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Review of Design of Process Parameters for Squeeze Casting

Jianxin Deng[1*], Bin Xie[1], Dongdong You[1,2] and Haibin Huang[1]

Abstract

Squeeze casting (SC) is an advanced net manufacturing process with many advantages for which the quality and properties of the manufactured parts depend strongly on the process parameters. Unfortunately, a universal efficient method for the determination of optimal process parameters is still unavailable. In view of the shortcomings and development needs of the current research methods for the setting of SC process parameters, by consulting and analyzing the recent research literature on SC process parameters and using the CiteSpace literature analysis software, manual reading and statistical analysis, the current state and characteristics of the research methods used for the determination of SC process parameters are summarized. The literature data show that the number of publications in the literature related to the design of SC process parameters generally trends upward albeit with significant fluctuations. Analysis of the research focus shows that both "mechanical properties" and "microstructure" are the two main subjects in the studies of SC process parameters. With regard to materials, aluminum alloys have been extensively studied. Five methods have been used to obtain SC process parameters: Physical experiments, numerical simulation, modeling optimization, formula calculation, and the use of empirical values. Physical experiments are the main research methods. The main methods for designing SC process parameters are divided into three categories: Fully experimental methods, optimization methods that involve modeling based on experimental data, and theoretical calculation methods that involve establishing an analytical formula. The research characteristics and shortcomings of each method were analyzed. Numerical simulations and model-based optimization have become the new required methods. Considering the development needs and data-driven trends of the SC process, suggestions for the development of SC process parameter research have been proposed.

Keywords Squeeze casting, Process parameter design, Process parameter optimization, Data-driven, Neural network, Research method analysis, Literature analysis, CiteSpace

1 Introduction

Squeeze casting (SC) is an advanced net manufacturing process that combines the advantages of liquid metal forming (such as casting) and solid pressure forming (such as forging), and realizes forced feeding and near-net shapes of castings through high-pressure solidification and a small amount of plastic deformation. It has the advantages of improving the casting performance, reducing casting defects such as blowholes and shrinkage, producing complex-shaped parts, energy conservation, and environmental protection [1, 2]. The SC process and its possible application were first proposed by Chernov in the Soviet Union, and attracted extensive attention [3]. Currently, SC is widely used in the preparation of high-performance materials such as aluminum and magnesium alloys and in the production and manufacturing of high-quality and high-performance components used in

*Correspondence:
Jianxin Deng
dengjxin@163.com
[1] Guangxi Key Lab of Manufacturing System and Advanced Manufacturing Technology, School of Mechanical Engineering, Guangxi University, Nanning 530003, China
[2] National Engineering Research Center of Near-Net-Shape Forming for Metallic Materials, South China University of Technology, Guangzhou 510640, China

automobiles, household appliances, and military applications [4]. SC has good prospects for development and application in manufacturing owing to the ongoing demand for lightweight structures, reduced energy consumption, environmental protection, and performance enhancement. To implement the SC process, the dies, SC mode, and SC process parameters must be determined. The SC process parameters directly affect the mechanical properties and microstructures of the SC casts, and appropriate process parameters are the prerequisites for producing SC casts with the aforementioned advantages. To obtain high-performance casts or materials, to determine the effects of the process parameters on the properties and microstructure, and to set reasonable process parameters, various studies on SC process parameters have been conducted around the world, and different process-parameter acquisition (design) methods have been developed. However, the SC process involves interactions and coupling between the process parameters. Although existing research methods, such as the orthogonal experiments and dimensional analysis methods, can reveal the laws describing the effect of a single process parameter on the casting properties, these methods are only applicable to specific materials or castings and thus have significant limitations. This restricts the applications of SC.

The objective of this study is to analyze the current state and the shortcomings of the existing SC process parameter design methods. A large amount of SC research in China and other countries was analyzed using the CiteSpace software. This paper systematically summarizes the relevant research status of the main process parameters of SC; the research methods and characteristics of the SC process parameters are summarized. Subsequently, research directions for the optimization of the SC process parameters were suggested to promote research on SC process parameter design methods and applications.

2 Analysis of Research on SC Process Parameters

2.1 Analysis Data Sources

In this study, relevant research on SC process parameters conducted from 2000 to 2020 was extracted and analyzed using the CiteSpace software. First, Chinese papers were extracted from the China National Knowledge Infrastructure (CNKI) database. Excluding conference abstracts, reports, and irrelevant papers, we searched for the keywords "squeeze casting" and "process parameter". A total of 328 valid papers (information) were obtained and used to analyze the status of research on the SC process parameters in China. Second, from the core collection databases of the Web of Science and SCOPUS, foreign (English) literature related to SC process parameter research with the theme word "squeeze casting process parameter" was extracted, and 336 retrieval results were obtained. These included 67 English-language papers published by Chinese authors, which were manually excluded from the foreign literature set and added to the Chinese literature set, and the records were set as the full records and cited references. Additionally, all research papers related to SC in the same period were counted, and the ratios of the number of papers on SC process parameters to the total number of SC research papers published within and outside China were found to be 14.2% and 13.4%, respectively. Although the research on SC process parameters is an important part of the overall SC research effort, it has attracted relatively little attention.

Previous studies on the SC process parameters were clustered in CiteSpace using the log-likelihood ratio algorithm. The Q values (module values) were all approximately 0.7, significantly larger than the boundary value (0.3) and indicating that the community structure of the cluster was significant. The S values (average contour values) were all approximately 0.9, significantly larger than the threshold value of 0.7 and indicating that clustering was efficient and convincing [5].

Figure 1 presents the annual number of published papers on SC process parameters from 2000 to 2020. It is observed that the published amount of Chinese and English literature related to SC process parameters generally trends upward, albeit with significant fluctuations. The number of Chinese papers reached a high level from 2012 to 2016 but has decreased slightly in recent years. In recent years, the average number of articles published annually worldwide has been approximately 30–40, exceeding the average for this period and indicating that research in this field remains relatively active.

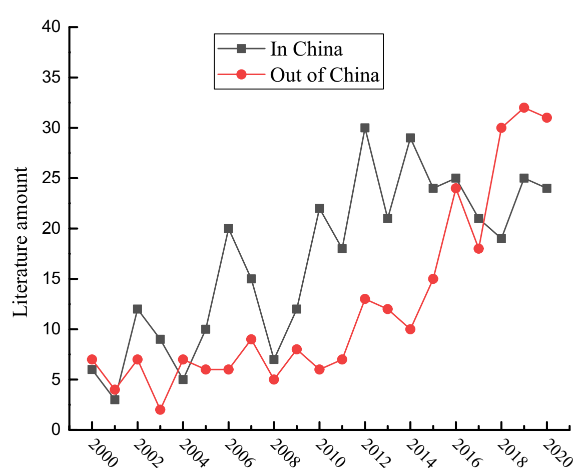

Figure 1 Annual publications on SC process parameters from 2000 to 2020

2.2 Analysis of Research Methods for Determination of SC Process Parameters

2.2.1 Research Focus Analysis

The top ten keywords and their centrality values were extracted from the statistical table after keywords with synonyms and the same semantics were merged. Centrality represents the core research focus (or topic) during a certain period as shown in Tables 1 and 2. Ignoring the ontology semantic keyword "squeeze casting" according to the frequency of keywords and centrality analysis, it can be observed that both in China and abroad, "mechanical properties" and "microstructure" have similar high frequencies. This reflects the significant effects of the SC process parameters on the properties of squeeze casts, so that studies that examine the mechanical properties and microstructure are often conducted simultaneously. With regard to materials, aluminum alloys are the most studied, followed by composite matrix materials and magnesium alloys. In China, research on process parameters has also focused on the mold because SC process research emphasizes the development of practical squeeze casts, whereas overseas research focuses on material preparation.

After ruling out high-frequency words such as research materials and obtaining keywords of the method used for the main subjects of the study of the SC process parameters, in the decreasing order of frequency, the hot methods for Chinese literature are numerical simulation, orthogonal experiment, and parameter optimization, and those for the international English-language literature are parameter optimization, orthogonal experiment, and numerical simulation. Among the research methods, numerical simulations exhibit the highest centrality. A numerical simulation is a virtual experiment, whereas orthogonal experiment is an experimental method. Thus, the experimental method remains the primary method for obtaining the process parameters, which is consistent with the findings obtained by actually reading the literature.

However, this is inconsistent with the finding that the cumulative proportion of the experimental method is still not high because conventional experiments do not appear in the hot research methods. This is mainly because the CiteSpace software extracts information according to the title, abstract, and keywords of the papers and analyses, and conventional experimental methods with no special features are not usually listed as key information in these parts of the literature. This leads to the failure of the software analysis to fully represent the actual situation. Therefore, a more detailed statistical analysis of the literature was required. In addition, the analysis results of CiteSpace still have high values.

Keyword frequency is associated with the size of the node label. Based on the size of the label and the

Table 1 High-frequency keyword information for the literature on SC process parameters

In China			Outside China		
Keyword (in Chinese)	Frequency	Centrality	Keyword	Frequency	Centrality
Squeeze casting	249	0.37	Squeeze casting	156	0.04
Process parameter	92	0.52	Mechanical property	108	0.15
Mechanical property	69	0.22	Process parameter	100	0.04
Aluminum alloy	68	0.52	Aluminum alloy	94	0.24
Numerical simulation	67	0.48	Optimization	82	0.13
Microstructure	55	0.27	Microstructure	77	0.18
Mold	41	0.27	Metal matrix composite	54	0.20
Taguchi method	22	0.15	Taguchi method	46	0.12
Magnesium alloy	21	0.19	Numerical simulation	27	0.21
Optimization	21	0.12	Reinforcement	25	0.06

Table 2 High-frequency keywords related to the research method for SC process parameters

In China			Outside China		
Keyword	Frequency	Centrality	Keyword	Frequency	Centrality
Numerical simulation	67	0.48	Optimization	82	0.13
Taguchi method	22	0.15	Taguchi method	46	0.12
Optimization	21	0.12	Numerical simulation	27	0.21

occurrence frequency of the keywords, it is observed from Figure 2 that owing to the limitations of the test cost, the insufficient amount of data, and the functional advantages of numerical simulation, such as simulation of the casting processes, numerical simulation (represented by simulation experiment) has become the main method for studying the SC process parameters in China, whereas mathematical optimization of the SC process parameters is preferred abroad. This indicates that foreign researchers have taken the lead in applying mathematical optimization techniques to the determination of the SC process parameters. From the perspective of centrality, numerical simulation is the main method used to study the SC process parameters.

2.2.2 Analysis by Literature Reading

To further investigate the development status of the research methods for the determination of SC process parameters, the literature analyzed using CiteSpace was classified via manual reading and statistical analysis, and a few redundant literature reviews were excluded. The final classification results are shown in Figure 3. There are currently five methods for obtaining the SC process parameters: Physical experiment (PE), numerical simulation (NS), modeling optimization (MO), formula calculation (FC), and use of empirical values (EV). Physical experiments are the primary research methods used in China and abroad. As discussed above, physical experiments and numerical simulations belong to the category of experimental research, and the method of modeling optimization also depends on the experimental data. Therefore, all of the three aforementioned research methods belong to the category of experimental research. As shown in Figure 3, most research on the SC process parameters (>90%) is based on experimental investigations. Although CiteSpace cannot accurately identify which research method is more extensively used because of the shortcomings of the key information extracted from the literature, it identifies the three most important research methods used for experimental research.

By combining the CiteSpace and reading analyses, it can be concluded that the major method for obtaining SC process parameters is experimental research, particularly physical experiments. Although physical experiment methods are highly accurate, they are costly and time-consuming [6].

2.3 Developmental Analysis of Research Methods for SC Process Parameters

Time-zone maps of keywords were used to further analyze the development of the SC process parameter research methods. In Figures 4 and 5, the thicknesses of the connecting lines between the keywords reflect the co-occurrence frequency of the keywords, and the time zone of the keyword is the year in which the keyword first appeared. The application intensity of each SC process parameter research method over time can be analyzed according to the connection distribution

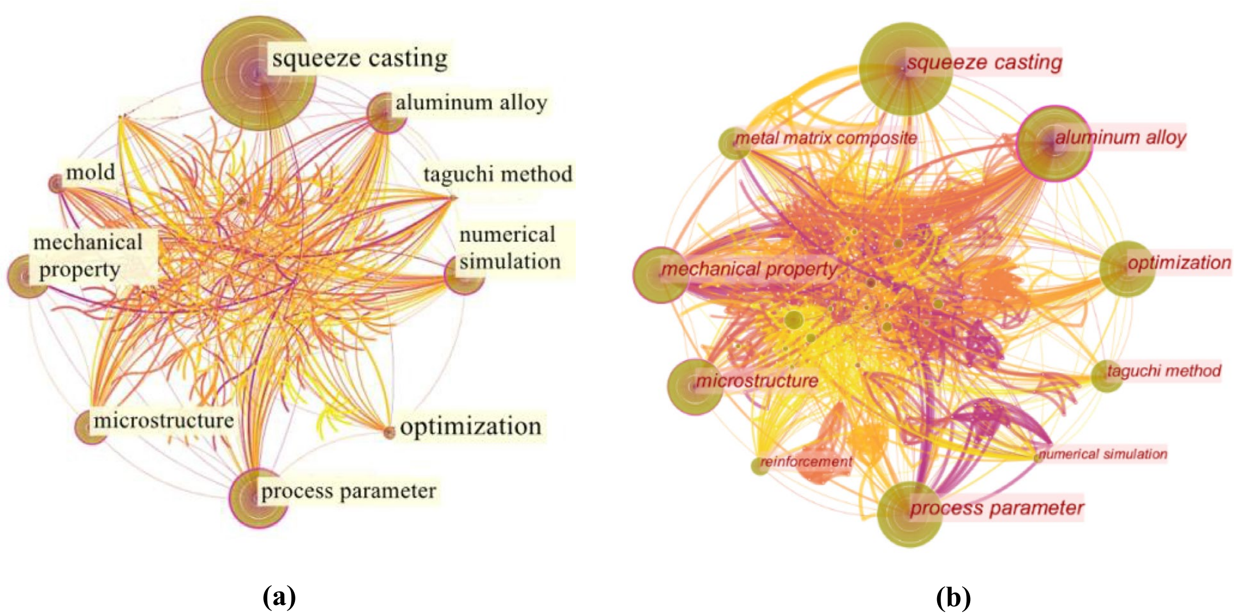

Figure 2 Keyword co-occurrence map of the literature on SC process parameters: (**a**) Based on Chinese literature, (**b**) Based on English-language literature

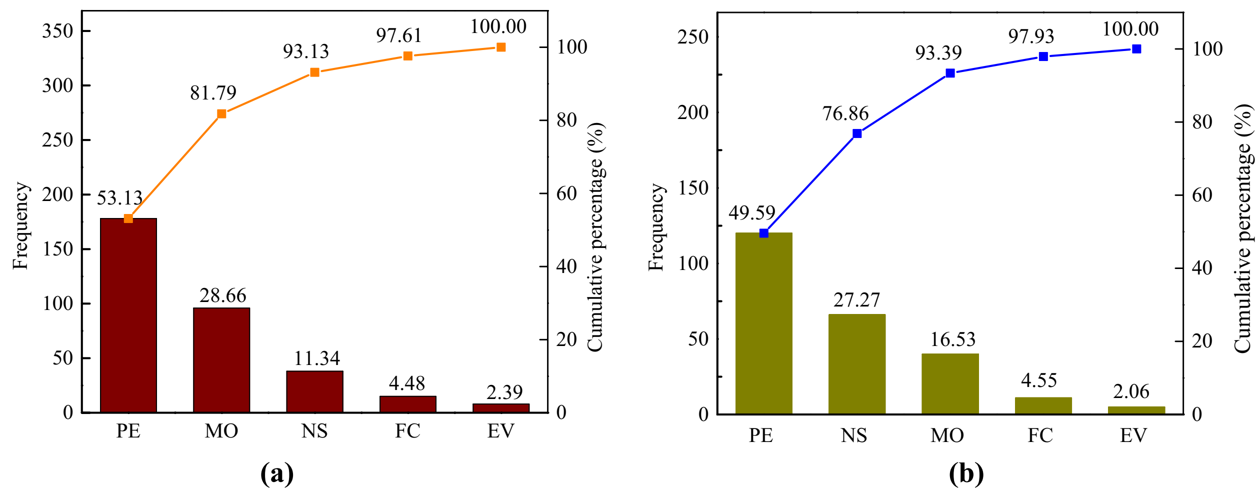

Figure 3 Statistics of research methods on SC process parameters: (**a**) In China, (**b**) Outside China

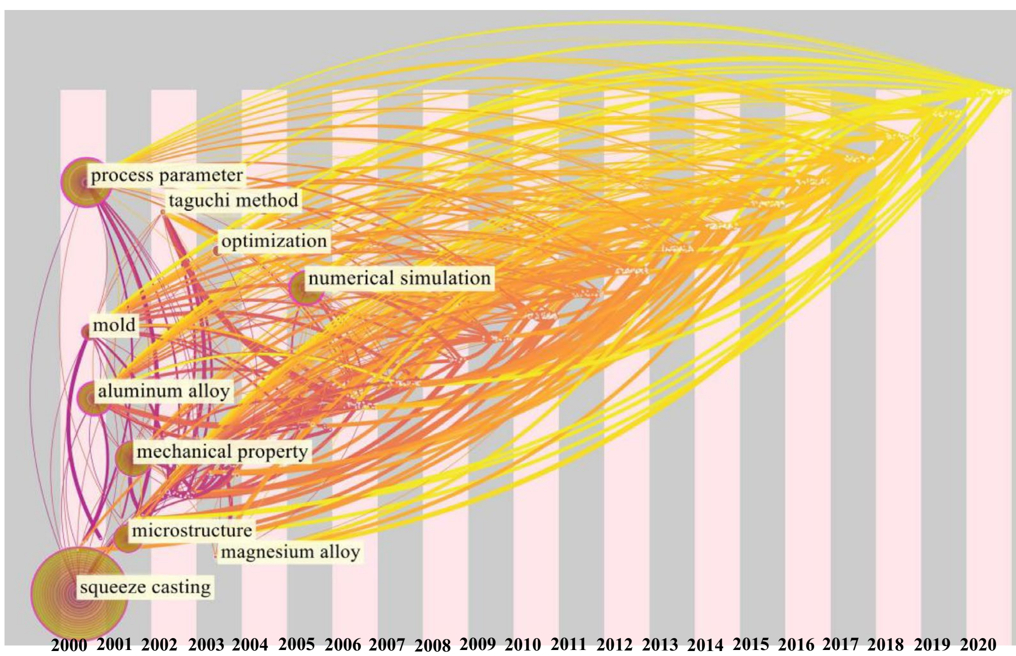

Figure 4 Time-zone maps of the keyword analysis of research methods for SC process parameters in China

among the research methods and other keywords [5]. As shown in Figures 4 and 5, the development trend of each research method over time (i.e., application intensity and time period) can be observed according to the connection (line) between the keywords after the keywords are divided by year. The orthogonal experimental method appeared the earliest, and is present throughout almost all time zones; however, its degree of application was not high. This is because, as mentioned previously, it is seldom used as a keyword, which leads to inadequate software analysis. Numerical simulations are a newly developed research method that have become widely applied in the research on SC process parameters owing to their low cost. The method for optimizing process parameters by applying data-modeling optimization in China is not late. However, its application remains limited and is mainly concentrated in recent years. Outside China, the application of this method began several years later and has decreased in recent years. This may be due to insufficient data quantity and quality. The results

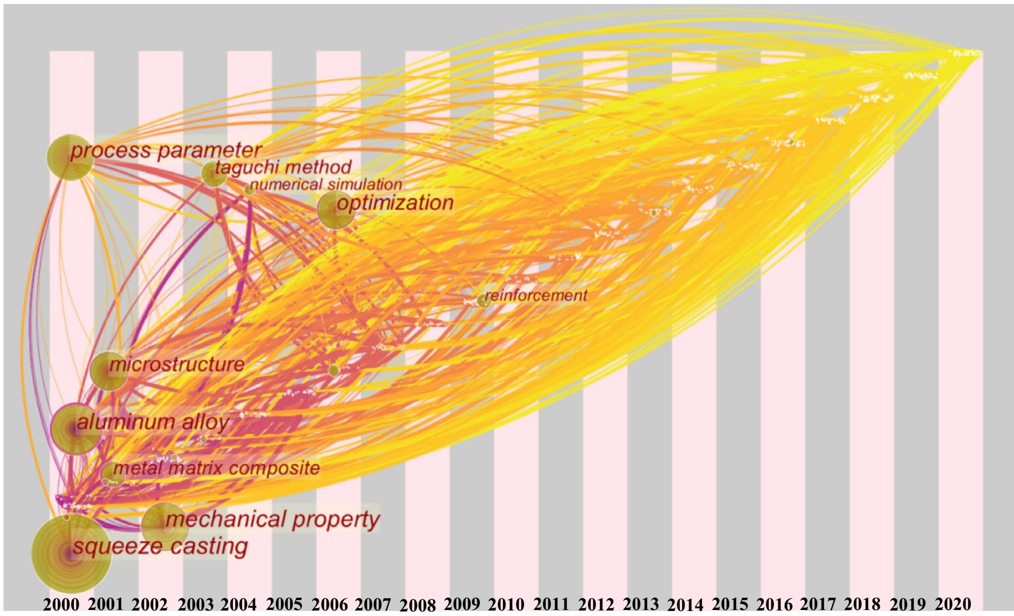

Figure 5 Time-zone maps of the keyword analysis of research methods for SC process parameters outside China

reflect the trend in the development of research on SC process parameters.

3 Detailed Status of Acquisition Methods for SC Process Parameters

As mentioned previously, according to the CiteSpace software and literature statistical analysis, the current methods for acquiring SC process parameters mainly include physical experiments, numerical simulations, and modeling optimization based on experimental data, theoretical calculations, and use of empirical values. A universal method is still lacking, and experiments remain the most important approach, while the proportion of the use of empirical values is low. Numerical simulations and model-based optimizations have become the newly required methods. Based on the characteristics of the research methods, numerical simulation is classified as an experimental method, and the main characteristics of the research methods for SC process parameters are further analyzed and summarized in three categories: fully experimental, modeling and optimization methods based on experimental data and theoretical calculation methods, as shown in Table 3.

3.1 Obtaining Process Parameters Using Experiments Only

This method is a traditional trial-and-error method and can be divided into physical experiments and simulation experiments (represented by numerical simulations) according to the experimental research. This is the most widely used method in SC research. The effects of certain process parameters on the properties of the materials or castings are experimentally observed to obtain the influence rules and determine the optimal process parameters. According to the specifics of the research namely its objects and methods, the research characteristics are reflected in two aspects, as shown in Figure 6.

The research objects can be divided into two categories: process parameters of specific materials, and castings with specific shapes. The first category represents the majority of the papers.

Table 3 Primary research methods for determining SC process parameters

Research method		Method characteristics	Merits and demerits
Fully experimental	Physical experiment	Finding optimal parameters via control variable method	Too many experiments, expensive
	Numerical simulation		Too many experiments, inexpensive
Modeling and optimization based on experimental data		Obtaining and optimizing experimental data using data-mining technology	Reliability of results depends on sample data, but amount of sample data is small
Establish empirical formulas		Establish design criteria or empirical formulas of process parameters according to the process	For certain types of casting, and the error is usually large

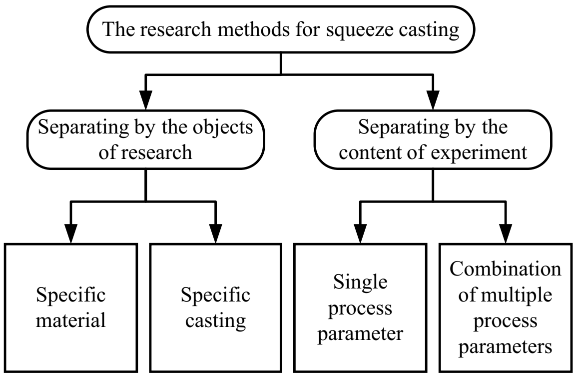

Figure 6 Classification of fully experimental methods

For example, in Refs. [7–12], aluminum and magnesium alloys, respectively, were used as experimental objects to study the effects of the SC process parameters on their microstructures and mechanical properties, and the optimal process parameters were determined. In Refs. [13–15], the SC process parameters of composite matrix materials were investigated. This type of research focuses on material preparation, and its main purpose is not to determine the optimal process parameters but rather to examine the effects of the process parameters on castings and to obtain the best performance of the material through SC and better process parameters, where the experimental castings are usually relatively simple (most are cylindrical casts) and differ significantly from the actual products. The materials involved in the research on SC process parameters carried out to date include aluminum alloys [7–9], magnesium alloys [10–12], zinc alloys [16–18], and metal matrix composites [13–15]. As indicated by the results of the statistical analysis of the keywords presented in Figure 1 and Table 1, aluminum alloys and metal matrix composites attracted the greatest research interest, followed by magnesium alloys, reflecting the current application and development direction of SC. In Refs. [19–21], the effects of different process parameters on the molding quality, microstructure, and properties of actual castings were analyzed experimentally, and the optimal process parameters were determined. Compared with the first category of research, the shape of the castings is more complex; that is, this type of research considers the requirements for the material and geometric shape and their effects on the process parameters. For example, the cast of Ref. [20] was an aluminum alloy gearbox, the cast studied in Ref. [22] was an automobile frame part, a magnesium alloy wheel was studied in Ref. [23], and a magnesium alloy automobile steering knuckle arm was studied in Ref. [24]. In conclusion, physical experiments are used for the first type of research; for the second type of research, although physical experiments are still the main methods, numerical simulation has been employed in an increasing number of studies. For example, in Ref. [22], the process parameters of automobile frame castings were studied using the ProCAST simulation software, and in Ref. [23], a numerical simulation was used to study the process parameters of a magnesium alloy wheel and then was eventually used to manufacture high-quality castings without defects; however, studies using numerical simulation prefer to design dies and optimize casting shapes. The existing hypotheses and simplifications of the numerical simulation process, as well as the limitations of the simulation software lead to inaccurate simulations of the SC process. To compensate for this deficiency, Refs. [25–27] have been performed in which the experimental and numerical simulation methods were combined to determine the process parameters for specific materials and shape casting. In such combined approach, numerical simulation is typically used to design and analyze process parameters and dies based on multiple simulation experiments, and physical experiments are then used to verify the optimal process parameters and dies obtained through numerical simulations [28–30]. However, in a few studies, the process parameters of specific materials were directly investigated through numerical simulations. Thus, the physical experiment method is applicable not only to the study of material properties, but also to the process parameters of specific castings. However, physical experiments focus on the process parameters of material preparation, that is, they consider the effects of material composition requirements on the process parameters, whereas the numerical simulation method focuses on the process parameters of actual castings, that is, the effects of the geometry and pouring mode (related to the dies) on the process parameters. Because both material composition and geometry affect the properties of squeeze castings, their combined use is expected to become a trend in future research. Moreover, due to the use of numerical simulations, the number of physical experiments can be significantly reduced, effectively reducing costs and improving the efficiency of process parameter determination.

The SC process parameters include the pouring temperature, die preheating temperature, squeeze pressure, holding time, pressure holding time, and pouring velocity. Accordingly, the experimental content can be divided into experiments involving single process parameters [31, 32] and those involving combinations of multiple process parameters [33–35]. Orthogonal experiments are the most commonly used method for studying combined process parameters. For example, in Refs. [31, 32], the effects of the squeeze pressure on the properties of castings were studied, and in Refs. [36, 37], the effects of the pouring temperature on the microstructure and mechanical properties of castings were examined, and suitable process parameters for the castings were identified. In Refs. [38–40], the effects of the solidification time and die temperature on the microstructures and mechanical properties of squeeze casts were studied. Many studies have been conducted on the combinations of multiple process parameters, including squeeze pressure, pouring temperature, die preheating temperature, and holding time. Various combined research approaches can be used with different numbers of process parameters and selected process parameters; for example, in Ref. [41], the effects of the squeeze pressure and die temperature on the mechanical properties and microstructures of aluminum alloy casts were studied; in Ref. [34], the effects of the squeeze pressure, die preheating temperature (and pouring temperature) on the mechanical properties of a SC LM-20 aluminum alloy were studied; in Refs. [42, 43], the effects of the combination of the squeeze pressure and the pouring temperature on the mechanical properties of an SC alloy were studied, and six groups of process-parameter combinations were obtained from these studies. Figure 7 presents the distribution of the process parameters in SC experimental research over the past five years. Combinations of three or more process parameters are commonly studied, and the combination of three process parameters accounts for the largest number of studies. The most commonly studied process parameters are the squeeze pressure and pouring temperature, highlighting the essential characteristics of SC for which these process parameters are the most important. Owing to the limitations of experimental cost, for all of these methods some parameters must be fixed during the experiments, such that the process parameters are not optimized and

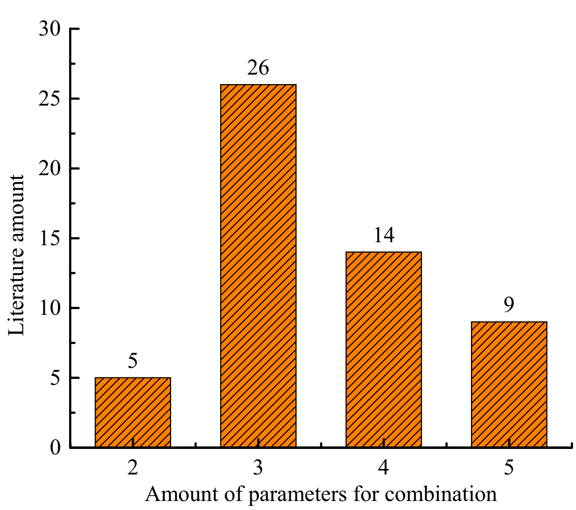

Figure 7 Determination of SC process parameters in the last 5 years

are usually determined empirically. However, both single- and combined-parameter studies focused only on specific materials. We note that the multigroup data of process parameters produced by the combined experimental method create conditions for the application of data-mining technology to the optimization of the process parameters.

This indicates that the process parameters obtained experimentally can only be tested for a single material and cast each time. However, the material compositions and casting geometries are diverse; thus, this method shows poor adaptability and flexibility (even for numerical simulations, casting replacement requires additional modeling, mold redesign, iteration, and incurs significant time consumption). In this approach, the obtained process parameters are selected from a discrete set of process parameters used in the experiment. A larger set of process parameters in the experiment corresponds to more optimal process parameters. However, additional experiments lead to a higher cost and longer time required to obtain the process parameters. Therefore, only a limited set of experiments can be conducted; some process parameters are usually fixed, and experimental studies of all process parameters are rarely carried out. If the selection of the experimental process parameter set is unreasonable, the process parameters can only be selected from these unreasonable process parameter sets, and there is a high probability that the experimentally obtained process parameters are only locally optimal. Second, experimental error is inevitable, and its influence on the results of the experiment may lead to an incorrect selection of the process parameters. Generally, production experiments of the same cast are conducted on a device, and the experimental results cannot escape the influence of different equipment; if the production equipment changes, the optimal process parameters obtained for a given device may not be optimal for other devices because of the different equipment performance characteristics. Additionally, previous experimental studies have focused on the influence of the material composition; thus, the final process parameters obtained are not necessarily suitable for actual casting production.

With regard to the casting space, which consists of the material composition and shape changes, this method is similar to "point mining". Moreover, the experimentally generated data were not fully utilized, and only supported the analysis of the relationships between the process parameters, microstructure, and performance of a single cast. There is no clear connection between the different studies (on casts of different materials and shapes); thus, it is difficult to determine the relationship between the material components and process parameters, as shown in Figure 8. Therefore, although many studies have

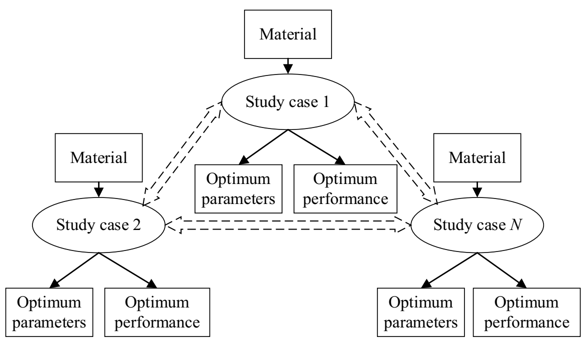

Figure 8 Relationship between the studies of SC process parameters

been performed on SC process parameters, it is difficult to obtain a method that can rapidly determine suitable parameter values.

3.2 Modeling and Optimization Based on Experimental Data

The process parameters determined by the first method depend completely on the preset process parameters in the experiments; this means that global optimization of the process parameters cannot be ensured. Furthermore, a large amount of data is produced in the concurrent multiple-parameter design, increasing the processing difficulty. However, this provides the basic conditions for a modern optimization algorithm to analyze the experimental results. With the emergence of various optimization algorithms and their wide application in other fields, multi-objective optimization, neural networks, and particle swarm optimization (PSO) have been successfully used to optimize the design of SC process parameters [33].

As indicated in Table 1, and Figures 4 and 5, an increasing number of studies on the optimization of process parameters have been conducted; however, these studies are still not abundant, reflecting the future development trend of research on SC process parameters. For example, in Ref. [44], based on 16 groups of experimental data from orthogonal experiments, a mathematical model for the relationship between the process parameters and part performance indices was established using a back propagation (BP) neural network combined with a genetic algorithm (GA) to optimize the process parameters. In Ref. [45], a multilinear regression analysis was used to establish the relationship between the ultimate tensile strength, hardness, and percentage elongation of Al-6061 alloy castings and the squeeze pressure, melt temperature, and SiC wt.%, respectively, and the optimal casting process parameters were obtained by employing grey relational analysis and desirability analysis. In Ref. [46], a mathematical model representing the process was developed using nonlinear regression analysis. The optimum casting parameters were obtained using the Taguchi method and GA optimization. In Ref. [47], a BP neural network was used to establish a mathematical model for the relationship between the mechanical properties of the AZ219D magnesium alloy and the SC process parameters, and the influence of the process parameters on mechanical properties of the alloy was analyzed. Comparison with experimental data showed that the model prediction accuracy reached 96%. In Ref. [48], a BP neural network and recursive neural network (RNN) were used to establish mathematical models for the relationships between the wear rate and process parameters of SC parts. The comparative experiments revealed that the RNN model achieved the best results. Patel et al. [49] designed a combined experiment using the central composite design and Box-Behnken design methods in the response surface experimental design method, studied the relationships between the process parameters and casting properties, and established nonlinear regression equations for the relationships between the process parameters and performance indices using experimental data together with the GA and PSO optimization methods. The combination of process parameters corresponding to the highest wear resistance of the castings was obtained. In Refs. [50–52], data mining technology was used to optimize the process parameters obtained from experimental research.

In contrast to the first method, the process parameters obtained via this method are not directly selected from the predesigned (finite) set of process parameters but rather are derived from the experimental data by assuming that there is a mathematical relationship between the process parameters and casting properties and that this relationship can be described by a mathematical model. A model relating the process parameters and casting performance is established using an optimization algorithm. Finally, the process parameters are obtained through the optimization solution, and the optimal value of the continuous global space is obtained. Evidently, this method gives results that are more optimal and accurate than those obtained by the first method. However, it is necessary to first obtain the data for modeling based on experiments. The data samples used were insufficient and limited to experiments for a single material. In essence, this approach is still an experimental method that is not universal and cannot be adapted to the wider application requirements of SC. Because only a small amount of experimental data is used, there is essentially no difference from the traditional experimental method of "point mining"; here, data-mining technology cannot truly provide its strong knowledge-discovery ability. Additionally, the established model is limited to the relationship between the process parameters and casting properties or molding quality and does not involve either the microstructure or the material composition. Elucidation of the relationships between the material and its processing, structure, and properties is a basic goal of materials research.

3.3 Theoretical Calculation Method

The theoretical calculation method is used to obtain the process parameters by establishing an analytical mathematical formula, so that the calculation of the specific parameters only requires the input of the basic parameters during production. This is undoubtedly the ideal method for rapid determination of process parameters. However, theoretical calculations must be based on the corresponding model. Because different understandings exist regarding the forming model of SC, there are many calculation formulas for the same process parameters. To date, most of the formulas for the SC process parameters have been reported for the holding time [38, 53] and squeeze pressure [53–55], and the partial formulas are complex, increasing the calculation difficulty; most formulas include unknown parameters that are obtained via testing. This requires a small-parameter test before the calculation, which is inconvenient. For example, in Ref. [54], two empirical formulas were established to calculate the squeeze pressure and holding time, as shown in Eqs. (1) and (2); however, they were not accurate for specific castings, which affected the casting quality.

$$p = K_1 K_2 \left[1 + 0.001 \left(\frac{H}{a} \right)^3 \right]. \tag{1}$$

Here, K_1, K_2 are the coefficient determined by the material and pressurization method, respectively, H is the maximum height of the cast, a is the maximum thickness of the cast, and H/a is the relative height.

The holding time is calculated using the square-root formula:

$$t = \left(\frac{M}{C} \right)^2, \tag{2}$$

where M represents the cast thickness, and C is the solidification constant.

Liu et al. [56] determined that holding time can be designed according to the following formula:

$$t = (0.9 \sim 1.3) \times d, \tag{3}$$

where d denotes the maximum cast thickness. Xing et al. [57] obtained theoretical design formulas for four key SC process parameters: Compacting pressure, metal-pouring volume, holding-pressure time, and squeeze-pressure force, according to the process characteristics and the related mechanical theory of SC. They verified the effectiveness of these formulas; however, many parameters for the physical properties of the material and the features of the mold were included in the formulas. Quantitative calculation models for the pressure starting time, holding time, and pouring height in the roll SC process were established according to the material mechanics and solidification theory proposed by Yang [58]; however, these formulas are only applicable to roller parts. In Ref. [53], formulas for the squeeze pressure and holding time were obtained by studying the metal solidification theory and heat transfer in the SC process. Because the holding time mainly depends on the cast solidification time, many researchers have studied the cast-holding time by examining the solidification behavior. Yang et al. [38] obtained a formula for the shell thickness X of a cylindrical casting and the solidification time by determining the cooling solidification curves of the parts. The solidification time is calculated as follows:

$$t = \sqrt[n]{X/K}, \tag{4}$$

where K is the solidification coefficient. K and the power exponent n are determined by the thermophysical properties of the material and the magnitude of the pressure. Li et al. [59] established equations for the relationships between the solidification time, pressure exertion time, and holding time of SC zinc-aluminum alloy plunger casts as follows:

$$\begin{cases} \tau_T = \tau_0' + \tau_H, \\ \tau_H = \dfrac{akT_{\mathrm{m}}^2 (R_0 - \delta_0)}{D_L \Delta H_0 \left(\Delta T_k^2 + \frac{\Delta V}{\Delta H_0} T_m P_b \right)}, \end{cases} \tag{5}$$

where τ_T, τ_0', τ_H, and P_b are the solidification time, pressure exertion time, holding time, and squeeze pressure, respectively. Additionally, in Refs. [38, 60], formulas for the calculation of the solidification time were established by simplifying the heat transfer process of SC.

The existing design formulas for SC process parameters have a significant limitation in that they are only applicable to a certain type of cast with uniform features. Theoretical calculation formulas have large deviations of the theoretical values from the experimental results because little attention has been paid to the interaction among the process parameters, and the coupling effects among the process parameters have been neglected.

In summary, all existing design methods for the determination of SC process parameters have shortcomings that make it difficult to satisfy the requirements of rapid SC process development. In particular, the SC process parameters must be determined through tedious experimental research and data analysis. There is no essential difference between the former two methods, both of which require experiments, and for both of which the results are limited to single-material casting. Even though optimization obtains more optimal process parameters, the research results cannot be generalized and widely applied, and the research process is time-consuming and laborious. The current design criteria and empirical formulas for SC process parameters have extended their application scope to a class of casts with the same features; however, there are numerous errors in practical applications owing to the incomplete consideration of the interaction between different parameters. Moreover, it is difficult to establish a connection among different studies to identify underlying knowledge rules.

4 Development Requirements and Trend of SC Process Parameter Research

4.1 Management and Utilization of SC Process-Parameter Data

A large amount of research on SC has produced a large amount of process-parameter data. However, currently, only the second process-parameter design method can be regarded as a direct application of the experimental data. There is a lack of more comprehensive application and mining of data and a lack of clear management of process-parameter data, resulting in the large waste of data resources. With the maturity of big data technology, data have become a new production resource, and data-driven technology has become a new paradigm in scientific research and an important direction for intelligent manufacturing. Additionally, to design new materials and shorten their design and manufacturing application time, material science research has increasingly used approaches based on data and models. For example, the "Materials Genome Initiative" proposed by the United States in 2011 [61] and "Materials Science System Engineering" proposed by China both emphasize the management and application of material data based on information technology and have established a series of material databases such as MatWeb established in the United States, and National Data Sharing Network of Materials Science established by University of Science and Technology Beijing.

Therefore, strengthening the management of existing SC process-parameter (research) data, particularly data in the published literature, and establishing a data-mining research method for SC have become development trends and inevitable requirements. Data mining relies on large sample sizes. Therefore, similar to the existing materials science research, we must establish an SC process-parameter big data system to support the sharing and application of the data, e.g., developing an SC process-parameter design method based on data and an SC forming mechanism based on data mining, and predicting the cast performance by establishing casting performance prediction models based on data. This necessitates the use of data-acquisition methods and ensuring data quality; for example, the extraction of existing literature on SC process-parameter data, the reliability evaluation of data from different sources, and the treatment of conflicting data.

4.2 Rapid and Universal Method for Obtaining SC Process Parameters

As indicated by the above analysis, there is no unified method for obtaining SC process parameters. Most methods depend mainly on physical experiments, which are expensive and inefficient; furthermore, each physical experimental study applies only to a single material or cast, limiting its adaptability. The existing theoretical calculation formulas are not comprehensive, and most are empirical formulas that are not accurate (the calculated values show large deviations from the actual values), do not consider the interaction between process parameters, or only apply to a certain type of cast. As advanced manufacturing processes, SC has good development potential. Therefore, to satisfy the requirements for the application and development of SC, a mature, universal, and rapid process parameter design method is urgently required. As the manufacturing of materials and products becomes increasingly digital, realizing a rapid digital design of SC process parameters based on data is an inevitable trend. In particular, after the establishment of an SC process database, the relationship between material composition and process parameter (microstructure) properties can be established via data mining through informatics and statistical methods, and a data-driven design method for universal process parameters adapted to different materials can be constructed. Based on the experience obtained to date with existing big data application technology and the data-based process parameter design of other processes [62, 63], several paths can be pursued for the construction of such universal data-driven design method. (1) Based on case-based reasoning, process design of SC process parameters is carried out using the SC process parameters obtained through an experimental study as a case, and the existing process parameters are generalized by establishing a suitable case-based reasoning model for SC application to obtain the process parameters of a new cast. This enables the direct application of SC process-parameter data with low cost and high efficiency. The accuracy of this approach depends on the similarity determination method and the number of cases. For example, we refer to the process parameters of the A-alloy wheel hub to obtain the process parameters of the B-alloy wheel hub with similar compositions. (2) Specific parameters of the theoretical formulas are obtained based on data mining. As mentioned previously, most theoretical formulas are essentially empirical formulas, in which a large number of parameters need to be fit or approximated. Thus, we can achieve a new understanding of the influence law and parameter values based on data, for example, correcting the formulas and establishing statistical engineering models for designing SC process parameters, and then improve the accuracy of the theoretical formulas. For example, the relationship between the height of the squeeze casts and the pouring temperature is obtained from the data, and then the temperature obtained solely based on materials is corrected, such that the process parameters of differently shaped squeeze casts are designed. (3) The direct design of SC process parameters through data mining (including machine learning). Data mining is a knowledge discovery process for extracting potentially useful information hidden in a large amount of noisy data. Compared with existing data-based modeling optimization, numerous mature mining algorithms (such as regression analysis, neural networks, and support vector machines) can be used to obtain the relationships among the material composition, geometric shape, process parameters, and material properties because of the richer data, and then to establish the design model. With continuous progress in machine learning algorithms, establishing an intelligent design model for process parameters based on machine learning is a new research direction. For example, a deep learning model of the material compositions and SC process parameters can be constructed using the process parameter database of different materials, and then the SC process parameters can be obtained directly by inputting the material compositions. In addition, numerical simulation techniques can be used to simulate the SC process with different process parameters to reduce the experimental cost of realizing a fully digital design of the SC process parameters.

4.3 Realization of Comprehensive Parallel Integration Design of Multiple Process Parameters

According to the principles of SC and extensive research, the material composition, casting geometry, die, and extrusion mode are all important factors that affect the SC process parameters. Material composition is the most important factor, followed by geometric shape. The current optimization method, which involves modeling based on experiments and experimental data, focuses on the influence of material composition, whereas the theoretical formula calculation method focuses on the influence of the geometric shape, and numerical simulations focus on the influences of the geometric shape and die design. However, all of these methods are limited to a single cast; that is, the current methods either do not fully consider the two main factors of the SC process parameters, or their adaptability is not strong. For the wide application of SC in the production of product parts, it is necessary to consider both material and geometry in the process-parameter design. It is necessary to develop a rapid SC process-parameter design method to adapt to different materials and shapes; therefore, it is important to develop a process-parameter design method that either considers both the material composition and cast shapes or integrates the existing meta-methods.

Although there are many SC process parameters, the current experiment-based process parameter design method has only focused on the research and acquisition of two or three main process parameters owing to the limitation of the experimental cost and the need for complexity control. Many studies have focused on only one process parameter, whereas other process parameters are set empirically. Some studies have indicated that the SC process parameters are related to each other; for example, the squeeze pressure changes the solid-liquid phase temperature and affects the solidification time. This indicates that an optimal combination of the process parameters exists. Individual or unit designs cannot reliably optimize casting performance. Therefore, it is necessary to realize concurrent design of SC process parameters.

5 Conclusions

SC process parameters are crucial for producing high-performance casts and have been widely studied. There are five methods for determining the process parameters: physical experiments, numerical simulations, modeling and optimization, theoretical calculations, and reliance on experience. An increasing number of researchers have begun using numerical simulations, modeling, and optimization. Based on the proportion of methods used, the main methods were divided into three categories: fully experimental, modeling, and optimization based on experimental data and calculations based on theoretical formulas. However, the existing methods for determining the process parameters are mainly experimental, and most studies have focused on determining the process parameters of SC materials. The experimental method does not make full use of the experimental data and is generally conducted only for specific materials and specific shape castings with poor adaptability, which is not in accordance with the SC development and application trends.

Therefore, there is an urgent need for universal and rapid parameter acquisition and design methods. The following directions are suggested: (i) Strengthen the management and utilization of SC process parameter data;

(ii) establish a universal and rapid method for obtaining SC process parameters, particularly a data-driven SC process-parameter design method; (iii) comprehensively consider the effects of different factors on the SC process parameters, such as the material composition and geometric shape of the casts, and develop an integrated method for the concurrent design of multiple process parameters.

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Authors' Contributions
JD and BX were in charge of the entire trial, and HH assisted with the sampling and laboratory analyses. JD and BX wrote the manuscript, and JD, BX, and DY assisted with revision. All authors read and approved the final manuscript.

Authors' information
Jianxin Deng, born in 1979, is currently a professor and master's supervisor in mechanical engineering at *Guangxi University, China,* and vice director at *Guangxi Key Lab of Manufacturing System and Advanced Manufacturing Technology, China*. He received his master's degree in industrial engineering from *Chongqing University, China,* in 2004 and his Ph.D. degree in mechanical engineering from *South China University of Technology, China,* in 2010. His research interests include manufacturing systems and informatics, squeeze-casting technology, e-manufacturing, product axiomatic design, and manufacturing service technology.
Bin Xie, born in 1996, is currently a master candidate at *Guangxi University, China*.
Dongdong You, born in 1973, is currently a professor at *National Engineering Research Center of Near-Net-Shape Forming for Metallic Materials, South China University of Technology, China*. He received Ph.D. degree in mechanical engineering from *South China University of Technology, China,* in 2007. His research focuses on squeeze casting and intelligent machine design methods.
Haibin Huang, born in 1994, is currently a master candidate at *Guangxi University, China*.

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No data available.

Declarations

Competing Interests
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