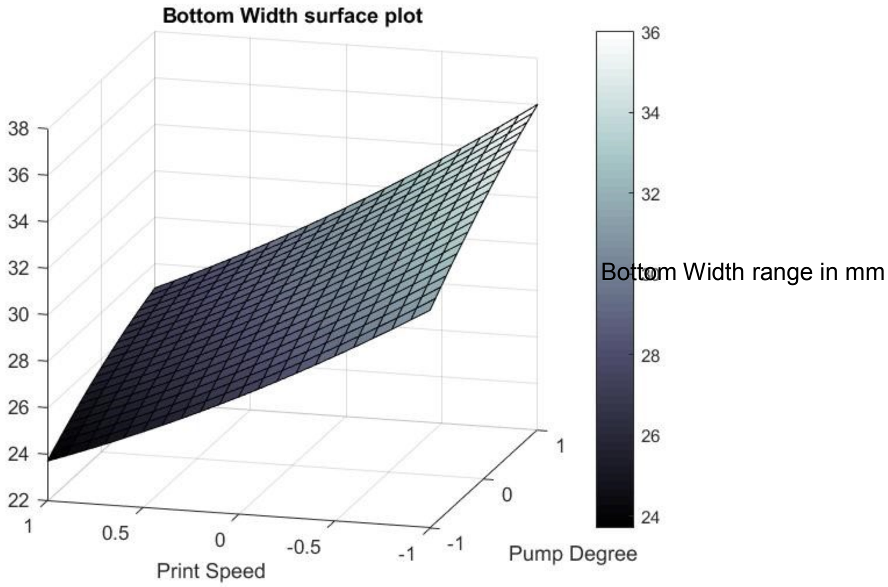


Figure 88: 3D response surface for Bottom Width

In Height contour graph, it can be noticed that the effect of varying Pump degree is less than Print speed, because of pressure dissipations occurred in the way of extruding concrete. The point which is noticeable in the Top width contour graph, is the point that at a constant level of speed, by increasing pump degree, the effect of pump degree on increasing Top width is decreasing, till it reaches to a point (Stabilizing Point) in pump degree level which Top width remains constant by increasing pump degree.

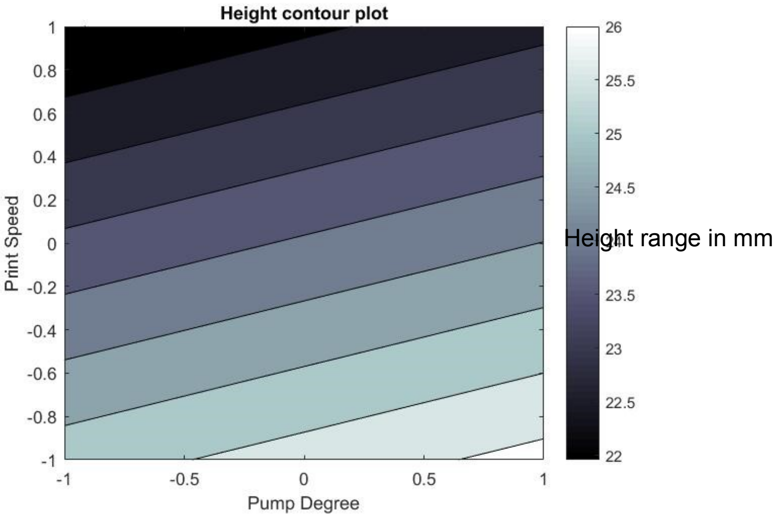


Figure 89: Height contour plot

The top layer is increased as more material is deposited due to higher Pump degree. While, deposited material deforms due to its own weight, flow toward bottom layer, and decrease the Top width. The reason is because of the fact that at Stabilizing Point, the effect of width increase by placing more material, is equal to the effect of width decrease because of deposition weight.

By increasing Print speed, Stabilizing Point is reached at lower levels of Pump degree. In the other word the effect of the flow of material toward bottom is getting more dominant and finally reaches the point where has the same reversed effect with width increase due to material deposition. This is because of the fact that less material is deposited at the certain time at the certain point, hence less material is needed to be deformed toward bottom and the Top layer is stabilized at the lower pumps with depositing lower amount of material. as in low print speeds, more material is deposited, and material has more time to decrease Top width by flowing toward Bottom layer.

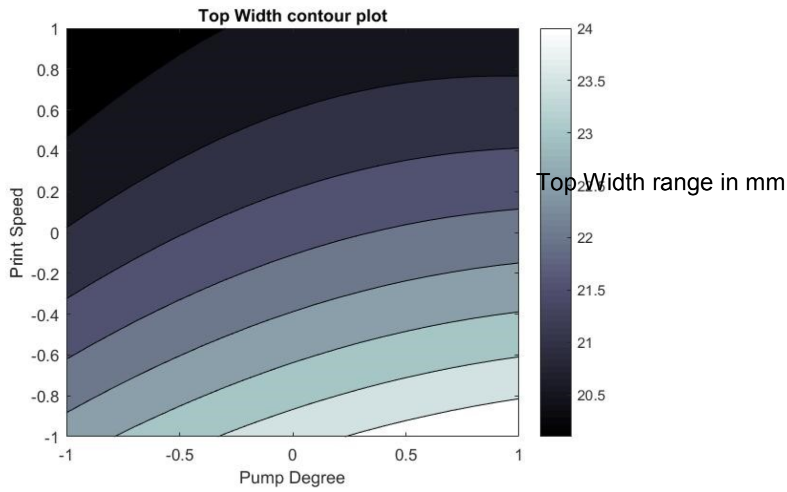


Figure 90: Top Width contour plot

In Bottom width contour plot, the slight curvature is noticed, which is because of the interaction between Print speed and Pump degree on Bottom width. Increase rate of Bottom width is decreased at lower Print speeds, because, of the behaviour of the material under deformation, which its deformation rate decreases when more material is deposited.

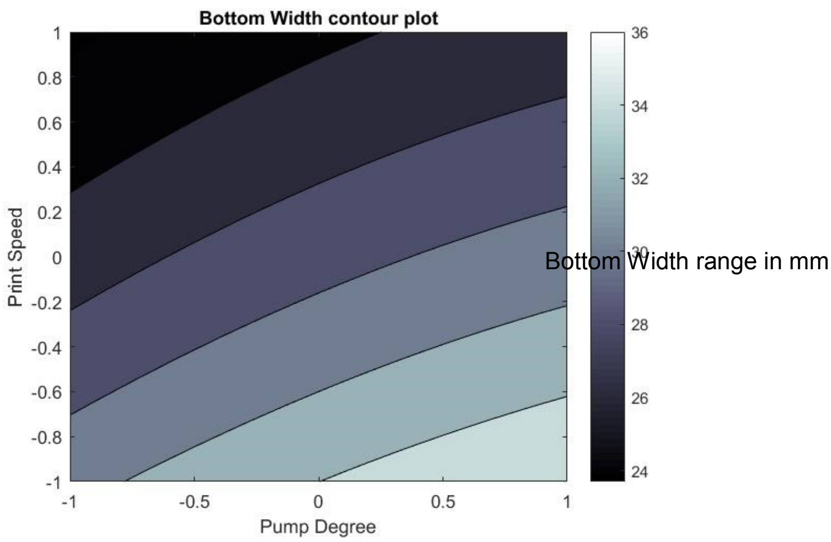


Figure 91: Bottom Width contour plot

6.1.1.2. Case 1: One input

If more one of the Pump degree or Print speed is known, and the effect of varying other parameter is needed, the user can input value of the parameter, by pressing Convert and Analyse in dDSS, the effects can be traced.

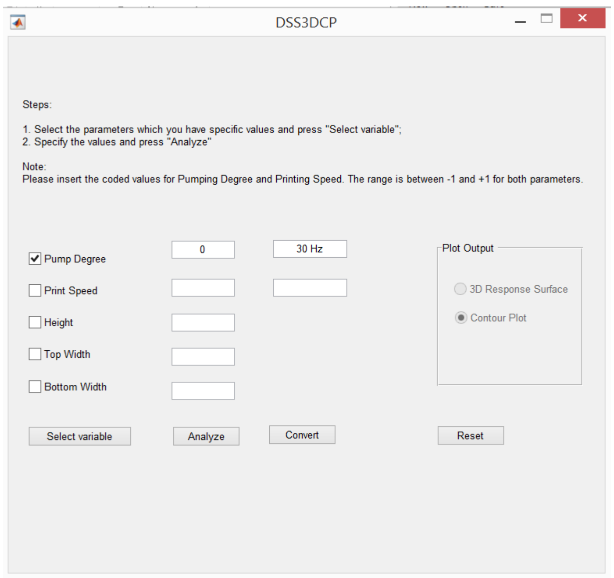


Figure 92: User interface One input case

This situation is used by 3D concrete operator or researcher when it is preferred to use a constant parameter during a special case of printing. Another situation is the case which one parameter is assumed to have a usual value. Pump degree value selection can face such situations, because pump degree modifications change material characteristics, as such a change affect material temperature and, viscosity. Hence in order to be able to print with the same quality in different Pump degrees, material related parameters such as water to cement ratio should also be adjusted.

The graph below shows the effect of different Print speed on Height as an example, when Pump degree is assumed to be chosen by decision maker at usual values of 30 Hz.

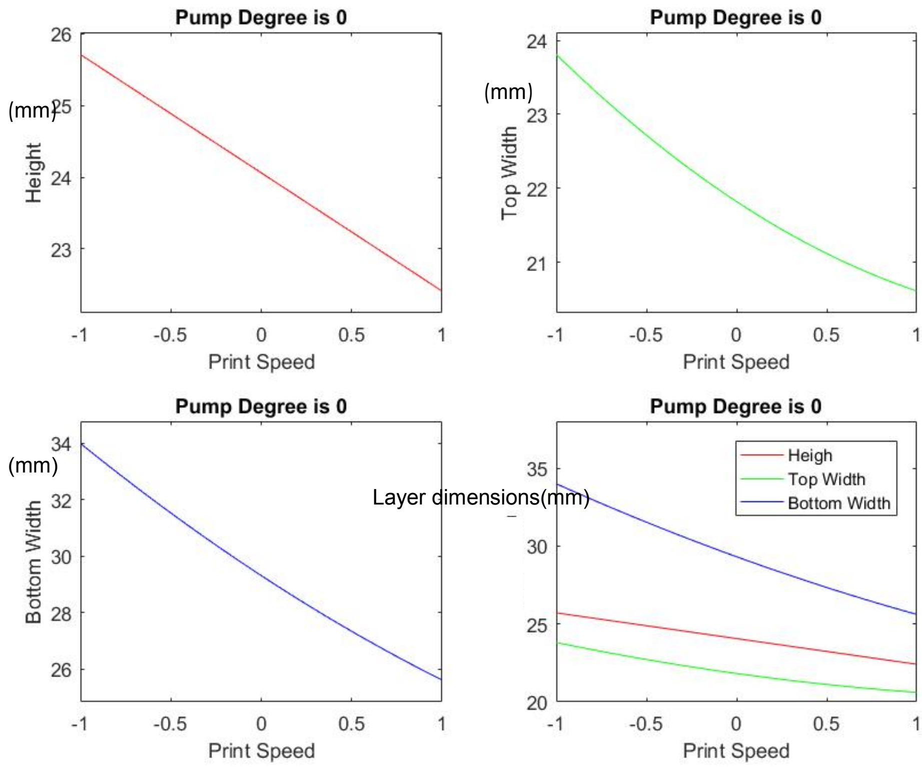


Figure 93: results of one process parameter input

In this case, from the plot in which all dimensions are represented, (below right), it can be seen that since there is no intersection between lines, there is not a Print speed value results in same height and top and bottom width. By increasing the Print speed, the difference between dimensions are decreased, and printed layer cross section is closer to the ideal square shape. On the other hand, BY increasing Print speed, deformation in Height is increased, and in order to reach desired final element height, more layers are needed, which means more time and resources are needed for the printing process. As a result decision maker is facing support in two levels: Managerial, when time, costs and arrangement of resources are needed to prolong 3D concrete process, and, Technical when it is needed to derive decision regarding process parameters, affecting final dimensions of a layer.

Another situation is the case that decision maker has a specific dimension known and introduce it as an input into dDSS. One of the most common situations is the case that decision maker want to reach the final element layer height in minimum possible numbers of layers. So the layer Height should be maximum, to reduce required number of layers to reach a specific element height. By getting overall insight about the possible values which printed layer Height can get, maximum layer Height is something around 26 mm (see Contour plot and 3D response surface for height). So decision maker suggests 26 mm as an input, to gain required process parameters needed to reach desired layer Height.

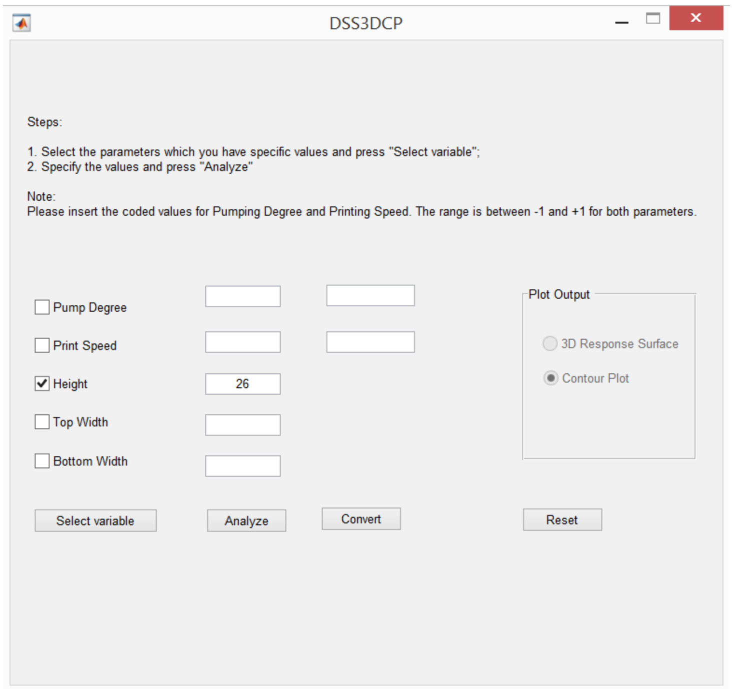


Figure 94: Height as an input

Retrieved knowledge from dDSS indicates the fact that such desired Height of 26 mm can be reached in a limited range when Pump degree is between 32 and 33 Hz, and Print speed is varying between 7200 and 7500 mm/min, which are located far from the usual values of both. Such a setting will impose extra pressure to concrete printer, which is not suggested for printing large scale elements. However, for limited purposes, it can be applicable. In that case, decision maker, select specific Print speed and Pump degree and then in the first and second contour plots, he/she can see the effects of such a choice on the Top width and Bottom width.

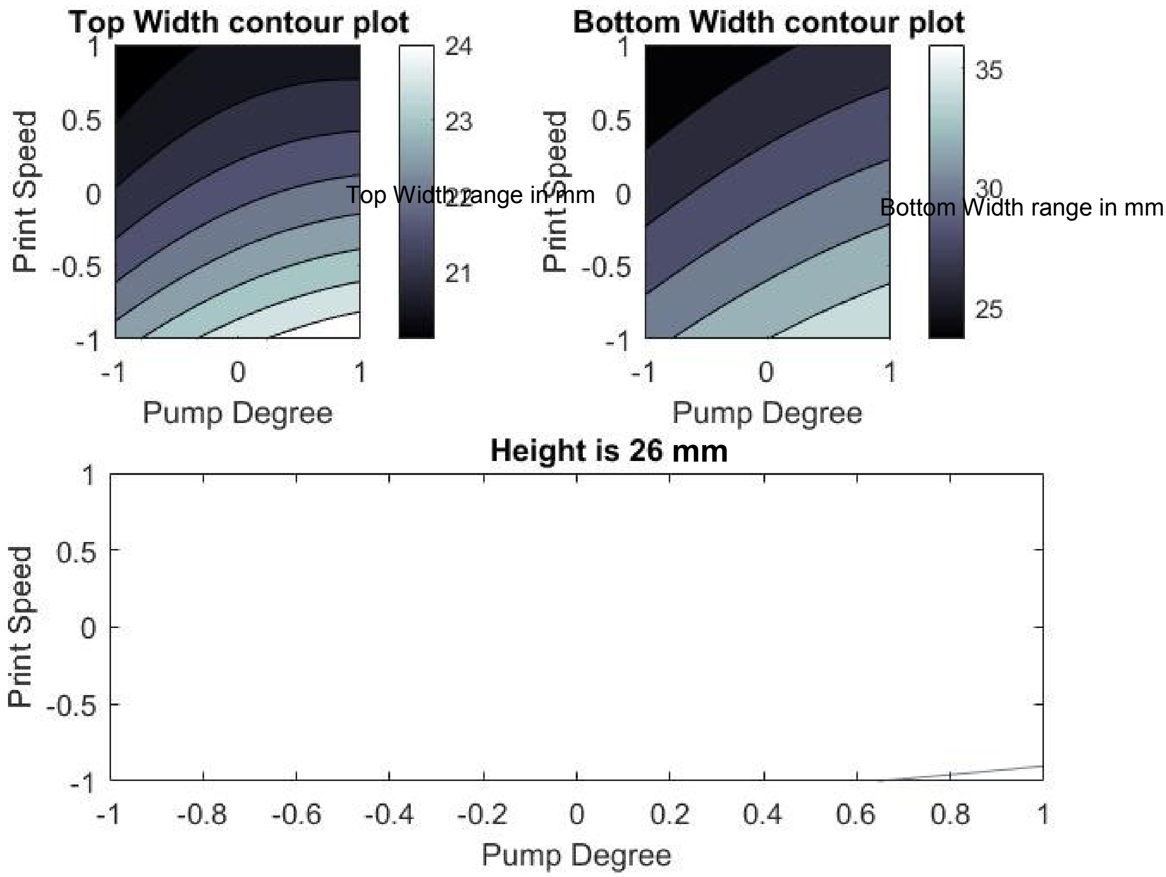


Figure 95: Output for having Height as the only input

6.1.1.3. Case 2: Two inputs

In case 2, two inputs are introduced to dDSS which one of the parameters is from process parameters and the other is whether from other process parameter or a required dimension.

There is cases where the open time between layers are important, or I the situation where total time of construction is an issue, then decision maker already sets Print speed and Pump degree to such priorities. The open time of the layers is important in defining the bond strength of the layers in printed elements. Such a property is the most critical mechanical property in concrete printing, which is affected by cohesion of layers, which is a function of time between extrusions (T. T. Le et al., 2012).

Print speed also affects the strength development of the structural element as a faster print result in imposing loads, under earlier stages of material maturity, a man-made parameters indicates the strength development. It is normally defined as the product of time and temperature of concrete. Hence, strength development is at tits earlier stages when loads are introduced to the element.

As a result, it is a common case as well, in which decision maker sets parameters according to primary criteria, and at the next step, wants to track the effect of such process setting on dimensional accuracy of printed layer, or deformation in Height, Top, and Bottom width. As a result, user input values selected for process parameters, and derive a dimensional prediction for a single printed layer, with a visualisation o the possible cross section, to give a better overview of the final results and outputs.

Figure 96: Cross section prediction

In the situation below, decision maker made the choice for Print speed in relation with satisfying desired bond strength and chose Pump degree as a result of total material consumption for printing the whole elements.

In case 2, there is another situation which decision maker sets dimensional accuracy in the priority level by which made the choice of one process parameter. For instance, assume that reaching a specific bond strength is the first important criterion to be met, and in a sequential decision making, layer dimensions should fulfil certain height to minimise the final deformation of the final object. So chosen Print speed and required layer height are introduced to dDSS as inputs, and required Pump degree and other dimension predictions will be calculated through the system.

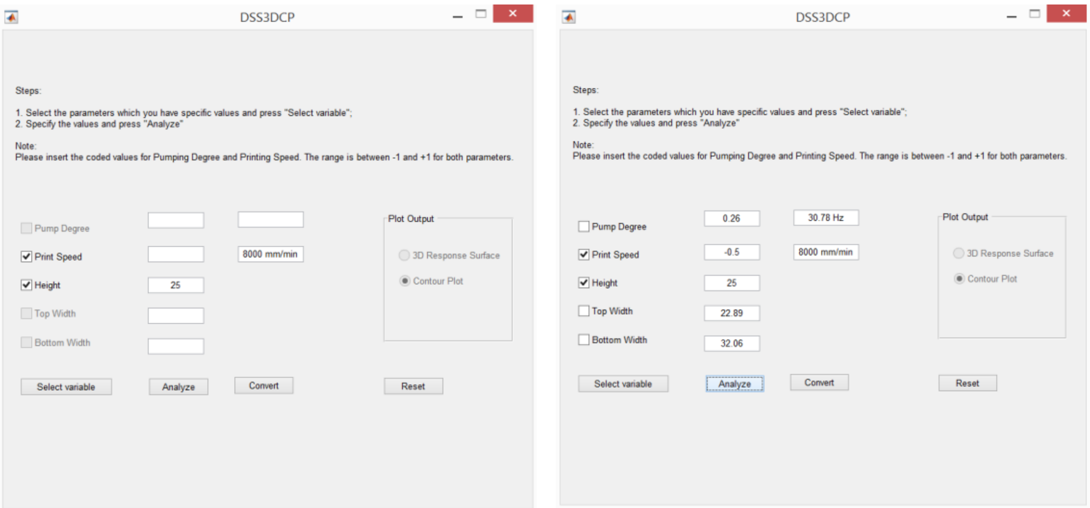


Figure 97: Outputs for Height and Print speed as inputs

Overall insight can be given by using dDSS over the interrelation of Print speed, Pump degree, and layer dimensions. Through 3D response surface or contour plots, layer dimension ranges can be derived.

Moreover, underlying relationships can be used to trace the effect of decision variable on other process and dimensional parameters.

Finally, parameter prediction can help decision maker to reach the exact dimensional performance, while suggesting the values that correspond with the desired setting.

The graph below summarise the application of dDSS to derive overall insight over the printing process and setting selection.

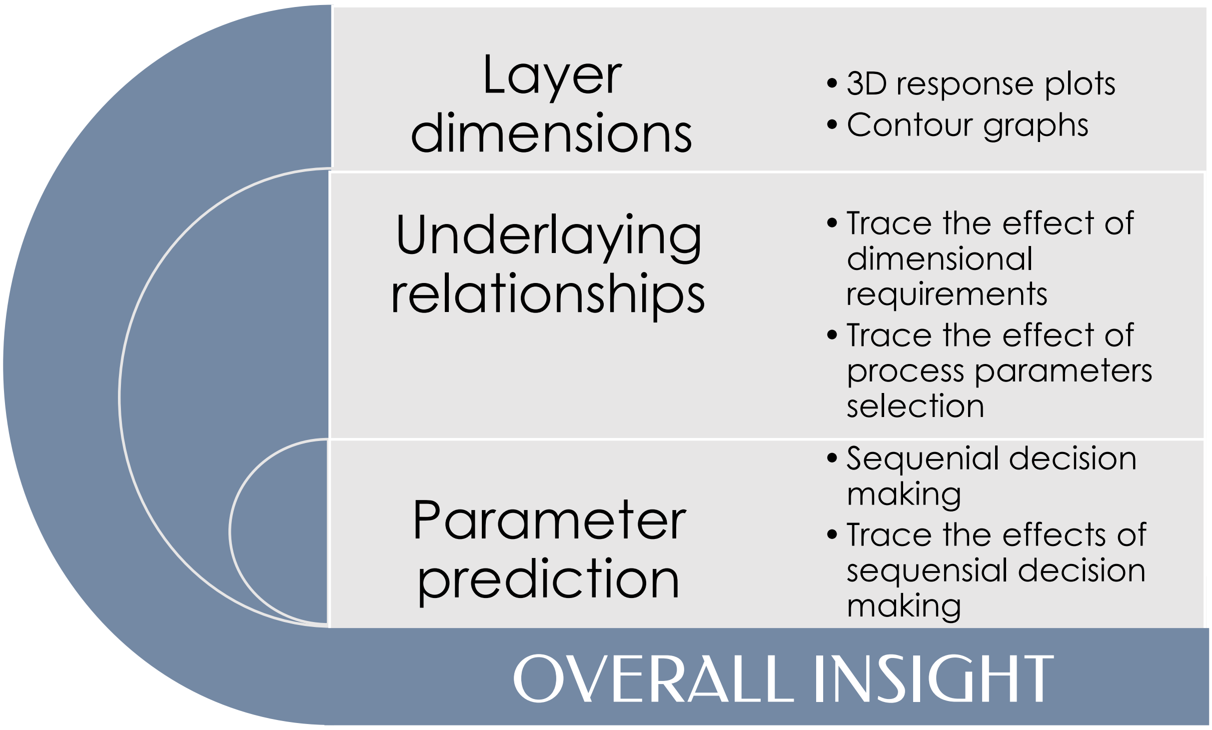


Figure 98: Application of dDSS to give overall insight on the process

6.1.2. Design- Production (DP) intersection

One of the main motivations of developing dDSS is bridging the gap between the design and production phase. As a result, assumptions are taken in design phase should encounter realities in concrete printing process, introduced by the interaction of interrelated process parameters with target properties of printed elements. dDSS is applied to encounter the constraints and requirements of the final printed elements dimensional deformations. Hence, the influence of concrete printing process setting, on dimensional constraints is traced. As a result, the effect of the process parameters is considered to meet dimensional constraints in the design phase, where, design decisions are made to fulfil product properties, such as dimensional constraints. This employment acts as an intersection between design and production phase, which bridge te gap between what is planned to be printed and what will be printed

One of the main applications to meet dimensional constraints is considering layer deformations of concrete process and find the corrections to meet the final element height.

During the design phase, after selection design parameters (see chapter 4), 3D model is sliced in layers to define printing tool path. According to the nozzle type and thus ideal layer thickness (nozzle height) chosen for printing the element, printing element is divided into a number of layers. So the total time of printing is calculated by the time of printing the sliced printing tool path and- calculated by Print speed and length of the printing tool path, and a number of printing layers. In this phase, the effect of deformation of the layer due to printing setting should be considered, as the main constraint is to meet the final height of the final product, and if it is applicable keep printing time at the designed level.

Deformations during printing process occur because of the weight of the layer itself and also the weight of the upper layers above. dDSS has investigated deformation of a single printed layer, hence it does not take the weight of the upper layers into consideration. But, it still provides wider understanding from layers deformation in concrete printing process. Moreover, the methodology and concept used in developing dDSS can be used and the effect of deformation in numerous layers get investigated. So, here dDSS also acts as a proof of concept to tackle constraints and requirements in the intersection of design and production phases.

Thus, here dDSS is used to show its application in predicting the *final deformation of concrete printing element*. Moreover, adjustments in time and cost estimation in the design phase will be another outcome of dDSS as number of extra layers are calculated. Hence:

I. *Technical level of decisions* is supported in DP, containing design and process related decision.
II. *Managerial level decisions* are adjusted and matched the reality of the 3D concrete printing.

IFC file of 3D model of the priming element is imported into the tool. The Industry Foundation Classes (IFC) model is aimed to contain Building Information Modelling data. Trough IFC file, dDSS extracts element to which the material of concrete is assigned, retrieve final height. Then in parallel, system inquires the setting to predict a layer Height for Three options:

I. First, layer height printed more than expected layer height (25 mm, equals to nozzle height, see section 5.2.2.),
II. Secondly, printed layer equal to the ideal layer height
III. And Finally, minimize the difference between printed and ideal layer height.

By option I, printed layers are higher than expected layers, which results in a decrease in a total number of layers, to reach a specific final height. Thus, the total time of production will be reduced, and costs will consequently be decreased.

If option II is applicable, initial design assumptions will hold no correction will be needed. And finally, option II seeks the best process setting to minimise the printed layer height, to reduce the corrections in excessive number of layers, printing time, and cost.

These options are tested against the selection of process parameters by which, the selection range lay in a reasonable distance from the mean values. As a result excessive pressure- especially imposed by Pump degree, is not introduced to the printer. Moreover, as the result the prediction of system's behaviour is more reliable, as it is closer to the centre of the design region, centres which were used to construct the model, relating process parameters to layer Height. Finally, selecting process parameters close to the usual values(means) provide the possibility to be flexible in leveraging them in the process, due to other considerations. For instance, of high print speeds with very low Pump degrees get selected, it is not possible to increase the speed or decrease the amount of extruding material, in the process. This may be required in corners, to have sharper corners, as the printer slows down at corners(regardless of the introduced printing speed and because of operational delays).

Selection of the reasonable range is to a large extent related to the case of the printing and its scale. If the scale is small, Printing speed is more limited to be increased, as the next layer should be placed on top of a layer which is not able to carry the weight of the coming layer. On the other hand, in a large- scale element, Print speed is sensible to the lower values of speed, as the open time of a layer affects the bond strength and also the development of strength in the whole element.

In another example, if the final element contains sharp corner, Pump degree should be limited in a range as it minimizes the excessive deformations in corners, due to operational delays of the printer.

As it can be seen, selection of a reasonable range for Print speed and Pump degree depends on the case of printing and also other considerations and constraints involved in 3D concrete printing process. Here, according to experience, and for the means of generalisation, half of the design region is considered as reasonable which means the following range:

28.5 Hz<Pump degree<31.5 and 8000 mm/min<Print speed<9600 mm/min

As a result, the result the highest possible layer Height is 25.11 mm when Pump degree is 28.5 Hz and Print speed is 9600 mm/min. Hence, for an element with the height of 4 meters, one layer would be printed less and time ad money is saved, which its magnitude is dependent on the complexity of printing tool path.

Bellow a case is schematically shown when there will be deformation of each layer relative to ideal layer Height, and hence there will be a total deformation in element final Height. This will be the case when Print speed and pump degree are in the reasonable range, and the range is assumed to be limited than mentioned above. So more layers are needed to be printed to reach the planned final height. dDSS finds the number of needed layers to fulfil height constraints. Moreover, added time of production and costs, due to excessive material and resources use can be calculated, by deriving Print speed suggested by dDSS and printing length of the element.

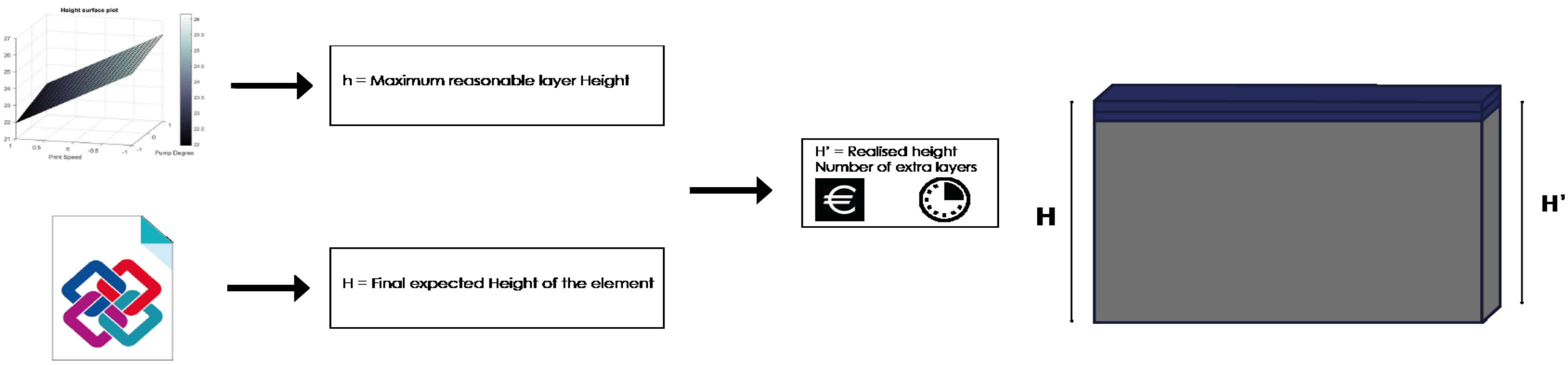


Figure 99: Steps of adjusting number of layer, time and cost adjustment

6.1.3. Post-processing reduction

One of the main characteristics of 3D concrete printing is ribbed finishing, due to layerwise construction and deformations in each layer. Different dimensional deformations in Top width and Bottom width of a printed layer, transforms expected square layer cross section to almost symmetric trapezoid. As a result, the ribbed final surface of the printed element is resulted. During printing, such a trapezoid cross section result in destabilization, when the other layers are being placed on top. So it is important to reduce this effect to be able to reach higher levels. Moreover, the ribbed properties of the will affect the functionality of the printed element which can limit its applications.

Figure 100: Ribbed finished surface of an end product

Post-processing is required to reduce or eliminate the uneven deformations in Top and Bottom width. By implementing dDSS, the need for post-processing is diminished and layers are closer to square shapes.

In order to reach the most square cross section of printed layers, the difference between deformations in Top and Bottom width should be minimum. As a result, the trapezoid shape is closer to square and instabilities and limitations due to the ribbed quality of surface finishing are reduced. Hence, decision maker introduces Top and Bottom width as inputs to dDSS which have minimum possible differences. If there are limitations in acceptance range of Print speed and Pump degree, the decision maker should consider them and seek the closest values for widths in that range.

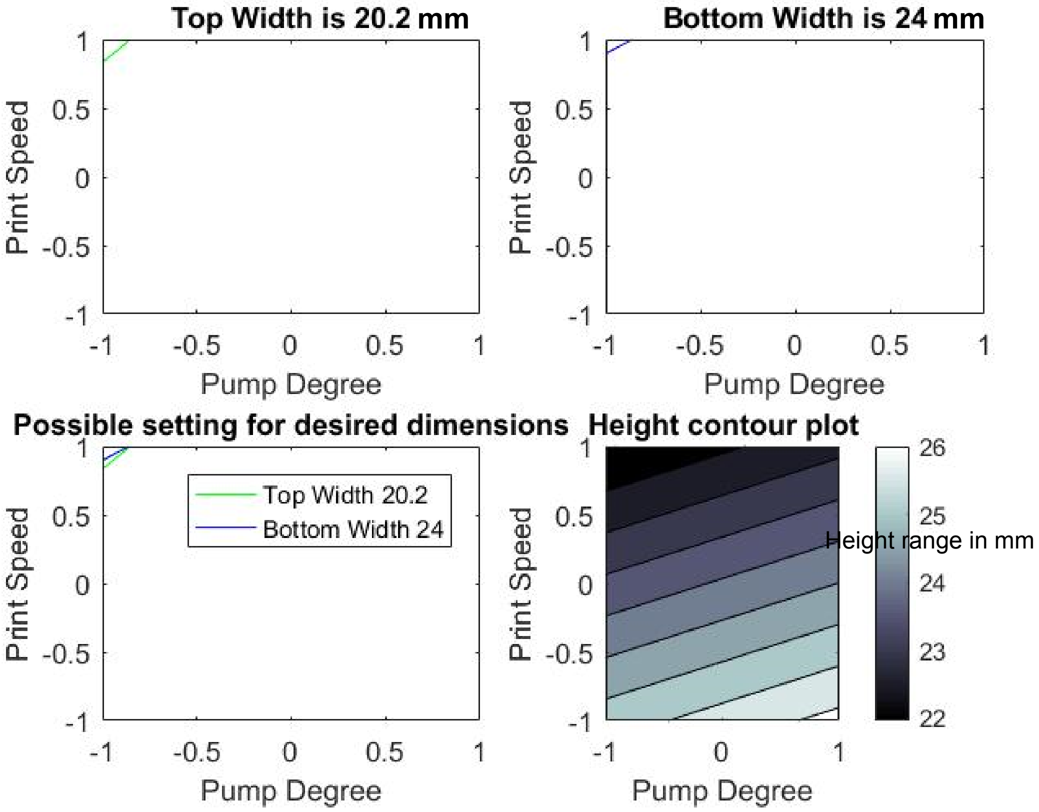


Figure 101: Analyzing dimensions for the most square cross section

It is a general rule, derived from the model discussed in chapter 5, which Bottom width hold low values at low Pump degrees and high Print speeds. This is same for Top width, in addition to the fact that Top width is varying between 20.1 and 24 mm, while Bottom width variation range is much bigger and between 24 and 36 mm. So, Bottom width should vary at its minimum levels, in order to have the minimum difference between widths. Because the whole range of Top width variation is closest to the minimum levels of Bottom width. So according to the defined acceptance range of process parameters, minimum levels of Bottom width is found, which is corresponding to minimum levels of Top width. Because both values are being changed in the same direction but with different magnitudes when are related to process setting. Here, specific range is not assumed, hence, First minimum Bottom width is selected as it is more sensitive to change in process setting. Then Top width is selected, which should be close to its minimum value as Bottom width is at its minimum value. By few try and errors, Top width in minimum distance from Bottom width is selected.

In graph below, it can be seen that at *Pump degree = 27.5* Hz and *Print speed = 7200 mm/min*, the cross section is the most square cross section. However, due to far distance of process setting from their mean value, this setting is not recommended for a long process.

7. Conclusion

In this chapter, conclusions derived from development and application of dimensional Decision Support System (dDSS) are presented. First, the extent of answering and meeting the research questions and objectives should be investigated. Then research scientific and social relevance is described to examine added values and limitations of the developed Decision Support System. At the end of this section, the limitations of this research and development graduation project are mentioned and recommendations are suggested to improve the models and framework,

7.1. Research objectives

This research and development graduation project aimed at increasing the knowledge and awareness of the complex process of 3D concrete printing, as a cutting-edge technology in the construction industry. The main motivation was to reduce the time and resource consuming trial and error efforts to reach proper configurations along with the respective machine settings in concrete printing processes. As a result, conscious choices can be made with the minimum effort and the results of decisions can be traced before the physical production (construction) process and, thus, decision makers can gain a better overview over their decisions.

The main goal of the research is :

PRODUCT AND PROCESS IMPROVEMENT OF 3D CONCRETE PRINTING.

In order to reach the aimed improvement in both product and process of 3D concrete printing, this project focuses in the current limitation of the technique on setting the process in a way which leads to the desired product. Numerous experiments are being done to conduct concrete printing and finding the most suitable process parameters.

Moreover, The quality of the final product is determined to a large extent by the process settings and in the current manner, there is not enough knowledge about quantitative relationships between such interrelations. More importantly, it is necessary to investigate the parameters which have the most significant effect on certain properties of the final product. It is also important to specify the levels of significance of influential parameters to narrow down the involved variables in the process in order to reach the required outcomes of the product.

Here, a methodology is investigated and implemented using the Response Surface Methodology (RSM), a type of experimental design, to efficiently generate required experiments, to detect significant parameters, specify the significance level and finally construct the empirical model. This is done in order to better understand the effects of process parameters on targets, defined for the final product. Moreover, in the case in which a specific value of a requirement is needed, process settings needed to meet desired values can be suggested through the developed Decision Support System. Such a system assist decision makers, researchers and 3D concrete printer operators to derive decisions about the printing process which lead to meet the expected quality of the final product. In the other words, a

Decision Support System provides the means to improve the quality of the product by suggesting the best possible process decisions, in a defined range of the design.

A “dimensional Decision Support System (dDSS)” is developed as a proof of concept, to show the methodology and construct the framework of a Decision Support System. Moreover, a current challenge is tackled by the implemented methodology and the developed prototype of a Decision Support System. The proposed dDSS supports process decisions to meet dimensional requirements of a printed layer within the context of the overall building element. The involved process parameters in dDSS are “Print speed” and “Pump degree”.

By developing explainable models in the core of dDSS, the level of significance of process parameters are detected, the empirical models are constructed and the relationships can be better understood by stakeholders. The user can visually gain knowledge with respect to different applications and dimensional requirements. The methodology employed in dDSS provide the opportunity for optimization of a target variable (dimensional requirements).

The dDSS improves the 3D concrete printing process by providing an interface which allows virtually and visually to trace the effect of process decisions, and required settings are derived in an efficient manner. Moreover, with a good precision, dimensional targets and requirements are met using the dDSS. Required dimensional values can be met and this improves the quality of the product comparing to the cases in which no Decision Support System is used.

By:

I. Investigating and implementing a methodology for visual simulation and analysis and,
II. Supporting the process decisions by *tracing the trade-offs among process parameters and targets.*

Both product and process of 3D concrete printing are improved and objectives of the research and development graduation project are met.

The prototype system developed provides the basis to improve different product characteristics, such as *bonding strength* and other mechanical properties. Influential parameters with the level of significance are detected by an efficient number of experiments, an empirical model is developed and used in a framework to derive knowledge and support decision makers in 3D concrete printing process.

7.2. Research questions

In order to reach the main objective and motivation of the research and development in the context of this graduation project, the main research question is:

I. HOW CAN THE CONCRETE PRINTING PROCESS BE IMPROVED IN A MANNER WHICH IMPROVES THE PROPERTIES OF THE FINAL PRODUCT IN THE PRINTING PROCESS?

One of the main challenges in the process is the lack of knowledge about the underlying relationships and effects of different domains of parameters. Tedious experiments are being done to reach the targeted properties of the printed building element and the necessary process parameters to achieve it.

The developed Decision Support System prototype improves the 3D concrete printing process by bringing the opportunity to reach process decisions and target properties of the building elements, and the number of necessary experiments can be reduced, so time and resources are saved.

The dDSS improves the process of concrete printing by allowing the user to *virtually and visually* track the process decisions. The user is enabled to make informed decisions according to the defined criteria and consciously make decisions regarding the process settings, which leads to meet the product requirements. As a result, the final outcome of the process is aligned with expectations to an acceptable range, while the process of reaching to a high-quality product is facilitated, and made more controllable and efficient.

In this graduation project, the 3D concrete printing is seen as a process which intersects different stages of *construction and design*. The dDSS provided a platform where process decisions are linked to design stage parameters and the effect of leveraging the mutual effects of process parameters and target properties can be simulated and visualized next to each other.

Design decisions about deformations of a printed layer are traced by leveraging the process parameters. Moreover, proper process settings are chosen to reach the required dimensional targets by using dDSS. Hence, design and production are bridged by the dDSS and the question mentioned bellow is answered.

II. HOW IS IT POSSIBLE TO BRIDGE THE DESIGN AND PRODUCTION PHASE IN 3D CONCRETE PRINTING PROCESS?

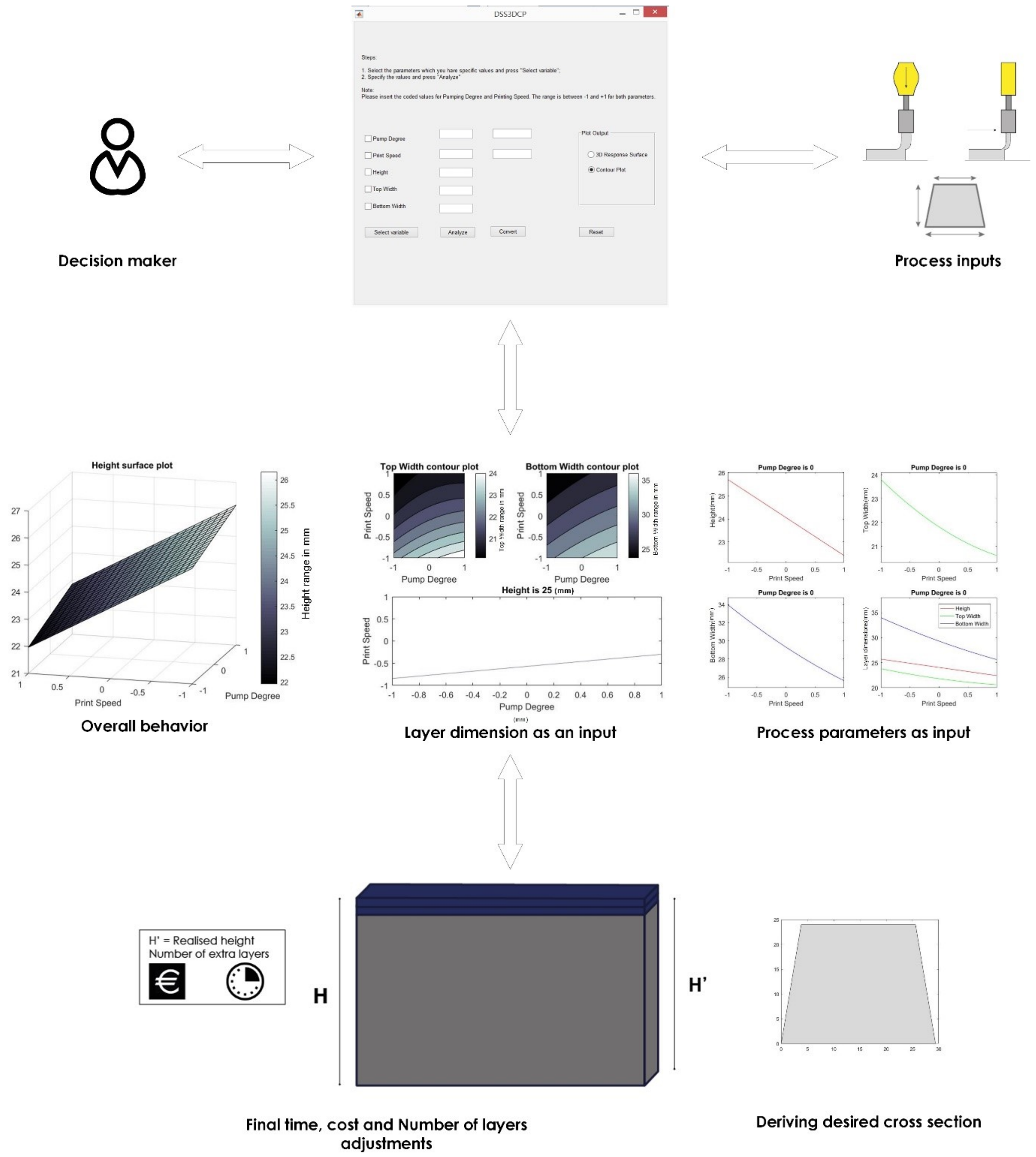


Figure 103: Process improvement by bridging design and production and reducing post processing

The following sub-questions are investigated to be able to bridge the design and construction stage by developing dDSS:

i. Which levels of decisions in design and production phase would be necessary at the current stage, to be focused?

Decisions in both technical and managerial level can be linked by dDSS. The technical level of decisions in dDSS is corresponding to selection the process setting of Print speed and Pump degree, in order to satisfy certain dimensional requirements of a single printed layer. Therefore, the user in the design phase can adjust certain decisions such as a number of printable layers, according to the suggested process setting, aligned with the defined dimensional requirements.

The managerial level of decisions is concerning about time and costs of the overall concrete printing process. By getting insight over the overall deformation or expansion of printed element, and adjusting a number of printing layers in design, the decision maker can predict the differences between as planned process and the reality of concrete printing. Hence he/she can adjust the time of the printing process, the material is needed and the planning for the project.

Moreover, a proper layer cross section can be reached aligned to the needs of the project, like the smooth surface of the final product. Hence the efforts for post-processing is reduced and resources can be reallocated by the decision maker.

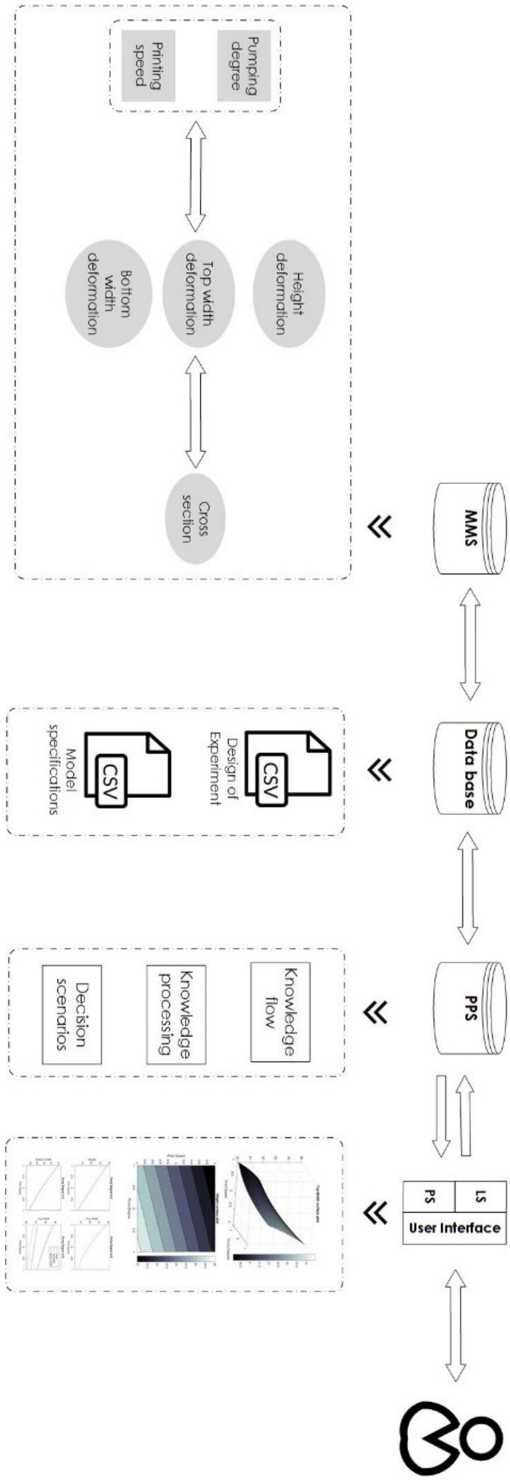
Thus a system is developed to assist decision makers with decisions affecting the design , concrete printing, and post processing. The main point here is the fact that the system is not deciding for given situations but support decisions by presenting consequences of decision scenarios and clarifying the relationships. Decision makers have the main role in decision making, because there are still lots of unknown relationships in concrete printing, and here only dimensional requirement of a single layer is studied. There are still constraints and assumptions made by decision maker aligned with the other criteria such as extrudability of the material. The following sub research questions are answered by considering the mentioned fact.

ii. What type of tool or system should be developed to act as the intermediator between design and construction?

iii. What are the components of the system?

Hence components, types and applications of Decision Support Systems (DSS) studied as means of providing decision makers knowledge which leads to more conscious decisions in 3D concrete printing. Model-based DSS is used in the context of this research and development project, linking dimensional requirements of a printed layer to process settings of *Print speed and Pump degree* and dimensional Decision Support System (dDSS) is shaped. Model Management System (MMS) provides the tool and environment to develop, store, and manipulate the prediction models, associated with linking dimensions of a printed layer to process settings. Problem Process System (PPS) is developed in an environment to flow knowledge through dDSS, from and to the user. Moreover, PPS process knowledge using models in MMS, generating or presenting the required knowledge through the user interface. Extended view on dDSS is showed as follows.

Figure 104: dDSS extensive



It should be clarified that:

iv. Who are the target groups of such Decision Support System?

dDSS and in general proposed a methodology and developed framework deals with two levels of technical and managerial. So the primary target group is researchers and experts defining process targets, requirements and final product specifications in both stages of design and production. These target groups aims to clarify influential parameters on specific characteristics and understand the relationships. These target groups can be structural designers and architects, aiming to support their decisions to meet requirements to reach the desired form, strength, and dimensions of concrete printing product.

Moreover, managers can use dDSS and the methodology to virtually and visually track the effect of the technical process setting selections in determining the time, cost and material usage of the whole project. He/she can experience the trade-offs bounded to the technical level criteria of product and find the proper setting to make the project on time, within the budget and fulfilling required quality. Of course, 3D concrete printing is not at the stage which a large-scale project can be performed, but the tool shows potential to be used in larger scale printing processes,

a. by including more process targets and parameters in the framework of Decision Support System,
b. Incorporating the effect of time as an influential parameter on process components such as pump and criteria, such as deformation and bonding strength.
c. increasing the robustness of material and printer compliment to be able to have a more constant performance.

It is important to elaborate on the core of dDSS, which contains models, shedding light on the relationship between the process settings and the layer dimensions.

III. HOW IS IT POSSIBLE TO ESTABLISH A BETTER UNDERSTANDING OVER THE 3D CONCRETE PRINTING PROCESS?

Which is followed by the following sub-questions:

i. What are key process decisions in 3D concrete printing?
ii. How is it possible to identify the significant parameters regarding a specific process target?
iii. What are the criteria for a method to be used in the system, which lead to efficient, understandable and explainable predictions of process decisions and targets?

Response Surface Methodology (RSM) is implemented as a type of experimentation design provides efficient and stepwise experimentation to detect the influential parameters, specify their level of significance and develop an empirical model, predicting the dimensions of a printed layers according to Print speed and Pump degree. The proposed methodology can increase the understanding of 3D concrete process. implementing the methodology which satisfies the following criteria (set according to literature and the context of 3D concrete printing), leads to an efficient and clear way of building up experts' consciousness over concrete printing process.

a. Generate efficient number of concrete printed data as means of interrelation studies,
b. Distinguish influential process parameters after parameter study (parameter screening), according to the defined target of 3D concrete printing,
c. Specify the level of influence of the process parameters (significance study),
d. Establishing a relationship among the process parameters and the targets (empirical model).
e. Incorporate possible on-linearity in the models and study interaction among the parameters,
f. Provide precise prediction of the process and the target parameters,
g. Visualize the results for a better and clearer understanding,
h. Pave the way of analysis toward the process optimization.

Concrete printing experiments are encountered as data to study the process and derive data-driven models, which are hard to be resulted through mechanistic models.

It is possible to incorporate a different process target such as hardened properties of the final product. Hence, blocks of designed and analysed experiments lead to the clear bridging of the process parameters and the targets. Each block contains the most influential parameters regarding the specific criterion. By integrating different blocks, the main criteria can be considered, while trade-offs within and among the blocks lead to an integrated approach to fulfil the most important targets, which improve the product and meet the requirements. Each of these designed and analysed blocks of experimentations is called here "Block of knowledge" because they discretize knowledge about the related process targets in blocks.

Key parameters affecting the 3D concrete printing are investigated and categorised in 4 different categories of Process parameters, design phase parameters, material properties and manufacturing constraints. Due to the great impact of the process on the final product quality (by shaping complex interrelations), process parameter are chosen to be studied. Because they shape complex interrelations and almost nothing is known about their effects on process targets. Influential process parameters are then detected and to define the element of the model, describing concrete process.

According to the current need of 3D Concrete printing Team, time and resources limitations, dimensional requirements is focused by investigating the Print speed, Pump degree in one model, and Nozzle distance and Print speed in the other model.

The latter case pre-processing showed noticeable randomness in the data, presenting the fact that more data with probably different experimentation setting should be generated. But the model containing Print speed and Pump degree presented the behaviour in an acceptable range of variation and resulted in an explainable model creation.

7.3. Scientific relevance

This research and development graduation project proposes a methodology in which data play the centric role in understanding the concrete printing process. Efficient experimentation provides the required data to investigate the interrelations of “layer dimensional requirements”. Data analysis provides the opportunity to find the circle of significant parameters, so non-significant parameters are put aside and the process should be controlled in a more narrow manner. Empirical models are then developed to express the relationship between process target (layer dimensions in dDSS case)and process parameters(Print speed and Pump degree in dDSS case). Then developed models are integrated, in a Decision Support System framework to derive multiple and divers formats of knowledge generation, leading the decision maker to make more proper process-related decisions. Such decisions are:

i. Dimensional prediction of a printed layer under certain process setting (Print speed and Pump degree),
ii. Proper process settings selection to meet a specified layer or the final product dimensions,

As a result, this research contributes to 3D concrete printing research field by *increasing the understanding of dimensional criteria of printing layer, as a result of dimensional Decision Support System (dDSS)*. In a broader sense, *dDSS proposes a successfully implemented methodology to study different process targets and is able to derive the quantitative knowledge about the impact of significant process parameters*. Such a methodology considers data and experimentations as the centric means of knowledge generations and analysis. dDSS can also be further developed by other researchers to make it more relevant to the challenges which are being changed due to the dynamic nature of research improvements.

7.4. Social relevance

Target groups of dDSS and in general proposed methodology are divided into two levels of technical and managerial. Technical decisions correspond to process and design decisions which are interesting in dDSS, and what-if scenarios can be traced regarding process parameters and targets values selections.

Managers can also track the influence of technical decision in terms of time, cost and quality of the process and product, by leveraging technical level decisions. As an example, the final dimensions of a printed element (like height) can be predicted, compared with the requirements and the required adjustments can be traced in terms of time and cost of construction, while satisfying dimensional requirements (technical level).

As a result, collaborations between two technical and managerial level can be improved and facilitated. Because from one level, the interactions between decisions and consequences are translatable to another level, due to their high interrelations. So a better understanding of the dimensional requirements of 3D concrete printing will be gained.

dDSS shows the potential of the proposed methodology and developed framework and enhances the collaborations between the architect, the structural designer and the managers, in the future, when more “blocks of knowledge” are developed according to the methodology.

In the shadow of a more robust printing process, and by using such blocks of knowledge, the complexity of the process is more under control. On the other hand, as more criteria are considered, deriving decisions cause contradictory results which should be traceable enough for decision makers with different backgrounds and concerns.

So *the methodology implemented in dDSS shows the potential to support decisions in an integrated and collaborative approach.*

7.5. Current research Limitations and recommendations

Dimensional Decision Support System (dDSS) has some limitations and context-related assumptions in:

I. Involved process parameters, and target
II. Deign of experiment and data generation,
III. Method assumptions, and
IV. Secondary validation.

The selections of Print speed and Pump degree in one model, and Nozzle distance and Print speed in anther model were limited to the availability of changing states of other process parameters such as nozzle type. Moreover, the aim is to make the model as simple as possible in the terms of involved parameter numbers, while holding the interaction among integrated parameters.

Moreover, it is recommended to try to integrate three parameters of Print speed, Pump degree and nozzle distance in a model, while considering room for measuring randomness of the experiment, as pre-processing showed that adding nozzle distance increase randomness drastically. Then, the complexity of the process is better modelled in an integrated model. And the understanding will improve.

Now with the possibility of producing different nozzles, different layer heights can be investigated to track the effect of layer height on layer deformation.

Another important parameter which can be used in further investigations is to increase the deformation study in more than a printed layer. So the effect of other layers' weight can be investigated on element deformation. Here then the open time between layers which takes for another layer to be placed on top of the current layer is another influential parameter. Because in time, placed material is setting and may show less deformation.

Apart from the dimensional study of printed elements, other criteria of a product are necessary to be studied, such as hardened properties of printed layer. Realising the concept of *"**Block of knowledge**"* to derive the hierarchical structure of process parameters and targets involvements. As a result, important criteria such as layers' dimensions, bonding strength, and compressive strength, are integrated which ca be analysed and investigate individually, then be used as a multi-objective process.

Numerous parameters are placed in blocks leading to criteria, requirements and objectives. Then it will be easier to track the changes in other blocks, while the specific block is leveraged. Moreover, instead of dealing with several parameters, the focus will be shifted to higher order criteria, in which related parameters are interrelated in known models. As a result, each developed block such as layer dimension block can be extended by introducing new process parameters and criterion, as a new block. These blocks are interlinked by common process parameters and changes in one block result modifications in process parameter and criterion values. These interacting, interlinked blocks provide system containing the most critical criteria for the final product, in a hierarchical approach.

In dDSS, already generated data is used as designed experiments, in order to save time and resources, and due to the main purpose which is to develop the methodology. Number of replications for the same process setting can be increased to gain more information about the behaviour of the material, printer components in a longer time, and have a better evaluation of data randomness, while increasing the precision of the models.

One important recommendation is to consider experimentations to design and analyse data leading to develop empirical mode, to benefit from efficient and stepwise data generations and analysis. Here, previous set off data is used from previous experience, so the stepwise experimentations and analysis are not applicable, as all required data is already available.

Moreover, One big assumption here is to ignore the effect of time on process performance, because the limited printing durations in one go. By gradual improvement of the process, printing duration is extending, hence it is important to encounter the effect of time on the process parameters and target behaviour. Behaviour of material such as deformation changes, the way which layers interact in terms of strength development will be varied and pump performance effects material due to imperfections and fluctuations in pressure and temperature.

Response Surface Methodology (RSM) is used as a type of experimentation design with specific design and analysis assumptions limited to the in hand data. Design strategy can be changed to CCD where more level of data are investigated and a better understanding over the design region is established. IN addition, selecting spherical design regions results in more homogenous distribution of prediction precision over the design region. Randomizing and blocking can also be considered in RSM design to improve the precision and robustness of the model. *Randomization* refers to the order of experiments run, and by including such a principle the experiments are not under the influence of previous or subsequent runs. *Blocking* is employed to improve the precision of targets and response parameters, by eliminating nuisance factors and increase the robustness of the process.

Finally, another limitation of developed dDSS is the fact that validation has been only performed for the same rounds of printing. So the behaviour of the process in layer dimensional performance is validated for the same rounds of concrete printing. It is recommended to also validate the models in different rounds of concrete printing to check the extent which the models can response to nuisance factors, such as variations in material characteristics. Models may not a response to secondary validation because in the assumptions making them robust against nuisance factors is not considered.

In order to be able to improve the 3D concrete printing, in addition to understanding the effect of process parameters on the process, improvements can be conducted in other disciplines such as material research, hardware developments of the printer by creating changeable nozzle types, employing pumps with more stable performance. By incorporating a comprehensive approach in developing different influential parameters, 3D concrete printing process is improved and more robust process leads to more stable and reliable printable elements while the scale is enlarged.

7.6. Future research recommendations

In this section, recommendations are mentioned more for mid and long term strategies to develop Decision Support Systems (DSS) in 3D concrete printing.

The mid-term strategy recommends to develop the concrete printer by connecting and employing sensors to concrete printer and use their data as the means of process investigation. As a result data collection and measurements will be an easy task to perform and plenty of data will be available to study the specific behaviour of concrete printing.

3D concrete printing as a medium to break the boundaries of design and construction needs to be investigated, to find its underlying behaviours. The data-driven approach can shed light on complex relations and approximates the realities which can be understood by data mining techniques. So, the computational process will discover the patterns in data sets, intersecting with methods of machine learning, artificial intelligence, and statistics.

Numerous data can be captured from sensors to gain geometrical information during the printing process, also the temperature of the environment, extruding concrete, and water. In addition to discovering patterns, those data can be used as inputs to capture the dynamics of the process and leverage the decision parameters to reach the desired outcome.

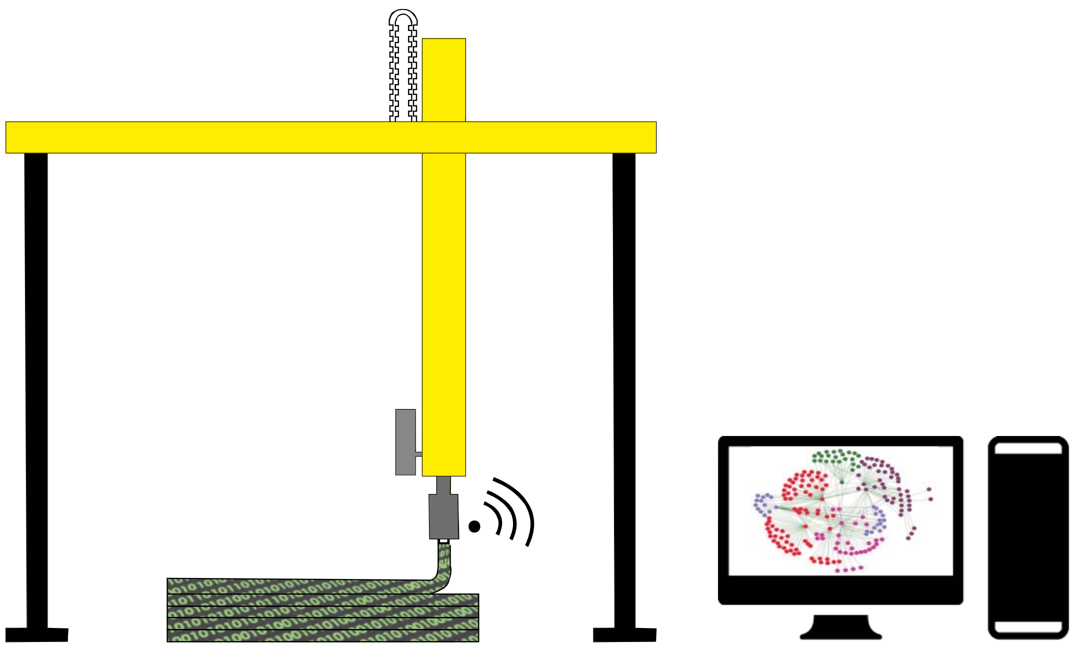


Figure 105: Big data in 3D concrete printing

After shaping the database, data mining methods such as Neural Networks, Decision trees, Genetic algorithm and rule inductions can be used, to extract possible hidden correlations, interrelations, and predictions.

Different methods of machine learning in the context of concrete printing may lay in the following categories:

I. Classification detects to which category defined in a printing object fits in.
II. Regression: Predicting values o process targets, such as layer dimensions, bonding strength and etc. The methods range from the ordinary least square methods to decision trees and more complex methods.
III. Clustering: Automatic grouping of printing objects and specifications into sets and clusters. This case if useful for the grouping experiments outcome of the printing process.

The important point is, first to detect key process targets which should be clustered, classified or predicted. Then incorporating the process parameters which seem to be influential and deriving process behaviour using sensor data, according to the defined attributes (process parameters levels for instance). Signal processing methods along with machine learning techniques, reveals fundamental characteristics of different sensor data and performs analysis techniques to classify, predict and recognize underlying patterns. The goal may be increasing the number of printable layers in one go, while outputs from previous printing experiences are clustered using sensor data and chosen process settings.

Here, as a long-term recommendation, the concept of the second generation of DSS is elaborated and an application example is mentioned.

Second Generation of Decision Support System (DSS) is defined as a system which is being used in real time of the concrete process. In addition to cover applications of a first generation DSS, which is used before or after printing process, the second generation of DSS is actively implemented to response dynamics of the process, and deriving deformation related decisions in real time. The development of such application requires another important component next to DSS, which retrieve data of the properties of printing material like temperature, and characteristics of the printing process, such as placement of layers. Such a component acts as eyes of the integrated system, directing information to be processed by dDSS as the brain of the system and be executed by the body, 3D concrete printer. In the integrated system of 3D concrete printer, includes the second generation of dDSS, interacting with a Sensor System. In general, sensors measure certain characteristics, use important data as process input in Decision Support System, selects proper levels for process parameters to meet defined targets and constraints. As a result, DSS improve the process by giving in time responses to dynamics of concrete printing. This is the essence of the Second Generation of DSS.

There are a number of limitations in implementing the second generation of DSS. They perform automated decision derived from meeting specific requirements. Although those targets are being met, but leveraged process setting may influence other targets set for the product of concrete printing.

First, the scope of decisions and parameter leverage limited, in a way that automated interventions do not significantly affect the other goals and settings.

In another step, goals and associated decisions should be prioritised, and constraints be set for variation ranges of process parameters. So assume that the automated decision of DSS sets a specific level for a process parameter, which affects another performance criterion. Then as a result of the set constraint, process parameter will be varied in the range and does not affect the other goals for the printing product. This needs to have a good understanding of the relationship between goals and target criteria.

Below an application of Second Generation of dDSS is presented. The sensor system is containing sensors responsible for retrieving geometrical data of printed layers and their placement. The current research in TU/e is investigate incorporating a height reading sensor to track the height of the nozzle and dynamically change G-code of the printer to conduct synchronised actions. These actions will satisfy some geometrical constraints of the printing process, such as nozzle distance from the top layer.

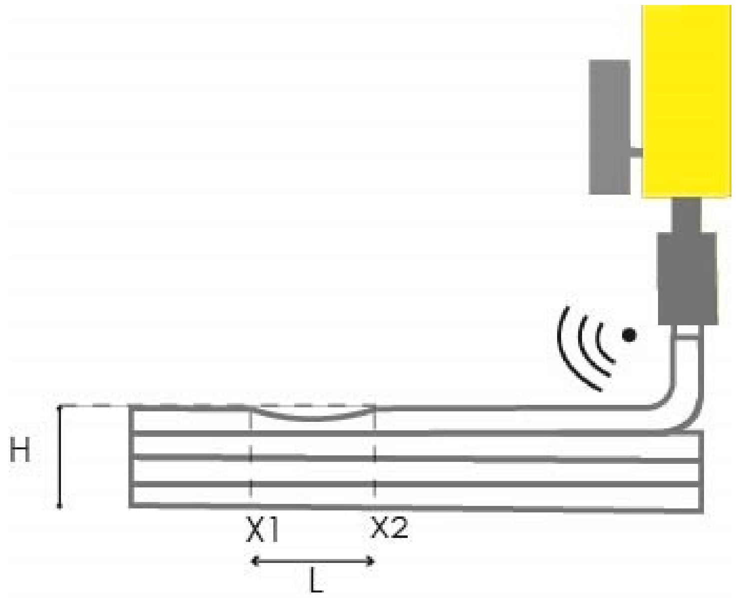


Figure 106: Imperfections in printing tool path

It is a common case when there are imbalances in printing tool path, resulting irregular corrugation in printed layers. Such a printing process characteristic, affect the stability and also functions of the elements in the operation phase. dDSS can be used to smoothen the top layers, and level them to the expected level. It is like levelling the final height of the element when levelling in micro level is also included. In the micro level, the aim is to level the layer to fill the micro-pits of printing or provide thinner layers to be just at the required layer level.

In the integrated system proposed for concrete printer, height detector sensor observes the printing path and input Height of the last printed layer. The sensor is attached to the printer in a way that it is scanning the just printed layer (sensor is looking back). The level of H is the expected elevation for the printed element at the time of printing. At a certain point X_1', the input H' is received to dDSS, in a way that "H-H' = h" is exceeding the tolerance range. In this case, the coordination (X1’) of the point in which the different elevation of H’ is observed. The distance between points “ $L = X_2' - X_1'$ ”, in which, h is the constraint, is the length which setting should be varied to be able to fill the gap (or deposit less material in the case where H is higher than expected).

There are two considerations at this stage. First, in registering X_1' and X_2', the distance between the actual point of nozzle point and sensor point (the point measuring height) should be calculated. And secondly, L should be reasonable (defined by the user) for the system to be compensated, which is case based and may vary between functionalities of the element.

For the new layer of printing, dDSS gives the suggestion to leverage a process parameter which is considered to be varied. Here it is assumed that Print speed is the variable, while changing Pump degree is not the recommended to perform in time modifications, due to the delay of effect (due to the length of the hose) and influencing material characteristics. Thus, changing Pump degree in several points during the printing will make the element heterogeneous, which makes predicting the behaviour of the element harder.

Therefore for the printing length of L between points X_1' and X_2', Print speed is adjusted, according to inputs received from sensor and concrete printer.

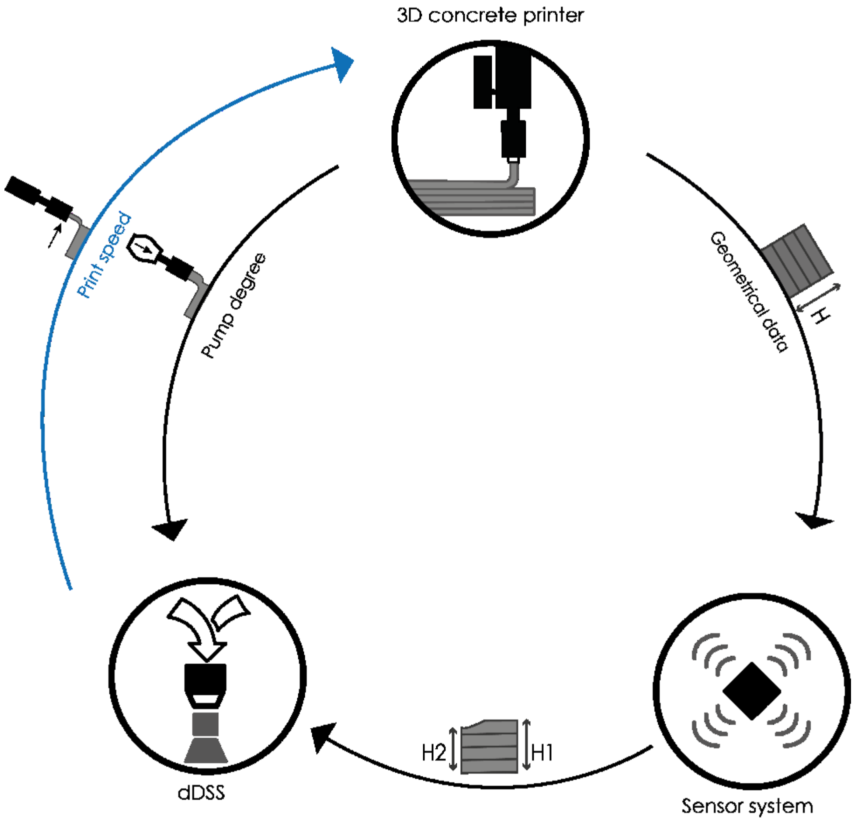


Figure 107: Decision supporting by sensor data

For the Second generation of dDSS, the system should also evolve to incorporate concepts, components and methodology of *Expert Systems ES).*

"An expert system is a problem-solving program that achieves good performance in a specialized problem domain that generally requires specialized knowledge and skill. The systems process the knowledge of experts and attempt to mimic their thinking, skill, and intuition (Nelson Ford, 1985)."

There is a difference between DSS and ES, which makes it necessary to evolve dDSS. The objective of ES is to provide the user and generally the system a decision, which is above suggestions of DSS. Here it is required automated interventions at specific lengths, during the printing process. So, dDSS should be able to check the (i)current situation, (ii) make comparisons with introduced constraints or *rules*, (iii)retrieve required knowledge from model-base and (iv) performs actions.

Hence, although dDSS should put the decision maker at the centre, more responsibilities should be shifted to DSS, by defined rules and constrained, which makes the system less flexible in controlling procedures. Because in DSS such a procedure is done by the user, now it should be done partly by the system, meeting defined limitations.

Main components of Rule-based systems should be added to dDSS, which activates certain decisions in response to a situation, comparing it with introduced rules (constraints) by the expert (also decision maker in this case).

In this approach of expert systems, problem-solving knowledge is expressed in sets of rules which consist of antecedents as conditions and they result in consequences if conditions have a true statement.

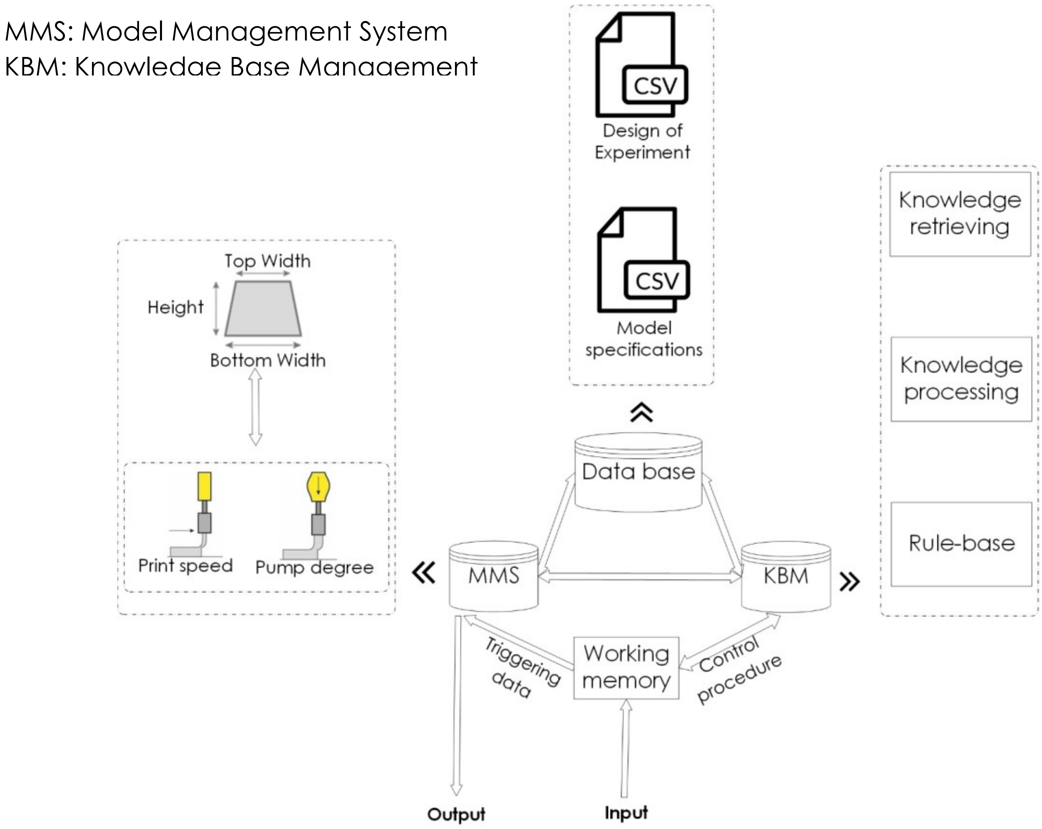
IF <antecedent> THEN <consequents>

They incorporate practical human knowledge in conditional *If-Then* rules (Hayes-Roth, 1985). In the other words, it follows the human reasoning for problem-solving and decision-making. RBSs adaptively determine the best sequence of rules to execute. Moreover, they explain their conclusions by retracing their actual lines of reasoning and translating the logic of each rule employed into natural language (H*ayes-Roth, 1985).

In evolved dDSS as the second generation of DSS, Knowledge Management System (KMS) is hold the knowledge processing capabilities of Problem Process System (PPS) in the first generation of DSS, while it contains Rule-based or Rule memory. Rule-base store constraints which, defines rules for control procedure of dDSS. It is activated when antecedent sensor data triggers consequents of Rule-based conditions. In addition to static memory, incorporating rules, working memory is added to dDSS to store temporary assertions, such as *printed layer elevations, differences in height and distances between* X_1' *and* X_2'. Hence working memory corresponds to the dynamic facts of a situation (Hayes-Roth, 1985).

Input from sensors are checked and processed by KMS, when it triggers sets of rules, through working memory, data is linked to Model Management System (MMS), infer related knowledge and performs a proper action via modifying process setting. Below the elaborated second generation of dDSS is depicted.

Figure 108: the Second generation suggested architecture



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