Proceedings of the 1st International Conference on New Materials, Machinery and Vehicle Engineering 257
J. Xu et al. (Eds.)

doi:10.3233/ATDE220235

Research Progress on Optimization Methods of Powder Injection Molding Process Parameters

Tong ZHAO[a], Baozhen EI[,b,1], Xunwei WANG[b], Guanghao QI[a] and Harald LOWE[c]
[a]*Beijing Key Laboratory of Information Service Engineering, Beijing Union University, Beijing, China*
[b]*Beijing Intelligent Machinery Innovation Design Service Engineering Technology Research Center, Beijing Union University, Beijing, China*
[c]*Institute for Partial Differential Equations, Technical University of Braunschweig, Braunschweig, Germany*

Abstract. The powder injection molding (PIM) process provides a possibility for high-volume, low-cost manufacturing of workpiece. During powder injection molding, besides mold design and material characteristics, injection parameters are critical in affecting the capability of molded commodities. Traditional injection molding parameter design relies on the experience of technicians, and it is difficult to ensure the consistency in the quality of injection parts. In this work, we analyze the optimization of technical parameters of current PIM technology and provide some perspectives on the future development of this field.

Keywords. Powder injection molding, parameter optimization, design of experiment

1. Introduction

Powder injection molding (PIM) is a technique that involves metal and non-metallic powders for manufacturing a large number of small and medium sized parts with complex shapes [1]. Due to its net or near-net shape process, high efficiency and low cost, it has had a wide of applications in the fields of aerospace, automotive medical, military, electronic, industrial, personalized products and others [2]. Being a branch of PIM, metal injection molding (MIM) is ranked in the top two advanced manufacturing technologies for the future by McKinsey & Company [3]. At the same time, parts with high density, good mechanical properties, and small surface roughness can be obtained, and parts with complex structures can be produced in large quantities and with high efficiency.

During the production process, warpage and shrinkage are the main defects in the products [4]. These problems are related to several factors, and it is difficult to avoid these problems by relying solely on the experience of the engineers. Especially for complex precision parts where there are dimensional matching requirements, the shape

[1] Baozhen Lei, Beijing Union University, No.97 Beisihuan East Road, Chao Yang District, Beijing, China, E-mail:leibaozhen@126.com.

and dimensional accuracy of the parts are often very high. Therefore, the development of an appropriate method for the optimization of the forming process of the parts is highly desired by the industry. In the following, we review some current research methods for PIM technical parameter optimization and provide some perspective on future development trend of this field.

2. The Status Quo of Optimization of PIM Process Parameters

2.1. Injection Molding Technology

The parts produced by MIM technology have better mechanical properties than plastic injection molding parts. The process consists of 4 stages: feedstock preparation, injection molding, debinding and sintering [5], as shown in Figure 1. In the first stage we need to mix metal powder and thermoplastic binders [6]. Since the metal powders' flow ability and permeability are mainly influenced by the binder, a suitable, precise recipe is important for MIM [7]. Then the feedstock is processed by the MIM machine into the green part. In the following debinding stage, removing the binder from the green part yields the so-called brown part [8]. During the final sintering stage, high temperature heating to densify. The parts has good mechanical properties [9]. Each stage must be strictly controlled, because it will directly affect the quality of MIM products. Therefore, the optimization in each stage will directly affect the quality of the final formed product [10].

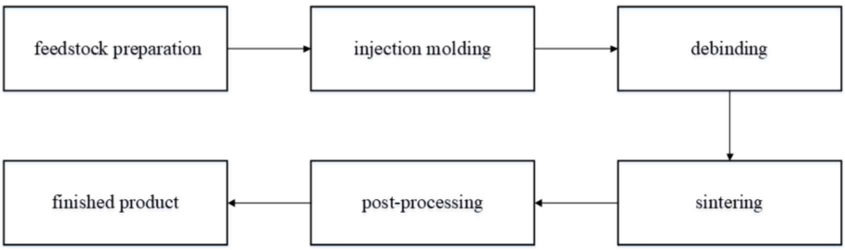

Figure 1. MIM process

The choice of suitable injection molding process parameters is critical for a good molding quality. One approach to a reliable parameter design is to use computer aided engineering (CAE). For example, Mahmud *et al*. [11] studied the main technical factors which influence the shrinkage of plastic injection molding product. Li *et al*. [12] used the Kriging model and design of experiment (DOE) to analyze the dependency of the shrinkage on the technical parameters; the results were applied to an effectively reduced warpage of PIM products. Saunders [13] applied the functional Gaussian process surrogate models to link microstructure morphology to mechanical properties. Nayak *et al*. [14] utilized Taguchi analysis, PCA and GA hybrid methods to research, analyze and optimize MIM technical parameters. Song *et al*. used SVM and BPNN to establish a function for predicting the quality of PIM products. Kun *et al*. [15] applied DOE approach, RSM and NSRGA-II for optimization. Qiao *et al*. [16] proposed an ant colony algorithm model to optimize MIM technical parameters.

Islam [17] found that the shrinkage of MIM products on the micro scale is uneven and that the thinner area of the part shows a higher relative shrinkage than the thicker area. Lin [18] used the Taguchi method and GRA minimize volume shrinkage. Maulana [19] adopted the orthogonal matrix method and found that the temperature had the greatest influence on the shrinkage rate.

There has been a major focus on the warpage of plastic products and the shrinkage of metal products. To produce high-precision parts, especially for gears, the characteristics of anisotropic shrinkage are worthy of deep studying.

2.2. Design of Experiment

Before establishing a model describing the relationship between technical parameters and shrinkage, experiments should be designed. Researchers have adopted a variety of experimental design methods, such as orthogonal experiments, central composite design (CCD) experiments, Box-Behnken design (BBD) experiments and sampling methods. Orthogonal experiment is a common experimental design method for studying multiple factors and multiple levels. It can be characterized as "evenly dispersed, neat and comparable". Sateesh *et al*. [20] used the orthogonal experiment method to design 9 sets of experiments with the L9 orthogonal table, and minimized warpage, volume shrinkage, and cycle time. Moayyedian *et al*. [21] applied a mixture orthogonal experiment design method and designed 18 sets of experiments with L18 orthogonal table. Bensingh *et al*. [22] used the orthogonal experiment method to design 44 sets of experiments on 7 process parameters. The count of tests will increase geometrically with the count of test factors, but for the accuracy of the test, certain factors cannot be ignored because of the increase in the number of tests.

Kastner *et al*. [23] utilized the CCD test method to design 25 sets of tests. Heidari used CCD approach to design 45 sets of tests. Kim employed the BBD design approach to design 15 sets of tests for 3 process parameters, and adjusted the optimized conditions by changing the variables. Guo *et al*. [24] applied the Latin Hypercube Sampling (LHS) approach to design 488 groups of experiments for network training, and performed finite element simulations and physical experiments.

Tsai *et al*. [25] made use of the Taguchi parameter design to analysis injection molding parameters and found the important factors affecting the shrink. Range analysis is used to research various technical parameter on the warpage deformation; the design of the test was done by an LHS method. Tian applied the DOE approach to experiment and process data, and then used statistical approach to condition the greatest association technical parameters. Amin *et al*. utilized the Taguchi method and took 7 process parameters into consideration in the design of experiments for MIM. Prathabrao analyzed MIM in detail and applied the L9 orthogonal table to design the experiment for MIM.

The CCD and BBD methods have higher experimental accuracy than the normal process experiment, but the corresponding number of experiments are also relatively large. Selection of experimental method depends on the specific production needs.

2.3. Mathematical Model

Traditional injection process optimization methods are mostly based on experimental design, analysis of variance and average response, and simple processing of data. This method can optimize the product quality of the injection process to a certain extent, but the quality prediction for the continuous unknown parameter combination product is

Unable to do it. According to mathematical statistical logic to find the best level of each control factor from the distribution of discrete points, only the existing local best combination can be obtained. Therefore, considering the non-linear relationship between control factors and optimization goals, many models of mathematical professional fields are used in the injection molding process.

Being a applicable multivariate regression model, RSM is widely used due to its simple application and mature technology. Rizvi *et al*. [26] used experimental design and RSM methods, as well as set the CCD and the technical parameters. Sudsawat *et al*. utilized orthogonal experiment, RSM, firefly algorithm (FA) and annealing process, and carried out experiments based on Moldex3D and injection molding machine and obtained the best solution of optimized warpage.

On the other side, neural networks have strong performance in processing nonlinear relationships between multi-inputs and multi-outputs, and can cope especially with the highly complex nonlinear relationships in manufacturing processes. Therefore, artificial neural networks (ANN) are extremely widely applied in process optimization parameter scenarios.

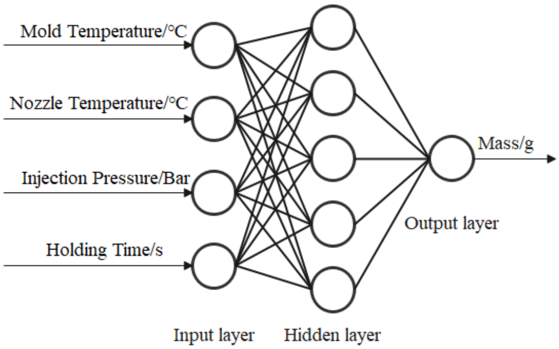

Figure 2. Structure of Artificial Neural Network.

Kitayama [27] used a RBF network and a few simulations to determine the optimal injection speed and pressure distribution. Shi *et al*. [28] deployed BPNN models and a parameter sampling evaluation (PSE) strategy to optimize product warpage.

Table 1. traditional method and the neural network method

traditional method	neural network method
RSM	BPNN
FA	RBF-NN
GA	BPNN
PCA	SVM

In summarize, neither the single traditional method nor the neural network method can solve complex engineering problems. For obtaining higher performance, suitable methods should be adopted.

3. Development Direction

Much research has been done to optimize MIM technical parameters. According to different needs, they have commonly optimized certain quality goals of a part, respectively conducted different experimental design schemes to obtain data. The model is analyzed and calculated to finally achieve the goal of quality optimization. Due to their high complexity, these optimization methods are rarely used in actual industrial manufacturing. Therefore, it is necessary to commercialize and modularize the technologies in these studies, integrate these functions into the injection molding machine, and operate the experiment through a visual interface, as well as to save the data in the process of an injection experiment. Moreover, the model should have the ability of self-learning, i.e. it should be capable to learn from data and to optimize itself.

It is also important to classify and compare existing models and establish a special model library. For example, one could collect typical materials, 3D models of parts and molds. It can provide the technicians with an initial range of processing parameters, and on this basis, the subsequent optimization is carried out. The above two strategies benefit reducing the experiment costs.

4. Conclusions and Prospects

In summary, techniques such as experimental design methods, genetic algorithms, and neural network models have been widely used for injection molding process optimization, but most of them optimize a single objective. However, the performance of both plastic and metal products does not only depend on a few indicators such as mechanical properties or shrinkage. Therefore, it is important to multiple indicators of products at the same time and to achieve comprehensive improvement of product quality through multi-objective optimization method, to guide injection molding more effectively.

Acknowledgments

This research is financially supported by National Natural Science Foundation of China(No.5177050098), Collaborative innovation project of Chaoyang District, Beijing (CYXC2102、CYXC1905), Academic Research Projects of Beijing Union University (No. JZ10202003). The authors gratefully acknowledge above financial support.

References

[1] Prathabrao M, et al. Review on sintering process of WC-Co cemented carbide in metal injection molding technology. IOP Conference Series: Materials Science and Engineering. 2017 Dec;165.

[2] Moon AP, Dwarapudi S, Sista KS, Kumar D, Sinha GR. Opportunity and Challenges of Iron Powders for Metal Injection Molding. ISIJ International. 2021 Feb; 61(7): pp 2015-2033.

[3] Ben S, Colin S, Colin S. Factory of the Future Issue One. 2018 Mar; pp 5-18.

[4] Engström S. Metal Injection Molding: A review of the MIM process and its optimization. 2017 July.

[5] Hossain, et al. Experimental and theoretical investigation of powder‑binder mixing mechanism for metal injection molding. Materials and Manufacturing Processes. 2015 Nov; 30(1): pp 41-46.

[6] Heaney DF. Powders for metal injection molding (MIM). 2019 Sep; pp 45-56.

[7] Banerjee, S, et al. Debinding and sintering of metal injection molding (MIM) components. 2019 Dec; pp 129-171.

[8] Soyama J, et al. Sintering behavior and microstructure formation of titanium aluminide alloys processed by metal injection molding. 2017 Oct; 69(4): pp 676-682.

[9] Shahbudin, S, et al. A Review of Metal Injection Molding-Process, Optimization, Defects and Microwave Sintering on WC-Co Cemented Carbide. In IOP Conference Series: Materials Science and Engineering. 2017 Aug.

[10] Ali. Metal injection moulding of titanium and titanium alloys: Challenges and recent development. Powder Technology. 2017 Dec; 319: pp 289-301.

[11] Mahmud, Nurul N, et al. Rheological properties of irregular-shaped titanium-hydroxyapatite bimodal powder composite moulded by powder injection moulding. Journal of Materials Research and Technology. 2021 Nov;11: pp 2255-2264.

[12] Li S, et al. Optimization of Injection Molding Process of Transparent Complex Multi-Cavity Parts. Arabian Journal for Science and Engineering. 2021 Jun; pp 1-11.

[13] Saunders R, et al. Mechanical behavior predictions of additively manufactured microstructures using functional Gaussian process surrogates. npj Computational Materials. 2021 Mar;7(1): pp 1-11.

[14] Nayak C, et al. Analysis and optimization of metal injection moulding process. Materials Forming, Machining and Post Processing. 2020 July; pp 41-74.

[15] Li K, et al. Multi-objective optimization of the fiber-reinforced composite injection molding process using Taguchi method. 2019 Nov; 91:pp 69-82.

[16] Qiao B. Optimization of copper powder injection molding process parameters based on ant colony algorithm. Fenmo Yejin Jishu(Powder Metallurgy Technology. 2011 Feb;29(3): pp 200-205.

[17] Islam A., et al. The shrinkage behavior and surface topographical investigation for micro metal injection molding. AIP Conference Proceedings. 2015 May; p 1664.

[18] Lin CM., et al. Hybrid Taguchi–Gray Relation Analysis Method for Design of Metal Powder Injection-Molded Artificial Knee Joints. Polymers. 2021 Jan;13(6): p 865.

[19] MAULANA, A. R. Pengaruh Temperature, Holding Time, dan Penambahan SN Terhadap Cacat Shrinkage Pada Proses Sintering Metal Injection Molding Al-Pp. Doctoral dissertation. 2020 Nov.

[20] Sateesh N, Reddy SD, Kumar GP, Subbiah R. Optimization of injection moulding process in manufacturing the flip cover of water meter. Materials Today: Proceedings. 2020 Nov;26:240-246.

[21] Moayyedian M, et al. Optimization of injection molding process based on fuzzy quality evaluation. CIRP journal of manufacturing Science and technology. 2018 May;21:pp 150-160.

[22] Bensingh RJ, et al. Injection molding process optimization of a bi-aspheric lens using hybrid artificial neural networks (ANNs) and particle swarm optimization (PSO). Measurement. 2019 Feb;134: pp 359-374.

[23] Kastner C, et al. Influence of process parameters on mechanical properties of physically foamed, fiber reinforced polypropylene parts. Journal of Applied Polymer Science. 2019 Dec;136(14): p 47275.

[24] Guo W, et al. A hybrid back-propagation neural network and intelligent algorithm combined algorithm for optimizing microcellular foaming injection molding process parameters. Journal of Manufacturing Processes. 2020 Feb;50: pp 528-538.

[25] Tsai KM. An inverse model for injection molding of optical lens using artificial neural network coupled with genetic algorithm. Journal of Intelligent Manufacturing. 2017 Nov;28(2): pp 473-487.

[26] Amin, et al. Green density optimization of stainless steel powder via metal injection molding by Taguchi method. In MATEC Web of Conferences. 2017 Feb;135(39).

[27] Prathabrao, et al. Parameter optimization of metal injection moulding: A review. Journal of Mechanical Engineering (JMechE). 2018 Oct; pp 100-114.

[28] Kitayama S, et al. Multi-objective optimization for minimizing weldline and cycle time using variable injection velocity and variable pressure profile in plastic injection molding. The International Journal of Advanced Manufacturing Technology. 2020 Feb;107(7): pp 3351-3361