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Industry 4.0 driven statistical analysis of investment casting process demonstrates the value of digitalisation

Rose Clancy[a], Ken Bruton[a], Dominic O'Sullivan[a], Dermot Keogh[b]

[a]*Department of Civil Engineering, University College Cork, Cork, Ireland*
[b]*DePuy Ireland Unlimited Company, Loughbeg, Ringaskiddy Cork, Ireland*

Abstract

The purpose of this research is to perform statistical data analysis of currently manually collected data in an area of the industrial manufacturing organisation employed in this study that is not digitalised to show the value that can be achieved through digitalisation. The insights gained through analysis of the data can be used to drive decision making in relation to the optimisation of input parameters to minimise the level of defective parts. The parts under investigation in this study were ceramic shells used in the manufacturing process of orthopaedic metal implants. The ceramic shell is a crucial element in the investment casting process because molten metal is poured into the ceramic shell to form the shape of the metal orthopaedic implant. Hence, by minimising the number of defective ceramic shells, there are fewer defective metal implants produced, resulting in cost savings and increased efficiency of the manufacturing process. A number of scientific questions to establish the relationship between the quantity of scrapped products and the level of the silica component in the ceramic slurry were defined and a series of independent t-tests were conducted to address these questions. The results from the t-tests showed the statistically optimal percentage of silica in the binder of the ceramic slurry to minimise the rate of a particular scrap type caused by thin or weak areas of the shell. These results demonstrate the value of analysing digital data relating to the manufacturing process to understand relationships between parameters in the manufacturing process and effectively root-cause scrap outputs. The results from the analysis gave rise to the implementation of a digitalised data collection system that allows continuous monitoring of the components in the ceramic slurry to ensure they are in the optimal specified range. Hence, the quality and yield rate of the orthopaedic implants are maintained at a high level. The digital data collection system also acts as a resource containing historical data for further potential scrap root-cause analysis.

Keywords: Digitalisation; Industry 4.0; Manufacturing, Data Analytics

1. Introduction

The German initiative "Industrie 4.0" is a strategic approach to the digitalisation of manufacturing. Digitalisation allows deeper insight into complex manufacturing processes, which is crucial, as only the organisations that can analyse their business operations and control their processes using data driven decision making will remain competitive in this digital era [1]. It is vital that organisations prepare for the challenges and take advantage of the benefits brought about by the digitalisation of the supply chain. Digitalisation refers to the integration of digital data (brought about by digitisation) with advanced technologies to optimise processes [2]. By creating a connected environment through digitalisation, businesses can extract and use key information from their processes in real-time

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to inform decision-making, resulting in improved supply chain management and performance [3]. The digitisation of production systems has been stated in research to have a positive influence on supply chain performance and has become an imperative part of organisation's transitioning process to Industry 4.0 [4]. A key benefit of the digitisation of manufacturing processes is the ability to use analytics to extract insights and key information to aid decision-making [6][7]. Traditional supply chains will all eventually face the challenge of updating to a digital supply chain [4]. One of the biggest challenges with the digitalisation of the supply chain is to write a defendable business case with uncertain outcomes and justify the additional costs [4][8]. There is hesitation amongst decision-makers regarding the efficiencies promised as a result of digitalizing manufacturing processes [8][9][10]. The aspect of Industry 4.0 focused on in this study is big data analytics. The objective of this research was to employ statistical techniques to identify if relationships exist using historical manually collected data. Insights found from the analysis could then be used as leverage to validate the need for the implementation of a digital data acquisition system. The data used for the analysis is currently manually collected, stored in an Excel file and is not connected to other data sources or accessible to the wider organisation. In summary, statistical analysis was conducted to gain insights into the relationships within the manufacturing process, which led to a clear justification for the implementation of a data acquisition system. This system allows the input parameters to be carefully monitored in real-time such that they can then be optimised to produce the best possible yield rate and aid in the beginning of the transition to Industry 4.0. Section 2 describes the manufacturing process in detail. Section 3 gives an overview of the methods used for data analysis and the scientific questions that were set for the study. Section 4 gives the results for the statistical analysis. Section 5 provides a discussion of the results found and the system implemented. Section 6 summarises the conclusion and findings from the study.

2. Manufacturing process description

The organisation in this study is located in Ireland and is one of the world's largest manufacturers of orthopaedic implants. They manufacture orthopaedic products for joint replacement, trauma, spine, sports medicine and others. The value stream in this use case is a foundry, which employs investment casting (also known as precision casting) methods to manufacture components of biomedical joint replacements. A foundry is a process in which castings are produced by melting metal, pouring liquid metal into a mould and then allowing it to solidify. The basic principles of an investment casting process are illustrated in [11].

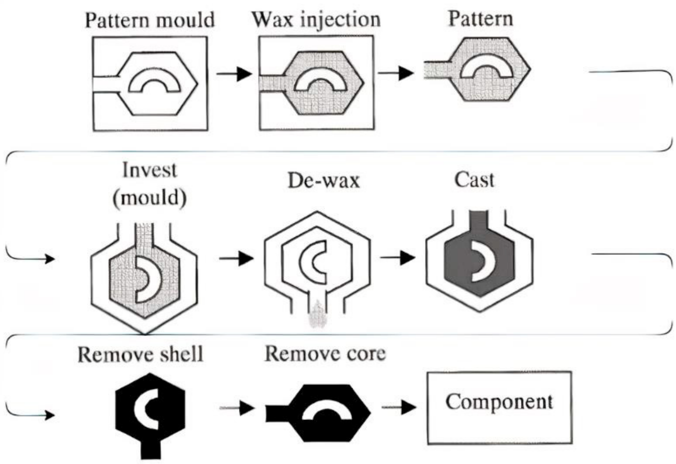

Figure 1. Basic principles of investment casting process

Investment casting uses mobile ceramic slurry to produce moulds with very smooth finishes [12]. This makes them suitable for use in automotive, aerospace and biomedical industries [13]. The ceramic shell is made by dipping a precise wax pattern usually 4-6 times into the slurry to build the layers of the ceramic shell. Each shell coat is dried for a set number of hours with controlled humidity, temperature and airflow [14]. After the wax pattern has been dipped into the ceramic slurry, it is sprinkled with a coarse refractory stucco and dried [11]. When the ceramic shell is complete, the wax is removed, usually with a steam autoclave, and filled with molten metal that solidifies inside the shell [11]. The ceramic shell is then removed mechanically to obtain the metal part. The investment casting technique has a number of advantages, including accuracy, versatility and integrity [11]. However, it is a labour intensive, time-consuming process and one study found that the production of larger moulds using silica bonded ceramics resulted in failure rates up to 40% [15]. Research in this area has stated that “it is becoming imperative that the investment casting industry improves current casting quality and reduces manufacturing costs” and that “optimisation of the mechanical and physical properties of the ceramic shell will be fundamental to achieving these aims” [15]. The production of the ceramic shell is a critical part of the investment casting process [11]. The prime coat of the ceramic is the most important as it is in contact with the metal and it must maintain strength and surface integrity during the casting process [16]. There are a number of key requirements for the ceramic shell in investment casting, including but not limited to, sufficient fired strength to withstand the weight of the metal, high thermal shock resistance to prevent cracking during metal pouring and sufficient permeability to allow heat transfer to allow the metal to cool [11]. The shell dipping process can take between 40-60 hours, making it a significant rate-limiting factor and costly process [17]. The ceramic slurry is composed of a refractory flour and a colloidal binder system [17]. The ingredients in the slurry play a crucial role in the properties of the shell [18]. In the investment casting industry, colloidal silica is the most popular binder used and it makes up the main part of the shell mould [16]. These colloidal silica binders usually contain between 20% w/w and 30% w/w amorphous silicon dioxide (SiO_2) particles and a typical level used in the primary slurry is 26% SiO_2 [11]. The SiO_2 particles are stabilised by Na+ counter ions which encourages crystallisation to produce a ceramic shell with the required strength to withstand metal casting [19]. The structural response of the mould lies within the mechanical properties of the binder system [19]. Silica represents the percentage of silica in the binder [11].

It is difficult to avoid the occurrence of defects taking place in the investment casting manufacturing process [20]. Defects are often caused by non-optimal settings of process parameters and there is a need for determining the optimal specification values for these parameters to ensure casting quality [20]. A number of approaches have been taken in attempt to determine the cause of investment casting defects, including cause-effect diagram [21], expert system [22], artificial neural network [23], computerised simulation [24] and Design of Experiment [25]. However, the development of many of these approaches requires a significant effort and considerable domain knowledge [20]. Furthermore, computerized simulation and Design of Experiment may prove effective in a research setting, however, in practice they are unsuitable and problematic to implement in industry [20]. The use of Bayesian inference in the application of foundry data analytics has been shown to be easy to implement and has been successful in identifying the optimal range of process parameters to prevent defects [20]. Other research agrees that the data analysis of historical data is required to aid the reduction of defective parts in an investment casting facility [26]. It also argues that a data acquisition system is required to automatically capture and monitor data for the major parameters in shelling, such as, the viscosity, the slurry temperature, the slurry pH and the drying time [26]. This research found the penalty matrix data analysis to be useful in helping to reduce the rejection of parts and find the optimal parameter ranges [26]. However, this research did not highlight the level of silica in the binder as a major parameter for analysis. This study proposes a type of statistical analysis that has not been seen in literature, a series of independent t-tests, to determine if the level of silica in the binder of the ceramic slurry is related to the number of defective products.

3. Methodology

The data used in this analysis is the process output data for the batches produced in the Foundry of the organisation for an eight week period in 2021. A change was made to the SiO_2 level in the prime slurry to test if there is a difference in the average level of the three most common scrap types for the foundry value stream. A one week difference was included between the scrap data and the testing data for silicon dioxide levels that allows for the time lag from when the products are dipped in the first prime slurry to when they are recorded as scrap on the manufacturing system. The

SiO_2 level is the % SiO_2 of the binder solids in the slurry mixture for the first prime slurry. The organisation in this study works within a tighter limit of the typical industry range of 22%-32% SiO_2 [11]. Of the 8 weeks of scrap data, the first four weeks had an average SiO_2 level of X% (level 1) and the last four weeks had SiO_2 levels of Y% (level 2) as seen in Table 1. The labels X% and Y% are used to represent the actual numerical values of the silica levels during this time period as it is sensitive information to the organization. Level 1 had a higher level of SiO_2 in the binder and Level 2 had a lower level of SiO_2 in the binder. The difference in Level 1 and Level 2 of SiO_2 is 8.2% as shown in Equation 1. For the reminder of the paper, the levels of SiO_2 are referred to as Level 1 and Level 2 for simplicity.

Table 1. Upper and lower level of SiO_2.

Level	Time Period	% SiO_2
Level 1 (Upper level)	Week 1-4	X%
Level 2 (Lower level)	Week 5-8	Y%

$$\frac{X\%-Y\%}{X\%} \times 100 = 8.2\% \tag{1}$$

The goal of the statistical analysis in this project was to investigate a set of scientific questions relating to the data to find potential insights into possible relationships between the silica level in the first prime and the rate of defective parts. The three most common scrap types for the foundry manufacturing process were selected for analysis. As this scrap information is sensitive to the organisation, they will be referred to as Scrap Type I, Scrap Type II and Scrap Type III. All three of these scrap reasons relate to the quality of the ceramic shell. The scientific questions were defined so as to determine if the level of silica in the binder of the ceramic slurry had a relationship with any of the three scrap types. The first three scientific questions were as follows:

1. Is there a difference between the mean quantity of Scrap Type I at level 1 (upper level) of SiO_2 and at level 2 (lower level) of SiO_2?
2. Is there a difference between the mean quantity of Scrap Type II at level 1 (upper level) of SiO_2 and at level 2 (lower level) of SiO_2?
3. Is there a difference between the mean quantity of Scrap Type III at level 1 (upper level) of SiO_2 and at level 2 (lower level) of SiO_2?

SPSS (a statistical software platform) was used to address the questions described in the introduction. This platform was used to perform descriptive analysis of the data and perform statistical significance tests. This section outlines the data analysis approach that was used for each question.

Q1: Is there a difference between the mean quantity of Scrap Type I at level 1 (upper level) of SiO_2 and at level 2 (lower level) of SiO_2?

An independent t-test was conducted using SPSS to test if there is a difference in the average number of defective parts with Scrap Type I per batch when SiO_2 is at level 1 (upper level) and at level 2 (lower level). An independent samples t-test is an appropriate test to use for each of the four set questions in this study as it is used to estimate whether the mean value of an outcome variable is significantly different between two groups of experimental units [27]. Experimental units are the units e.g. people or objects, to which the treatment is applied in the experimental study. The independent samples t-test is typically used when the outcome variable is a continuous variable and the explanatory variable is binary, in that it takes only two values [27]. The data used for this test originates from the organisation's management execution system and includes all batches processed for the eight-week period in 2021. In this case, the other types of scrap have been set to zero to represent no Scrap Type I, as Scrap Type I is the response variable of interest. The outcome variable for this question is the quantity of Scrap Type I per batch. The explanatory variable in this question is the level of SiO_2, this is a binary variable as the two groups are level 1 and level 2. The rejection of the null hypothesis of a two sample t-test indicates that the differences in means of the two groups is large and is not due to chance or sampling variation [27]. The hypothesis test to address this question is as follows:

- H_0: $\mu 1 = \mu 2$ (There is no difference in the average amount of defective parts with Scrap Type I per batch between products produced with the first prime at level 1 (upper level) and level 2 (lower level) of SiO_2.)
- H_A: $\mu 1 \neq \mu 2$ (There is a difference in the average amount of defective parts with Scrap Type I per batch between products produced with the first prime at level 1 (upper level) and level 2 (lower level) of SiO_2.)

The assumptions for the independent samples t-test are given in Table 2 (Watt, 2008).

Table 2. Assumptions for independent t-test.

Assumption	Description
1.	Groups are independent
2.	Measurements are independent
3.	Outcome variable is on a continuous scale
4.	Outcome variable normally distributed in each group

The first assumption for the groups to be independent is met as the batches produced with the first prime SiO_2 at level 1 (upper level) were different batches to the batches produced with the first prime SiO_2 at level 2 (lower level). This is true for all scientific questions set in this study. The second assumption for the measurements to be independent is also met as each batch is only included once in both the group of batches produced with the first prime SiO_2 at level 1 (upper level) and the group of batches produced with the first prime SiO_2 at level 2 (lower level). This is true for all scientific questions set in this study. The assumption of the outcome variable being on a continuous scale is met, as the data in this study for the number of defective parts with Scrap Type I, Scrap Type II and Scrap Type III are quantitative. The fourth assumption for the independent samples t-test, is that the outcome variable must be normally distributed in each group. However, the independent t-test is robust to non-normality if the sample size is large (>30) [27]. This assumption is met for all scientific questions set out in this study, as all sample sizes are large (>30) [27]. The exact sample sizes used are given in the results section.

Question 2: Is there a difference between the mean quantity of Scrap Type II at level 1 (upper level) of SiO_2 and at level 2 (lower level) of SiO_2?

An independent t-test was conducted using SPSS to test if there is a difference in the average quantity of Scrap Type II per batch when SiO_2 is at level 1 (upper level) and at level 2 (lower level). In this case, the other types of scrap have been set to zero to represent no Scrap Type II, as Scrap Type II is the response variable of interest in this question. The hypothesis test to address this question is as follows:

- H_0: $\mu 1 = \mu 2$ (There is no difference in the average quantity of Scrap Type II per batch between products produced with the first prime at level 1 (upper level) and level 2 (lower level) of SiO_2.)
- H_A: $\mu 2 \neq \mu 2$ (There is a difference in the average quantity of Scrap Type II per batch between products produced with the first prime at level 1 (upper level) and level 2 (lower level) of SiO_2.)

Question 3: Is there a difference between the mean quantity of Scrap Type III at level 1 (upper level) of SiO_2 and at level 2 (lower level) of SiO_2?

An independent t-test was conducted using SPSS to test if there is a difference in the average quantity of Scrap

Type III per batch when SiO_2 is at level 1 (upper level) and at level 2 (lower level). In this case, the other types of scrap have been set to zero to represent no Scrap Type III, as Scrap Type III is the response variable of interest for this question. The hypothesis test to address this question is as follows:

- H_0: $\mu 1 = \mu 2$ (There is no difference in the average quantity of Scrap Type III per batch between products produced with the first prime at level 1 (upper level) and level 2 (lower level) of SiO_2.)
- H_A: $\mu 1 \neq \mu 2$ (There is a difference in the average quantity of Scrap Type III per batch between products produced with the first prime at level 1 (upper level) and level 2 (lower level) of SiO_2.)

4. Results

Question 1

Table 3 presents descriptive statistics for the breakdown of the quantity of Scrap Type I at level 1 (upper level) and level 2 (lower level) of SiO_2. The majority of data points are at the value zero Scrap Type I; this can be explained by the fact that the data is from a manufacturing process with the majority of batches going through the process without defective (scrap) parts. Table 3. (iii) presents the results from the independent t-test conducted to address the first question. The t-test assumes equal variances. A useful guide is that one standard deviation should not be more than twice the other standard deviation. In this case the standard deviation of 0.635 units at level 1 (upper level) is more than twice the standard deviation of 0.266 units at level 2 (lower level). Therefore, the results from the t-test in which equal variances are not assumed in the second row of the results will be used. The results indicate that the H_0 (i.e. that there is no difference in mean Scrap Type I per batch between products produced with the first prime at level 1 (upper level) and level 2 (lower level) of SiO_2) can be rejected as the significance or p-value <0.01. This leads to the conclusion that there is a statistically significant difference in the mean quantity of Scrap Type I (per batch) between high levels of SiO_2 and low levels of silica. The mean quantity of Scrap Type I with SiO_2 at level 2 (lower level) is lower than the mean quantity of scrap when SiO_2 is at level 1 (upper level). The mean quantity of Scrap Type I at the higher levels of SiO_2 (level 1), is 0.12 units with a standard deviation of 0.635 units and the mean quantity of Scrap Type I at lower levels of silica (level 2), is 0.03 units with a standard deviation of 0.266 units as seen in Table 3. (ii). The difference in the mean quantity Scrap Type I is 0.09 units with a standard deviation of 0.006 units. The 95% confidence interval is 0.078 units to 0.1 units. The sample size of batches produced with SiO_2 at level 1 (upper level) is 13869 and the sample size of the batches produced with SiO_2 at level 2 (lower level) is 15637.

Table 3. (i) Frequencies of Scrap Type I quantity at level 1 and level 2 of SiO_2.

Scrap Quantity	Level 1	Level 2	Total
0	13135	15300	28435
1	290	208	498
2	187	84	271
3	117	30	147
4	66	10	76
5	38	4	42
6	16	0	16
7	14	1	15
8	2	0	2
9	4	0	4
Total	13869	15637	29506

Table 3. (ii) Descriptive statistics for Q1.

	Level	Count	Mean	Standard Deviation	Standard Error Mean
Scrap Quantity	1	13869	0.12	0.635	0.005
	2	15637	0.03	0.266	0.002

Table 3. (iii) Results for independent samples t-test for Q1.

		Levene's Test for Equality of Variances		t-test for Equality of Means					95% Confidence Interval of the Difference	
		F	Significance	t	df	Significance (2-tailed)	Mean Difference	Standard Error Difference	Lower	Upper
Scrap Quantity	Equal variances assumed	1036.178	0.000	16.110	29504	0.000	0.090	0.006	0.079	0.100
	Equal variances not assumed			15.446	18120.323	0.000	0.090	0.006	0.078	0.101

Question 2

Table 4. (i) presents descriptive statistics for the breakdown of quantities of Scrap Type II at level 1 (upper level) and level 2 (lower level) of SiO_2. In this case, the standard deviation of 1.293 units at level 1 (upper level) is not more than twice the standard deviation of 1.211 units at level 2 (lower level) as seen in Table 4. (ii). Therefore, the results from the t-test in which equal variances are assumed in the first row of the results in Table 4. (iii) will be used. The results from the independent t-test conducted to address the second question are given in Table 4. (iii) The results indicate that the H_0 (i.e. that there is no difference in the average quantity of Scrap Type II per batch between products produced with the first prime SiO_2 levels at level 1 (upper level) and level 2 (lower level)) cannot be rejected as the p-value = 0.998 ($p>0.05$). This leads to the conclusion that there is not a statistically significant difference in the mean quantity of Scrap Type II (per batch) between higher levels of SiO_2 (level 1) and lower levels of SiO_2 (level 2). The sample size of batches produced with SiO_2 at level 1 (upper level) is 13869 and the sample size of the batches produced with SiO_2 at level 2 (lower level) is 15637.

Table 4. (i) Frequency of Scrap Type II quantity at level 1 and level 2 of SiO_2.

Scrap Quantity	Level 1	Level 2	Total
0	13715	15449	29164
1	8	13	21
2	8	6	14
3	5	9	14
4	28	20	48
5	8	7	15
6	12	20	32

7	3	8	11
8	5	19	24
9	0	4	4
10	1	0	1
11	0	1	1
12	51	62	113
21	1	0	1
22	0	1	1
23	0	1	1
24	24	17	41
Total	13869	15637	29506

Table 4. (ii) Descriptive statistics for Q2.

	Level	Count	Mean	Standard Deviation	Standard Error Mean
Scrap Quantity	1	13869	0.11	1.293	0.011
	2	15637	0.11	1.211	0.010

Table 4. (iii) Results for independent samples t-test for Q2.

		Levene's Test for Equality of Variances				t-test for Equality of Means			95% Confidence Interval of the Difference	
		F	Significance	t	df	Significance (2-tailed)	Mean Difference	Standard Error Difference	Lower	Upper
Scrap Quantity	Equal variances assumed	0.000	0.984	0.003	29504	0.998	0.000	0.015	-0.029	0.029
	Equal variances not assumed			0.003	28528.861	0.998	0.000	0.015	-0.029	0.029

Question 3

Table 5. (i) presents descriptive statistics for the breakdown of quantities of Scrap Type III at level 1 (upper level) and level 2 (lower level) of SiO_2. In this case, the standard deviation of 0.636 units at level 1 (upper level) is not more than twice the standard deviation of 0.628 units at level 2 (lower level) as seen in Table 5. (ii). Therefore, the results from the t-test in which equal variances are assumed in the first row of the results in Table 5. (iii) will be used. The results from the independent t-test conducted to address the third question are given in Table 5 (iii). The results indicate that the H_0 (i.e. that there is no difference in the average quantity of Scrap Type III per batch between the first prime SiO_2 at level 1 (upper level) and at level 2 (lower level), cannot be rejected as the p-value = 0.617 ($p>0.05$). This leads to the conclusion that there is not a statistically significant difference in the mean quantity of Scrap Type III (per batch) between higher levels of SiO_2 (level 1) and lower levels of SiO_2 (level 2). The sample size of batches produced with

SiO_2 at level 1 (upper level) is 13869 and the sample size of the batches produced with SiO_2 at level 2 (lower level) is 15637.

Table 5. (i) Frequency of Scrap Type III quantity at level 1 and level 2 of SiO_2.

Scrap Quantity	Level 1	Level 2	Total
0	12498	14078	26576
1	768	825	1593
2	8347	424	771
3	148	188	336
4	69	86	155
5	20	25	45
6	13	29	22
7	3	1	4
8	2	0	2
9	0	1	1
14	1	0	1
Total	13869	15637	29506

Table 5. (ii) Descriptive statistics for Q3.

	Level	Count	Mean	Standard Deviation	Standard Error Mean
Scrap Quantity	1	13869	0.17	0.636	0.005
	2	15637	0.18	0.628	0.005

Table 5. (iii) Results for independent samples t-test for Q3.

		Levene's Test for Equality of Variances		t-test for Equality of Means					95% Confidence Interval of the Difference	
		F	Significance	t	df	Significance (2-tailed)	Mean Difference	Standard Error Difference	Lower	Upper
Scrap Quantity	Equal variances assumed	0.989	0.320	-0.500	29504	0.617	-0.004	0.007	-0.018	0.011
	Equal variances not assumed			-0.500	28997.242	0.617	-0.004	0.007	-0.018	0.011

Development of Question 4

The results from the t-test conducted to address the first question indicated that there is a statistically significant difference in the average quantity of Scrap Type I at level 1 (upper level) and level 2 (lower level) of SiO_2. The insight of the relationship between the level of SiO_2 and the quantity of Scrap Type I led to the development of a further scientific question. The majority of Scrap Type I that occurred during the eight-week period was for a specific type of product. The name of this product is sensitive to the organisation; hence, it will be referred to as product family A. A fourth question was set to investigate if there is a difference in the average quantity of Scrap Type I for the product family A when SiO_2 is at level 1 (upper level) and level 2 (lower level). The fourth scientific question addressed in this study was as follows:

Question 4: Is there a difference between the mean quantity of Scrap Type I for product family A at level 1 (upper level) of SiO_2 and at level 2 (lower level) of SiO_2?

An independent t-test was conducted using SPSS to test if there is a difference in the average quantity of Scrap Type I per batch for a specific type of product, product family A, when SiO_2 is at level 1 (upper level) and at level 2 (lower level). In this case, the other types of scrap have been set to zero to represent no Scrap Type I, as Scrap Type I is the response variable of interest. The hypothesis test to address this question is as follows:

- H_0: $\mu 1 = \mu 2$ (There is no difference in the average quantity of Scrap Type I per batch of product family A produced with the first prime at level 1 (upper level) and level 2 (lower level) of SiO_2.)
- H_A: $\mu 1 \neq \mu 2$ (There is a difference in the average quantity of Scrap Type I per batch of product family A produced with the first prime at level 1 (upper level) and level 2 (lower level) of SiO_2.)

Table 6. (i) presents descriptive statistics for the breakdown of Scrap Type I for product family A at level 1 (upper level) and level 2 (lower level) of SiO_2. In this case, the standard deviation of 1.131 units at level 1 (upper level) of SiO_2 is more than twice the standard deviation of 0.521 units at level 2 (lower level) of SiO_2 as seen in Table 6. (ii) Therefore, the results from the t-test in which equal variances are not assumed in the second row of the results in Table 6. (iii) will be used. The results from the independent t-test conducted to address the fourth question are given in Table 6. (iii). The results indicate that the H_0, i.e. that there is no difference in mean Scrap Type I per batch for product family A between SiO_2 levels 1 and 2, can be rejected as $p<0.01$. This leads to the conclusion that there is a statistically significant difference in the mean quantity of Scrap Type I (per batch of product family A) between level 1 of SiO_2 (upper level) and level 2 (lower level) of SiO_2. The mean quantity of Scrap Type I with SiO_2 at level 2 (lower level) is lower than the mean quantity of Scrap Type I when SiO_2 is at level 1 (upper level). The mean quantity of Scrap Type I per batch of product family A at high levels of SiO_2 (level 1) is 0.42 units with a standard deviation of 1.13 units. The mean quantity of Scrap Type I per batch of product family A at lower levels of SiO_2 (level 2) is 0.13 units with a standard deviation of 0.52 units. The difference in Scrap Type I mean is 0.3 units with a standard deviation of 0.02 units. The 95% confidence interval is 0.255 units to 0.335 units. The sample size of product family A batches produced with SiO_2 at level 1 (upper level) is 3781 and the sample size of product family A batches produced with SiO_2 at level 2 (lower level) is 3321.

Table 6. (i). Frequency of Scrap Type I at level 1 and level 2 of SiO_2.

Scrap Quantity	Level 1	Level 2	Total
0	3107	3063	6170
1	257	146	403
2	171	73	244
3	113	25	138
4	63	9	72
5	35	4	39
6	15	0	15
7	14	1	15
8	2	0	2

9	4	0	4
Total	3781	3321	7102

Table 6. (ii) Descriptive statistics for Q4.

	Level	Count	Mean	Standard Deviation	Standard Error Mean
Scrap Quantity	1	3781	0.42	1.131	0.018
	2	3321	0.13	0.521	0.009

Table 6. (iii) Results for independent samples t-test for Q4.

		Levene's Test for Equality of Variances		t-test for Equality of Means					95% Confidence Interval of the Difference	
		F	Significance	t	df	Significance (2-tailed)	Mean Difference	Standard Error Difference	Lower	Upper
Scrap Quantity	Equal variances assumed	712.565	0.000	13.799	7100	0.000	0.295	0.021	0.253	0.337
	Equal variances not assumed			14.393	5461.864	0.000	0.295	0.020	0.255	0.335

5. Discussion

The first question was set to test if a relationship existed between Scrap Type I and the level of SiO_2. The results from the independent t-test indicated a statistically significant difference in the mean quantity of Scrap Type I between SiO_2 at level 1 (upper level) and level 2 (lower level) ($p<0.01$). The results showed that the mean level of Scrap Type I was lower (0.03 units) when SiO_2 was at level 2 (lower level) for the second four weeks in comparison to the mean of 0.12 units when the SiO_2 was at level 1 (upper level) for the first four weeks of the eight week period. The second question in this study was to investigate if a difference existed between the mean quantity of Scrap Type II at level 1 (upper level) and at level 2 (lower level) of SiO_2. This question was addressed with an independent t-test. The results from this test established that there is not a statistically significant difference in the mean quantity of Scrap Type II between SiO_2 at level 1 (upper level) and level 2 (lower level) ($p>0.05$). The third question examined if mean quantity of Scrap Type III at level 1 (upper level) differed to the mean quantity of Scrap Type III at level 2 (lower level) of SiO_2. The results from the independent t-test for the third question revealed that there is not a statistically significant difference in the mean quantity of Scrap Type III between SiO_2 at level 1 (upper level) and level 2 (lower level) ($p>0.05$). The fourth question was developed as a result of the findings that a relationship existed between the mean quantity of Scrap Type I and the level of SiO_2 in the binder. This question was formulated to test if a difference existed between the mean quantity of Scrap Type I for product family A at level 1 (upper level) and at level 2 (lower level) of SiO_2. The results from the independent t-test to address this question determined that there is a statistically significant difference in the mean level of Scrap Type I for product family A between SiO_2 at level 1 (upper level) and level 2 (lower level) ($p<0.01$). The results showed that the mean level of Scrap Type I per batch of product family A was lower (0.13 units) when SiO_2 was at level 2 (lower level) in comparison to the mean of 0.42 units of Scrap Type I for product family A per batch when the SiO_2 was at level 1 (upper level). Scrap Type I is caused by thin or weak areas of the shell failing during dewax or casting allowing metal to leak into the void of the shell [28]. It is a very expensive type of scrap as the metal material is much more expensive in comparison to the wax material. Almost all of this type of defect is believed to be related to the quality of the ceramic shell [28]. The results of these statistical tests have shown that the level of silica in the colloidal binder is related to the quantity of Scrap Type I, which is caused by thin or weak areas in the shell. Specifically, the mean quantity of Scrap Type I for this investment casting process is lower when the % of silica in the binder was at the lower level. These results show that there was less occurrences of Scrap Type I when the % SiO_2 was reduced to the lower level. As Scrap Type I occurs after the casting stage, in which the metal is poured into the ceramic shell, it results in a large financial and material loss for the manufacturing organisation. By identifying this relationship through statistical analysis of historical data, this type of scrap related to the level of silica in the binder can be preventing from occurring, through continuous monitoring. To achieve this continuous monitoring a digital data acquisition system was required. As outlined in Figure 2, the slurry parameter levels, including SiO_2, were tested and collected manually. This information was then stored in an Excel spreadsheet on a single PC. A new system was implemented, in which the information is entered into a wireless tablet. This information is then fed to a server that allows it to be brought into a business analytics platform for continuous monitoring. This study provides an example of how analysis of data can provide insights into relationships for manufacturing processes.

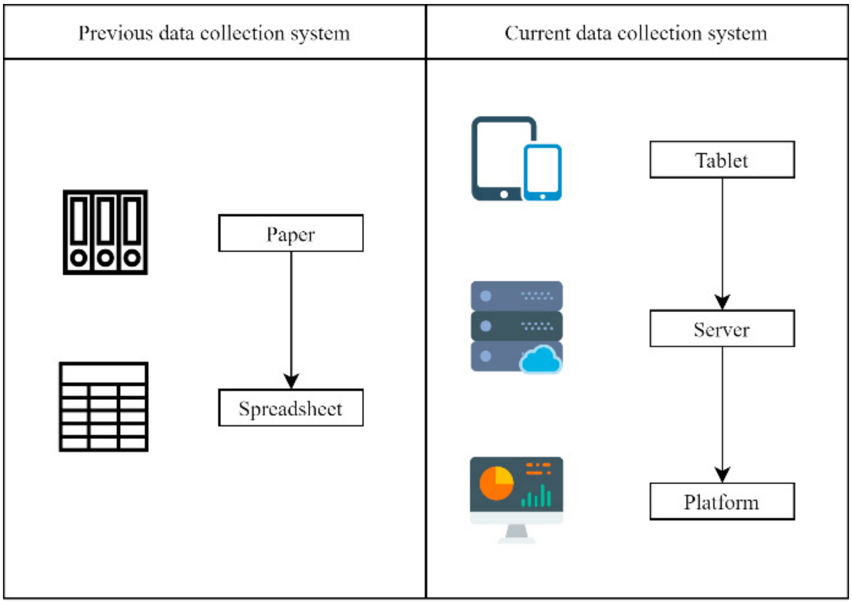

Figure 2. Digitalised data collection

6. Conclusion

The results from the statistical analysis gave valuable insight into the optimal setting of the silica % in the binder of the ceramic slurry to minimise the quantity of Scrap Type I. These insights resulted in the implementation of a data acquisition system to allow continuous monitoring of the ceramic slurry parameters. The knowledge gained from the analysis and the digitalisation of this information has helped to reduce the waste and financial losses for this manufacturing process in the organisation. This study has demonstrated the value that can be achieved by analysing and digitalising data to improve the yield of the process and gain a deeper understanding of the relationships within the process. In conclusion, this study has shown that insights gained from analysis of historical data can be used to write a defendable business case with uncertain outcomes and justify the additional costs. Unlike more complex approaches, such as neural networks, statistical analysis is easier to implement and a more approachable initial step that can be taken by organisations to begin the transition to digital production and Industry 4.0.

6.1. Assumptions and limitations

This study focused on the effect of changing a single factor (the percentage level of SiO_2) on the quantity of three scrap types for an investment casting process. It has been assumed that other factors in this process remained reasonably unchanged during the eight week period. One of the limitations of this study is that the interaction of SiO_2 with other factors has not been analysed.

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References

[1] J. Krumeich, S. Jacobi, D. Werth, and P. Loos, "Big data analytics for predictive manufacturing control - A case study from process industry," *Proc. - 2014 IEEE Int. Congr. Big Data, BigData Congr. 2014*, pp. 530–537, 2014.

[2] T. Ritter and C. L. Pedersen, "Digitization capability and the digitalization of business models in business-to-business firms: Past, present, and future," *Ind. Mark. Manag.*, vol. 86, no. December 2019, pp. 180–190, 2020.

[3] T. Wagner, C. Herrmann, and S. Thiede, "Industry 4.0 Impacts on Lean Production Systems," *Procedia CIRP*, vol. 63, pp. 125–131, 2017.

[4] M. M. Queiroz, S. C. F. Pereira, R. Telles, and M. C. Machado, "Industry 4.0 and digital supply chain capabilities: A framework for understanding digitalisation challenges and opportunities," *Benchmarking*, 2019.

[5] R. Clancy, D. O. Sullivan, and K. Bruton, "Data-driven quality improvement approach to reducing waste in manufacturing systems," 2021.

[6] S. Bag, L. C. Wood, L. Xu, P. Dhamija, and Y. Kayikci, "Big data analytics as an operational excellence approach to enhance sustainable supply chain performance," *Resour. Conserv. Recycl.*, vol. 153, no. November 2019, p. 104559, 2020.

[7] Z. Ge, Z. Song, S. X. Ding, and B. Huang, "Data Mining and Analytics in the Process Industry: The Role of Machine Learning," *IEEE Access*, vol. 5, pp. 20590–20616, 2017.

[8] R. Joppen, A. Kühn, D. Hupach, and R. Dumitrescu, "Collecting data in the assessment of investments within production," in *Procedia CIRP*, 2019, vol. 79, pp. 466–471.

[9] M. Ghobakhloo, "The future of manufacturing industry: a strategic roadmap toward Industry 4.0," *J. Manuf. Technol. Manag.*, vol. 29, no. 6, pp. 910–936, Oct. 2018.

[10] H. Hirsch-Kreinsen, "Digitization of Industrial Work: developments paths and prospects," *J. Labour Mark. Res.*, vol. 49, no. 1, Jul. 2016.

[11] S. Jones and C. Yuan, "Advances in shell moulding for investment casting," *J. Mater. Process. Technol.*, vol. 135, no. 2-3 SPEC., pp. 258–265, 2003.

[12] M. J. Donachie, "Titanium: A Technical Guide, 2nd Edition," *October*, p. 128, 2000.

[13] ASM, "ASM Handbook Volume 3 - Alloy Phase Diagrams," *ASM Handb.*, vol. 3, p. 500, 1992.

[14] M. Jolly, "Advancing current materials and methods used in the Investment Casting of COBALT prosthesis," no. April, 2012.

[15] S. Jones, "Improved Sol based Ceramic Moulds for use in Investment Casting," *Univ. Birmingham*, no. May, 1993.

[16] J.-E. Jeon, S. Lee, B.-J. Choi, and Y. Jig Kim, "An Investigation of pH Control on Binder for Investment Casting of Titanium," *Proc. 13th World Conf. Titan.*, pp. 393–396, 2016.

[17] P. R. Beeley and R. Smart, *Investment Casting*. London: Institute of Materials, 1995.

[18] S. N. Bansode, V. M. Phalle, and S. S. Mantha, "Influence of Slurry Composition on Mould Properties and Shrinkage of Investment Casting," *Trans. Indian Inst. Met.*, vol. 73, no. 3, pp. 763–773, 2020.

[19] S. Jones, X. Miao, C. B. Ponton, and P. M. Marquis, "The influence of stabilising additives and alumina on the crystallisation of colloidal silica," in *Proceedings of the European Ceramic Society Second Conference*, 1991.

[20] Amit Sata, "Foundry Data Analytics to Prevent Defects in Investment Castings," no. February, 2016.

[21] P. A. For, "Analysis of Foundry Defects," *Analysis*, vol. 42, pp. 57–59, 2003.

[22] T. Elbel, Y. Králová, and J. Hampl, "Expert system for analysis of casting defects - ESVOD," *Arch. Foundry Eng.*, vol. 15, no. 1, pp. 17–20, 2015.

[23] J. Zheng, Q. Wang, P. Zhao, and C. Wu, "Optimization of high-pressure die-casting process parameters using artificial neural

network," *Int. J. Adv. Manuf. Technol.*, vol. 44, no. 7–8, pp. 667–674, 2009.

[24] T. Roy, "Analysis of casting defects in steel foundry by computerized simulations (CAE) - A new approach along with some industrial case studies," in *71st World Foundry Congress: Advanced Sustainable Foundry, WFC 2014*, 2014, pp. 1–9.

[25] D. H. Wu and M. S. Chang, "Use of Taguchi method to develop a robust design for the magnesium alloy die casting process," *Mater. Sci. Eng. A*, vol. 379, no. 1–2, pp. 366–371, 2004.

[26] R. Prajapati, S. Agashe, M. Ransing, and R. Rege, "DATA ANALYSIS IN AN INVESTMENT CASTING FOUNDRY FOR," pp. 2–5, 2018.

[27] W. W. Watt, "Continuous Variables: Comparing Two Independent Samples," *Med. Stat.*, no. 2005, pp. 51–85, 2008.

[28] I. C. Institute, "Atlas of Casting Defects," no. December, 2004.