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# **Optimization of Injection Molding Parameters by Data Mining Method in PIM Process**

Azizah Wahi<sup>a\*</sup>, Norhamidi Muhamad<sup>a</sup>, Khairur R. Jamaludin<sup>b</sup>, Javad Rajabi<sup>a</sup>, Abbas Madraky<sup>c</sup>

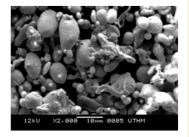
<sup>a</sup>Department of Mechanical and Material Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia <sup>b</sup>UTM Razak School of Engineering & Advanced Technology, Universiti Teknologi Malaysia, International Campus, 54100 Kuala Lumpur, Malaysia <sup>c</sup>Department of Computer Science, Faculty of Science Information and Technology, Universiti Kebangsaan Malaysia, 43600 Bangi, Malaysia

\*Corresponding author: a\_azh84@yahoo.com

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Graphical abstract



#### Abstract

Data Mining is a method that can be used to analyze large amount of data and produce useful information. In this study, clustering which is one of data mining tasks is used to clustered machine based on the injection moulding data. This paper is the first documented results on the optimization of Injection Moulding via Data Mining. Powder injection moulding is a process to produce near net shape with intricate part in mass production. This work focus on the optimization of injection molding process with combination of fine, coarse and bimodal water atomized SS 316L powder particles. The parameters involved in the optimization are injection pressure, injection temperature, mould temperature, holding pressure, injection rate, holding time, powder loading, cooling time and particle size. These variables are based on the defect score, green density and green strength. The key influencer report shows that the most influencing factors are injection rate, holding pressure as well as mould temperature where defect score lower than 2.4 can be achieved. The density higher than 5.34g/cm<sup>3</sup> is also influenced most by the mould temperature. Injection rate and mould temperature gives the highest impact on the defect score and green strength value. While highest green density is significantly affected by powder loading and injection pressure.

Keywords: Data mining; optimization; powder injection molding (PIM)

#### Abstrak

Lombongan data merupakan kaedah yang boleh digunakan untuk menganalisis sejumlah data yang besar dan menghasilkan maklumat yang berguna. Dalam kajian ini, pengkelompokan yang merupakan salah satu kaedah lombongan data digunakan untuk menganalis kelompok data pengacuan suntikan. Kertas kerja ini merupakan yang pertama didokumenkan berkaitan keputusan pengoptimuman Pengacuan Suntikan melalui lombongan data. Pengacuanan suntikan serbuk adalah satu proses untuk menghasilkan komponen yang menghampiri dimensi sebenar, komponen berekabentuk kompleks dan menghasilkan produk secara pukal. Penyelidikan ini memberi fokus pada pengoptimuman proses pengacuan suntikan dengan kombinasi serbuk keluli tahan karat 316L halus, kasar dan bimodal. Parameter yang terlibat dalam pengoptimuman adalah tekanan penyuntikan, suhu penyuntikan, suhu acuan, tekanan pegangan, kadar suntikan, bebanan serbuk, masa penyejukan dan saiz partikel. Pemboleh ubah ini adalah berdasarkan output skor kecacatan, ketumpatan dan kekuatan jasad hijau. Hasil laporan kunci penyumbang menunjukkan bahawa faktor yang paling mempengaruhi proses ini adalah kadar suntikan, tekanan pegangan serta suhu acuan di mana skor kecacatan lebih rendah daripada 2.4 boleh dicapai. Ketumpatan yang lebih tinggi daripada 5.34g/cm3 juga lebih dipengaruhi oleh suhu acuan. Hasil kajian juga menunjukkan bahawa keadaan optimum boleh dicapai dengan menggunakan zarah bimodal. Kadar suntikan dan suhu acuan memberikan impak tertinggi kepada skor kecacatan dan nilai kekuatan jasad hijau. Manakala ketumpatan jasad hijau tertinggi ketara dipengaruhi oleh beban serbuk dan tekanan suntikan.

Kata kunci: Lombongan data; pengoptimuman; pengacuanan suntikan serbuk

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# **1.0 INTRODUCTION**

Data mining is a concept which by utilizing it we can isolate significant data with unimportant data and discover hidden data relations. By using data mining techniques, useful data will be able to be detected and use them in queries so we can enhance speed of information accessibility. Data mining supports knowledge discovery by finding hidden patterns and associations, constructing analytical models, performing classification and prediction. One of the widely used tasks in data mining is clustering. Clustering as a data mining task is also called segmentation. It is used for identifying natural groups of data based on attributes specifications. Each group consist similar attributes. Iteration has an important role in clustering methods for converging of model [1].

PIM process is evolved when the world are urged for smaller scale product with complex geometry in mass production with lower cost than machining. It combines the conventional injection moulding and powder metallurgy to produce high volume with high quality, near net shape products. In PIM process, the metal or ceramic powder is mixed with binders to form feedstock and then injected to a mould, followed by debinding and sintering to produce parts. In this process, the injection moulding step is very much influenced by parameters such as injection pressure, injection temperature, mould temperature, holding pressure, injection rate and holding time [2]. Other optimization method has been done using Taguchi and Response Surface Method by other researchers [3],[4]. However, this study will apply data mining as an optimization tool. The difference of Taguchi and Response surface method (RSM) compared to data mining is data mining produce one algorithm for optimization based on results while, Taguchi and RSM has one algorithm that need to be followed before the experiment started.

The data mining techniques has been widely use in manufacturing process such as automotive, LCD, semiconductor, steel manufacturing for predictive maintenance, fault detection, diagnosis, and scheduling [5]. Data mining has also been applied to find optimum condition or optimization of a process [6]. In this study the optimize parameters of injection molding process by data mining is reported. The scope of study is based on data reported and this work is focused on data optimization by data mining only.

#### 2.0 METHODOLOGY

The optimization work was carried out based on Jamaluddin et. al. previous works [7]. They used fine and coarse water atomised SS316L powders as shown in Table 1. The powder sizes used were 15 $\mu$ m for large size powder, while 7 $\mu$ m for small size powder. The SEM image or the morphology of the powder is as in Fig. 1. The powders were mixed with 73 % PEG weight of polyethylene glycol (PEG) and 25 % weight of polymethyl methacrylate (PMMA) to produce feedstock.

The optimization parameters for the injection molding step includes injection pressure, injection temperature, mould temperature, holding pressure, injection rate, holding time, powder loading, cooling time and particle size based on defect score, green density and strength. The defect score was evaluated by surface observation, the more defect observed the more defect score value. The green density was obtained by using densimeter based on MPIF42 standard. While strength of the part was obtained by INSTRON 5567. Each feedstock was injected for 27 run and repeated 5 times [3]. The average data for each run was then used for optimization. The data were arranged as shown in Table 2.

Table 1 SS316L water atomised powder particle size distribution [3]

Particle Size	Particle size (Micron)				
	D <sub>10</sub>	D <sub>50</sub>	<b>D</b> <sub>90</sub>		
Coarse	4.99	15.05	34.75		
Fine	3.34	7.16	17.52		

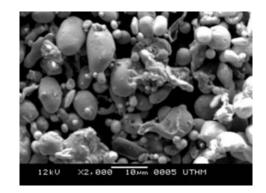


Figure 1 Morphology of the SS316L water atomised powder [3]

Data mining tools in Excel 2007 is used for data processing with an add-in facility which is SQL Server. Generally, these features acted on information tables and they are able to perform several tasks such as calculation of column influence, categorize of similar rows, the same row, forecasting based on information series and finding unlike rows in a table. The results of these tasks are able to analyze and they are presented by using charts and mining tables [8]. The relevant tools and methods for data mining process are categorized into four main groups. They are classification, clustering, association rules and regression. In this paper we used clustering as a main data mining tool. Clustering or segmentation is another data mining method. It is utilized for identifying natural data groups based on their attributes. Each group includes similar objects. Usually, clustering used unsupervised methods. And also two main tools are used for providing analytical information:

1. The Analyze Key Influencers Tool

Data dependency and data influences are able to calculate by using this tool. It analyzed the column correlations in a table depend to a target column as a result. The influence values are presented by a table. In this paper we consider Defect Score, Density and Strength as a target value and calculate the other column dependencies according to the target columns.

2. The Detect Categories Tool

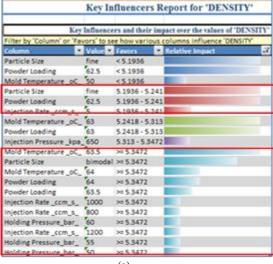
This tool enables identifying natural groups in data. This is one of the most important methods for data processing which is called Clustering. By utilize clustering, information patterns or similar objects can be determined. Actually, information have categorized based on their adjective attributes. To determine similarity for two rows of a table, the sum of difference should be calculated. The differences are related to corresponding variables. The rows with fewer differences are located in the one group. We can select several variables for calculating the differences. In addition, we can define the maximum number of clusters. The result includes three parts. These outputs are general table for displaying number of objects in each cluster, descriptions of clusters by values and the visualization of data distributions in a cluster [9].

No	Injection Pressure (kPa)	Injection Temperature (°C)	Mould Temperature (°C)	Holding Pressure (bar)	Injection Rate (ccm <sup>3</sup> /s- <sup>1</sup> )	Holding Time (s)	Powder Loading (%)	Cooling time (s)	Particle size (µ)
1	750	160	60	800	15	15	64	10	Fine
2	650	155	55	1000	10	10	63.5	6	Coarse
3	550	150	50	1200	5	5	63	2	Bimodal

 Table 2 Optimization parameters for injection moulding parameters

## **3.0 RESULTS AND DISCUSSION**

Based on the key influencers report for density [Figure 3(a)], the mould temperature should be set at  $63.5^{\circ}$ C which has the most influence to increase the green density value more than 5.34 g/cm<sup>3</sup>. The highest density is achieved by using bimodal particle. In addition, the mold temperature has more impact on the density (>5.34g/cm<sup>3</sup>) compared to bimodal particle size. The



(a)

injection rate at 5 ccm<sup>3</sup>/s<sup>-1</sup> demonstrates less significant to the density, in the range of 5.19 to 5.24. The most impact to the density between 5.19 g/cm<sup>3</sup> to 5.24 g/cm<sup>3</sup> is related to the fine particles as well. While as shown in Figure 3 (b), the holding pressure at 800 bar with mould temperature at  $63.5^{\circ}$ C is able to produce defect score ranging from of 3.14 -3.77 and 3-77 to 4.62 respectively.

Key	Influencer	s and their impact over the	values of 'DEFECT SCORE'
Filter by 'Column' or 'Favors	' to see how	e various columns influence	'DEFECT SCORE'
Column	Value .	Favors	<ul> <li>Relative Impact</li> </ul>
Injection Rate_com_s_	10	< 2.40803682	
Holding Pressure_bar_	1000	< 2.40803682	
Mold Temperature_oC_	50	<2.40803682	
Injection Pressure _kpa_	750	< 2.40803682	
Particle Size	coarse	< 2.40803582	
Holding Pressure_bar_	800	3.1420918592 - 3.775176739	2
Injection Temperature_oC	150	3.1420918592 - 3.775176739	2
Mold Temperature of	63.5	3.7751767392 - 4.629476426	4
Particle Size	bimodal	3.7751767392 - 4.629476426	4
Injection Temperature_oC	155	3.7751767392 - 4.629476426	4
Injection Rate_com_s_	1200	3.7751767392 - 4.629476426	4
Injection Rate_com_s_	800	3.7751767392 - 4.629476426	4
Holding Pressure_bar_	50	3.7751767392 - 4.629476426	4
Holding Pressure_bar_	60	3.7751767392 - 4.629476426	4
Powder Loading	64	>= 4.6294764264	A REAL PROPERTY AND A REAL
Mold Temperature_oC_	64	>= 4.6294764264	

Figure 3 Key Influencer report for (a) density and (b) defect score

From data mining result, the optimized condition for injection molding parameters is shown in Figure 4. Based on all results, it is obviously found that bimodal powder has an ability to increase the strength and density, on the other hand decreases the defect scores number. The smaller powders will interstiticed between the gaps of larger size powders in bimodal structure thus decreases the porosity and increase density [10].

Attribute	💌 Value 💌	Relative Impact 💌	Attribute	Value 💌	Relative Impact 💌
Injection Pressure _kpa_	550	55	Injection Pressure _kpa_	550	119
Injection Temperature_oC	150	105	Injection Temperature_oC	150	27
Mold Temperature _oC_	50	141	Mold Temperature _oC_	50	0
Holding Pressure_bar_	1000	97	Holding Pressure_bar_	1000	19
Injection Rate _ccm_s_	10	165	Injection Rate _ccm_s_	10	11
Holding Time _s_	10	99	Holding Time _s_	10	49
Powder Loading	63.5	129	Powder Loading	63.5	128
Cooling Time _s_	10	6	Cooling Time _s_	10	36
Particle Size	bimodal	17	Particle Size	bimodal	106

Value 💌	Relative Impact 💌		
550	9		
150	104		
50	106		
1000	13		
10	122		
10	27		
63.5	26		
10	1		
bimodal	57		
	550 150 50 1000 10 10 63.5 10		

Figure 4: Optimum parameter condition to achieve the (a) lowest defect score, (b) highest density and (c) highest strength

Injection rate and mould temperature gives the highest impact on the part strength and defect score. This is good agreement with studies done by [3]. Higher mould temperature provides the better or higher viscosity which allows the material to flow smoothly into the mould. Injection rate and mould temperature influence the mean value of part dimension [11]. Low injection can cause shrinkage, irregular injection rate can cause flow marks or jetting, while higher injection rate can cause flashing. Thereby, adequate injection rate is crucial to produce high quality injection part.

The density of injected part is significantly affected by injection pressure and powder loading. Insufficient injection pressure will cause short shot because the pressure is not enough to feed the material inside the mould. An optimum powder loading is desirable to produce high density part. This is the most preliminary study that should be done before injection moulding stage. However, the particle parameters as well as the binder used should be taken into account [12].

From data mining result, Injection pressure has no significant effect on the part strength. This statement is also mention by Rosato *et al.* in their handbook [13]. Cooling time is also found to have less effect on the injection moulding process.

### **4.0 CONCLUSIONS**

Data mining is one of useful tool to optimize injection moulding parameters. The conclusion for optimization of 316LSS by data mining is summarized as follows:

- Injection Temperature, Injection rate, Injection pressure and powder loading is the most significant variables that affect the injection moulding process for the highest green strength part.
- (2) From the key influencer density report, the most influencing factor is mould temperature. While based on defect score the most significant factors are injection rate, holding pressure as well as mould temperature.
- (3) Optimized moulding parameters enable to improve the part green strength and density, as well as improve quality which is verified by numerical method (Data Mining).
- (4) The future study of this research is to verify the optimize PIM parameters by experimental study.

Acknowledgement

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# References

- Han, J., M. Kamber. 2006. Data Mining: Concepts and Techniques. 2nd ed. University of Illinois at Urbana-Champaign.
- [2] Kamaruddin, S., Khan, Z. A., and Foong, S. H. 2010. Application of Taguchi Method in the Optimization of Injection Moulding Parameters for Manufacturing Products from Plastic Blend. *International Journal* of Engineering and technology. 2(6).
- [3] Jamaludin, K. R. 2009. Kesan Saiz dan Bentuk Partikel Serbuk SS316L Terhadap Parameter Pengacuanan Suntikan Logam Menggunakan Rekabentuk Eksperimen. Tesis PhD. Universiti Kebangsaan Malaysia.
- [4] Amin, S. Y. M, Muhamad, N. and Abdullah, S. and Jamaludin, K. R. 2008. Application of RSM Technique to Optimize the Solvent Debinding Process for MIM Compacts. Brunei International Conference of Engineering & Technology (BICET).
- [5] Harding, J. A., Shahbaz, M., Srinivas & Kusiak, A. 2006. Data Mining in Manufacturing: A Review. *Journal of Manufacturing Science and Engineering*. 128: 969–976.
- [6] Braha, D., & Shmilovici, A. 2002. Data Mining for Improving a Cleaning Process in the Semiconductor Industry. *IEEE Transactionson* Semiconductor Manufacturing. 15(1): 91–101
- [7] Jamaludin, K. R., Muhamad, N., Rahman, M. N. A., Ahmad, S., Ibrahim, M. H. I. and Nor, H. M. 2011. Optimizing the Injection Parameter of Water AtomisedSS316L Powder with Design of Experiment Method for Best Sintered Density. *Chiang Mai J. Sci.* 36: 349–358.
- [8] MacLennan, J., Zh. Tang, B. Crivat. 2009. Data Mining with SQL Server 2008. Wiley Publishing, Inc.
- [9] Jafar, M. J. 2010, A Tools-Based Approach to Teaching Data Mining Methods. Journal of Information Technology Education: Innovations in Practice. 9.
- [10] German, R. M. & Bose, A. 1997. Injection Molding of Metals and Ceramic. *Metal Powder Industries Federation*. Princeton, New Jersey U.S.A.
- [11] Beck, M., Piotter, V., Rupecht, R., HauBell, J. 2006. Dimensional Tolerances of Micro Precision Parts Made by Ceramic Injection Moulding. 2nd International Conference on Multi-Material Micro Manufacturing. 135–138
- [12] Benson, J. M., W. Richter, and H. C. Chikwanda. 2011. Rheological Assessment of Titanium MIM Feedstocks. *The Journal of The Southern African Institute of Mining and Metallurgy*. 111: 133–136.
- [13] Dominick V. Rosato, Donald V. Rosato, Marlene G. Rosato. 2000. *Injection Molding Handbook*. 3<sup>rd</sup> Edition. Springer.