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Injection molding manufacturing process: review of case-based reasoning applications

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Abstract
Although manufacturing technology has been developing rapidly, injection molding is still widely used for fabricating plastic parts with complex geometries and precise dimensions. Since the occurrence of faults in injection molding is inevitable, process optimization is desirable. Artificial intelligence (AI) methods are being successfully used for optimization in different branches of science and technology. In this paper, we review the application of one such method, case-based reasoning (CBR), to injection molding. CBR is an AI approach for knowledge representation and manipulation which considers successful solutions of past problems that are likely to serve as candidate solutions for a given problem. This method is being used increasingly in academic and industrial applications. Here, we review CBR systems that are used in injection molding for different purposes, such as process design, processing parameters, fault diagnose, and enhancement of quality control. In addition, we discuss trends for utilization of CBR in different phases of injection molding. The most significant challenges associated with application of CBR to injection molding are also discussed. Finally, the review is concluded by contemplating on some open research areas and future prospects.

Keywords Injection molding · Case-based reasoning · Manufacturing process · Artificial intelligence · Fault detection

Introduction

Thermoplastic polymeric products are indispensable in today's life, and injection molding is the most widely used in fabrication of plastic parts. With worldwide increasing demands on plastic parts, it seems necessary to facilitate the production process by increasing its efficiency and productivity. Injection molding is a four-phase cyclic process that includes the phases of filling, packing, cooling, and ejection. In this approach, molten material moves into molds at high pressure, while granular or pellet-like raw plastic material is converted to the final product. The quality of the final product depends on several parameters, such as raw materials, mold design, and process-specific parameters. It is possible to increase the quality of the final product by optimizing process-specific parameters and production conditions.

Artificial intelligence (AI) dealing with systems that exhibit intelligent behavior, and has been increasingly used in different branches of science and technology for solving difficult problems. Moreover, AI has been applied considering significant increasing in utilizing sensors to capture data at all stages of a product's life (Kusiak 2017). Recently, data mining applications are developed for knowledge acquisition in modern manufacturing environments. In work Choudhary et al. (2009) a comprehensive review on data mining applications in manufacturing is presented, e.g., data mining prototype for fault diagnosis (Li et al. 2006). AI-based systems are likely to be appropriate for optimization of process parameters in injection molding, as well as for the detection of faults and for increasing the efficiency and productivity of this manufacturing technique. Different methods, such as Taguchi technique, artificial neural networks (ANNs), fuzzy logic (FL), genetic algorithms (GAs), response surface methodology, principal components analysis, and case-based reasoning (CBR) are briefly reviewed in Yadav et al. (2012). As a result the researchers found that the implementation of CBR systems increased simplicity of setting process.

CBR as a problem-solving method of AI relies on learning and reasoning based on the previous experiences. It is

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a commonsense reasoning approach that is similar to the problem-solving method used by humans, and is based on the recall and reuse of knowledge of past cases and experiences. Several successful applications of CBR to engineering problems demonstrated that this approach exceeds initial expectations and can be used in other fields. Hence, CBR has been used in real-world applications in various areas, such as fracture mechanics, and process engineering design (Khosravani et al. 2019a; Reyes et al. 2015). Using the CBR approach, problems can be solved faster and more efficiently, compared with conventional methods. Recently, applications of CBR to injection molding were considered, and much of this work is comprehensively reviewed in what follows.

The preliminary objective of this study is reviewing applications of CBR methodology in injection molding process to determine how this method can shorten the process design, predict parameters and diagnose failures. Obviously, a quick-cycle process could yield a significant amount of final product. In this case, using CBR systems can help to optimize the production time and increase the productivity significantly. Several researchers investigated different intelligent systems, aiming at specific tasks in injection molding. For instance, in Ozcelik and Erzurumlu (2006) response surface methodology and GAs were used for minimizing the warpage of thin-shell plastic parts. Appropriate dimensional parameters were determined and predictive models for minimal warpage were developed. The computational cost of optimization was reduced using the response surface methodology, and the methodology was combined with GAs to determine optimal process parameters. Using the results of that approach, a significant reduction in warpage was obtained, suggesting that the method can be used for optimization of other thin-shell plastic parts in injection molding. However, as reviewed and described in Mok et al. (1999), ANNs and GAs can be used for determining processing parameters in injection molding, but training and retraining of ANNs are time-consuming. In addition, the rate of convergence to an optimal set of parameters may be very slow in some cases. Various methods require different amounts of user expertise and time to effectively use the software. For instance, software packages are very expert-dependent and require years of experience to take full advantage of their functionality. Therefore, methods should be selected with an eye toward optimization and increasing efficiency.

Despite significant advances in AI systems that use the CBR approach, the breakthrough point is still hindered by a slow rate of development of methods to control the parameters of injection molding using AI approaches and by a slow implementation of systems that use AI techniques. The goal of this article is to provide a review of available CBR systems that are used in injection molding. The review aims at identifying specific areas in injection molding that could be developed and optimized using CBR systems. Also, this study presents some open research problems and proposes orientation and topics for future research and development. The remainder of this paper is organized as follows. The next section provides an overview of CBR, fundamentals of injection molding, and position of CBR methodology in injection molding. In "Applications of CBR in injection molding" section, applications of CBR and hybrid intelligent systems are comprehensibly reviewed. The last section lists some suggestions, conclusions and prospects.

Overview of CBR and injection molding

The principles of CBR

CBR is a recommendation approach that models the way humans think when building intelligent systems. CBR covers a range of various techniques for organizing, matching, using, and indexing the knowledge retained in past cases (Mantaras et al. 2005). It reuses the past experiences, either partially, completely, or in a modified form, in the context of a given problem. Therefore, to retain the knowledge, the obtained new experiences should be stored in the case base for future reuse (Aamodt and Plaza 1994). A case is not a rule, but rather is a description of a particular situation. Cases contain the features of the problems that occurred, as well as the associated values and solutions. CBR is mainly utilized when, on the one hand, cases exist and are easy to find, and on the other hand, domain experts are not available or are too expensive, e.g., application of CBR for process conditions selection in camshaft grinding (Jiang et al. 2019) and remanufacturing process planning (Zhang et al. 2013). The main assumption in CBR is that similar problems have similar solutions. As is illustrated in Fig. 1, which is adapted from Aamodt and Plaza (1994), CBR consists of five main processes which amount to refining, retrieving, reusing, revising, and retaining case-related information. In the refine phase, a given new problem (request) should be mapped onto CBR from the case structure (features and values) as a new case. In the second phase, utilizing similarity measures, a new case is retrieved from the collection of documented existing cases, and most similar cases are chosen. The proposed solutions of these cases serve as the input to the third phase of CBR. In the reuse phase, different methods, such as rule-based methods, should be used for transformation of previous similar solutions or some of their parts. Two aspects of the reuse process were described in Aamodt and Plaza (1994), the first of which relates to finding the differences between the selected case and the new case, while the second amounts to determining which parts should be transferred. Therefore, these present the two main approaches to reuse, which are (1) transformational reuse for reusing previous solutions, and (2) derivational reuse for

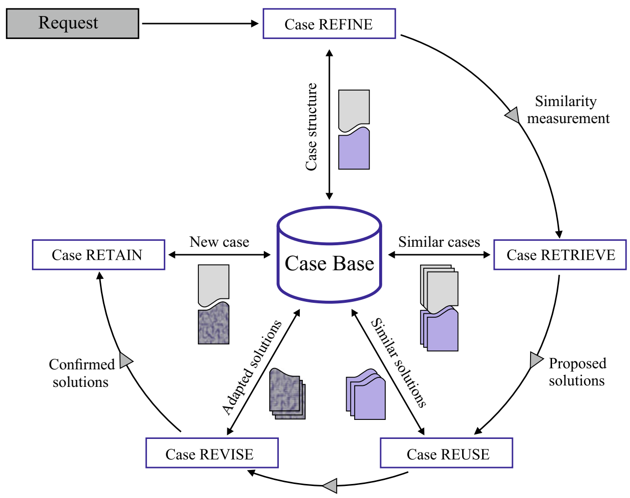

Fig. 1 Main component processes of CBR

reusing the methods that were used for obtaining these previous solutions.

After adapting similar previous solutions, a new solution requires validation. The next phase of CBR is revision, in which the new solution is checked with selected solutions from similar cases. This new solution can be revised by using adaptation methods and the knowledge of domain experts. The last step, following the validation of the quality of the new solution, is the retaining process for storing the new confirmed case. This is the learning phase, in which the newly obtained useful knowledge is added to the existing stored knowledge, based on the new problem-solving results, to modify the case base structure. This learning process can also improve the similarity procedure and the adaptation mechanism.

Fundamentals of injection molding

Injection molding is one of the most important and efficient manufacturing techniques. Today more than one third of all thermoplastic materials are injection-molded (Dai and Fan 2014), and this manufacturing process has been widely investigated, e.g., injection molding of acrylonitrile butadiene styrene materials (Tranter et al. 2017). This already justifies the need to develop and implement systems that borrow the latest development from different scientific disciplines, to increase the efficiency and productivity of this manufacturing process. The first plastic injection molding machine (IMM) was developed by the Hyatt brothers in 1872, based on the 1870 patent of injection metal casting (Hyatt and Hyatt 1872). In 1919, engineers developed a processing condition that enabled injection molding of celluloid parts of complicated shapes. Throughout the 1930s and 1940s, several companies produced IMMs in Europe and in the Unites States. In 1943, H. Beck filed a patent that described using a plasticizing screw as an injection molding piston. In the same year, W.H. Willert filed a similar patent. Reciprocating-screw machines were commercialized some years later. Modern IMMs descend from Beck's and Willert's reciprocating screw IMMs.

Injection molding is a cyclic process that consists of plasticizing stage and an injection stage. In the plasticizing step, plastic is injected into a mold via a heated cylinder. In IMMs, a hopper is used for feeding the machine with raw materials. A rotating screw is used for moving the raw material into the screw channels. The raw material is molted owing to the heat of friction that is generated by rotating the screw and by the conduction from the heating units, and moves to the tip of the screw. Pressure develops and the screw moves backward to fill a reservoir of the melt at the front end of the screw barrel. When the desired volume of the molten material is achieved, the screw rotation stops and the plasticizing stage is finished. Then, the injection phase begins, which consists of four major steps: filling, packing, cooling, and ejection. In the filling phase, the empty mold is closed by a clamp unit and the screw moves. In the next step, the mold is filled and the screw is held in the forward position or moves with a small displacement in order to hold the pressure, and the material cools down. In the cooling phase, the cavity pressure is reduced and the part continues to cool down and solidify. Finally, after sufficiently long cooling time, the part becomes sufficiently stiff, the mold opens, and the part is ejected. After that, the mold closes and the cycle starts over (Zheng et al. 2011). A schematic of IMM and the described process is shown in Fig. 2.

Position of CBR methodology in injection molding

Several parameters define the above-mentioned stages of injection molding process. The most critical processing-related parameters are injection speed, nozzle and barrel temperature, holding pressure, holding time, coolant temperature, and cooling time. Determination of appropriate processing parameters is an important issue which plays a crucial role in determining the quantity and quality of parts. During the injection molding process, the raw material experiences notable changes in its mechanical and rheological properties owing to the enormous pressure, high temperature, and rapid cooling to which it is subjected. Amassing more knowledge about these processes can help to increase production efficiency. On the other hand, many functional products should satisfy certain life-cycle expectations. This life expectancy might be time duration or repetitions of an applied load or condition. Thus, this parameter can also affect decisions related to the choice of the processing method, mold design, and assembly techniques, to name a few. In all of the above-mentioned phases, parameters and factors, it is possible to apply AI techniques for improving the produc-

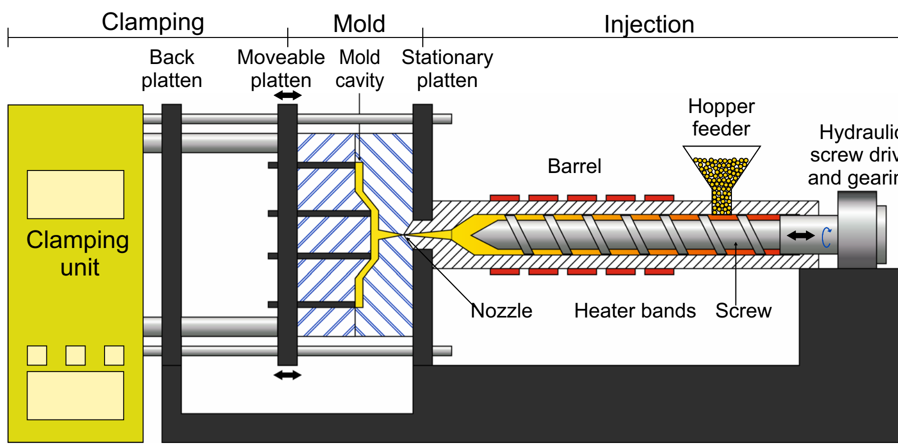

Fig. 2 Main components of IMM and injection molding process (Khosravani et al. 2019b)

tion process. However, the current survey of these methods reveals that they are limited in their ability to achieve the highest possible efficiency in the production phase, because some of these AI methods depend on appropriate training protocols, which reduces the achievability and precision of their performance.

In injection molding-based production, different faults can occur. Warpage, bubbles, sink marks, brittles, cracks, and burn marks are examples of these faults. It is possible to reduce the occurrence of these faults using appropriated AI methods. In Kumar (2017) a review on applications of AI systems in process planning is presented. Although in the last century process conditions were optimized using modified sophisticated methods and designs of experiments [as described in Sahu et al. (1997), e.g., warpage fault occurrence has been significantly reduced], the approach was found to be costly and time-consuming. Researchers have been exploring the capabilities of the knowledge-based system (KBS) in plastic production design, and several expert systems were proposed to help determining the set-point of process parameters in injection molding (Steadman and Pell 1995; Chin and Wong 1996; Bozdana and Eyerciglu 2002). A review of the implemented expert systems indicates that they suffer from two main limitations. Firstly, the knowledge that is stored in the expert system is qualitative and is not adequate for situations in which quantitative values are needed for determining injection process parameters. Secondly, since the rules in expert systems usually deal with individual defects, handling a situation that features multiple errors remains a challenging issue. Another drawback of these methods is that they require constant improvement and continuous flow of information (new training data), which increases the associated cost. With recent developments in electronics, selecting between all-electronic or hydraulic injection molding machines remains a debatable issue. All-electronic injection machines achieve faster cycling in a smaller space, while hydraulic injection machines are cost-effective and energy-efficient. Combining the best of the both, hybrid injection molding machines combine the advantages of hydraulic machines with benefits of all-electronic machines, for better performance. However, it is possible to use different AI methods in hybrid and all-electronic injection molding machines, which can potentially help to utilize the full potential of all of these machines at all times. Thus, it is essential to develop a time- and cost-efficient approach that would yield accurate and effective solutions. CBR, based on AI techniques offers one such a solution approach.

Applications of CBR in injection molding

In this section, we review the applications of CBR and hybrid intelligent systems in injection molding process. Despite the relatively small number of studies reporting CBR applications in injection molding, the reported results are quite encouraging. Figure 3 summarizes the state of the affairs related to the applications of CBR to injection molding.

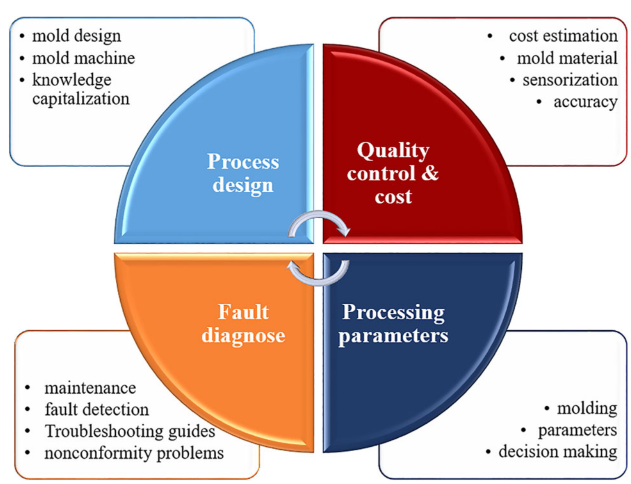

Fig. 3 Applications of CBR in injection molding

The applied domains are (i) processing parameters (PP) which used CBR to determine process parameters, (ii) quality control and cost (QC) which focuses on quality control aspects by CBR to increase final product quality, (iii) process design (PD) that contains CBR applications in molding machine and mold design, and (iv) fault diagnose (FD) which helps to detect probable faults that could be occurred in injection molding process during production and maintenance.

Intelligent systems by CBR

CBR offers some advantages compared with other methods. Due to CBR applications in some fields such as injection molding process, solutions are sharply shaped by previously solved problems, this approach could not be fully integrated into the hypothetico-deductive approach. Codification and transfer of expert experience to others can be problematic, but CBR approach successfully addresses this problem. The CBR applications in injection molding manufacturing process are reviewed based on four described categories as following.

CBR in processing parameters

During manufacturing that uses injection molding, the operator should monitor the process parameters and the checklist for any changes. If the product quality does not meet preset requirements, the operator must change the process settings to achieve good product quality. In Malek et al. (1998), a CBR system was developed to guide and help the operator to make decisions during injection molding. The authors considered a molded part as a case study, and described the system using all of the parameters that were found to contribute to the molded part, mold injection process, and appearance of defects in the molded part. Modification of quality implies that a new problem and set of plausible parameters were determined to form the entire set of injection parameters. Previous cases were catalogued, and each of them contained a complete set of parameters that described/represented the same case. As stated above, a set of cases was obtained for each defect and was saved according to their similarity. The proposed solution was composed of two parts; the first part captured the changes in the quality of the corresponding case (increase or decrease), while the second part captured the set of changes to the parameters regarding the sign of modification (increase or decrease). Researchers developed a user interface, and added an option to change settings if those were determined not to be consistent with the system. Finally, the developed system was used for experimental detection of flash defects which is a thin layer of plastic outside the cavity.

In the early 2000s, CBR was used to develop a case-based system for design of injection molding processes (Kwong 2001). Since several issues should be considered when designing an injection molding process (such as selecting the molding machine, mold design and selecting process parameters), these issues are usually performed by experienced staff. As a result, the design process is not smooth and relied on sufficiently experienced personnel. As the same authors explained in Kwong et al. (1997), a case-based system consisted of the user interface, a case-based reasoner, a case library, and an editing interface. Researchers consulted with some experts, and several features were considered for indexing which expressed numerically. The system's complexity was captured by an adopted system based on the group technology complexity rating approach. The system stored pre-defined cases. In this regard, problem description, solution and outcomes were considered for each case. Combination of searching and matching was required for case retrieval, and similarity analysis was applied to find the closest case. The best matching case was suggested as the reference case. In the last step, case adaptation was performed. When the case was derived, the solution associated with the selected case was adopted as a solution of the current problem. In the implemented system, two types of adaptation, namely substitution and transformation, were utilized. The implemented system with CBR exhibited a self-learning capability and significantly shorter injection molding design.

Mok et al. presented a system for the determination of initial process parameters for injection moulding, called HSIM. The basic architecture of the HSIM that mainly consists of an input interface, a CBR module, and a hybrid neural network and genetic algorithm (NN–GA) module (Mok et al. 2001c). The main characteristic of this research is that unlike the conventional CBR systems, HSIM can provide solutions even if there is no similar case stored in the case library. The preliminary validation of the proposed system showed that a set of initial process parameters provides quickly, without relying on domain experts.

In work Costa et al. (2012) CBR is utilized to provide product design decision support. To this aim, the researchers selected injection molding and friction material as product development scenarios to evaluate their presented idea. In detail, the cases are defined, and experiments are performed regarding to the manufacturing process. As a conclusion, they stated that since types of knowledge and information heavily depends on the type of product, configuration of support system must be adapted to type of knowledge and type of product. Later, in Mourtzis et al. (2014) CBR is employed to estimate the lead time as shown in Fig. 4. The lead time is the amount of time between the the placement of an order and receipt the final product. Since estimation of the lead time significantly impacts customer satisfaction, it is important for the companies to predict it precisely. However, researchers utilized their proposed system in a mold making industry as an industrial case study. By this application, it is concluded that CBR system predicted the lead time precisely compared

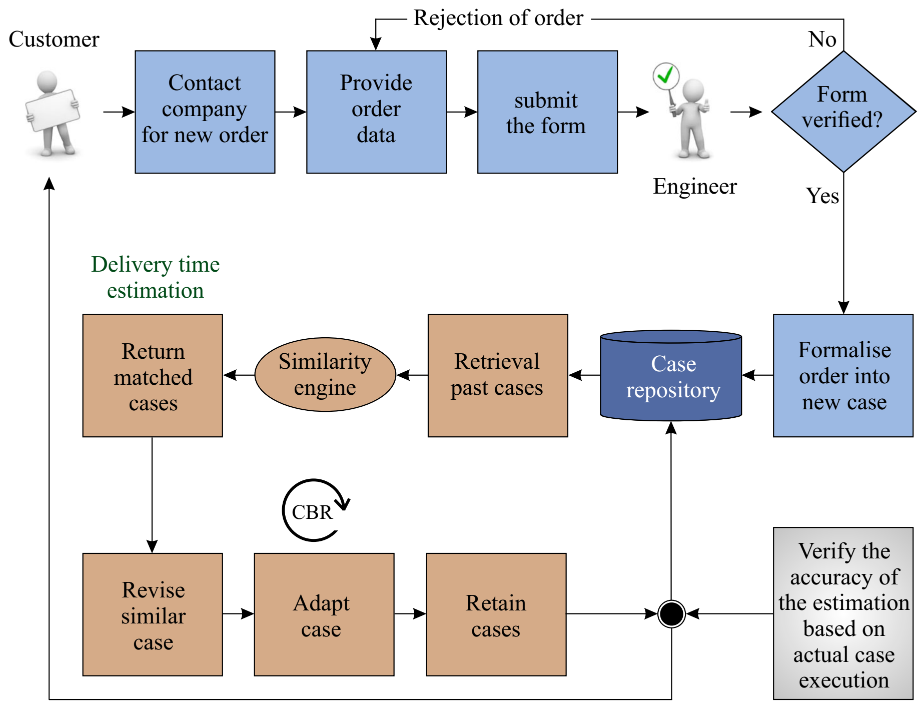

Fig. 4 Workflow of lead time estimation containing CBR steps, adopted from Mourtzis et al. (2014)

to the real values. This approach leas to improving costumer satisfaction.

CBR in quality control and cost

Since quality control plays a vital role in various manufacturing processes, changing from traditional quality inspection to the holistic quality control has been an important topic of research over the years. In this respect, in work Nedess and Jacob (1997) CBR is used for proposing a concept in quality control loop in design step, and also fault detection on the shop floor. As the similar molds are needed for similar products, the preconditions for utilizing CBR are fulfilled. The researchers claimed that the proposed concept is beneficial during the sampling procedure of injection mold, and it must be integrated with the computer-integrated manufacturing environment for a holistic quality control. Thus, the implemented system is functionally integrated with the CAD system for design of mold. Finally, a prototype is implemented to present the concept illustrated in Fig. 5.

CBR in process design

CBR was used in Kwong et al. (1997) to derive molding parameters. As it takes several years to become a molding expert in injection molding, CBR was very helpful in determination of molding parameters. Researchers implemented a CBR system that featured a user interface, a case-based reasoner, a case library, and an editing interface. They considered two heuristic methods for index selection. The first model used a checklist that was provided by the system designer, while the second one was explanation-based. In addition, a two-level similarity analysis was introduced for improving the accuracy of matching. In the case of adaptation, previously solved documented problems were compared in terms of their descriptions to the problem that demanded solution, the differences were extracted, following which the old solution was modified, to obtain a new solution. When the proposed system was used, the top five most similar cases were displayed, and an interface was provided for the user to edit molding parameters based on real-world experience.
As an example the researchers described the adaptation phase (see Table 2) for clamping pressure which shows systems' self learning and the human learning through the process of problem solving.

Case-based formulation was used for knowledge capitalization in design of plastic injection molds (Butdee 2010). The developed system enabled to reduce the mold design time. Knowledge capitalization is the procedure of knowledge reuse, which consists of different phases. The study authors described the model formulation process for knowledge capture using the CBR approach. In the described procedure, the mold data were collected, documented, and categorized. A rule base and frame were chosen for data analysis presentation and were converted into knowledge (see Fig. 6).

In the next phase, a database and relations were created, following which the input definition for the problem data was provided by the researchers. Then, a memory organi-

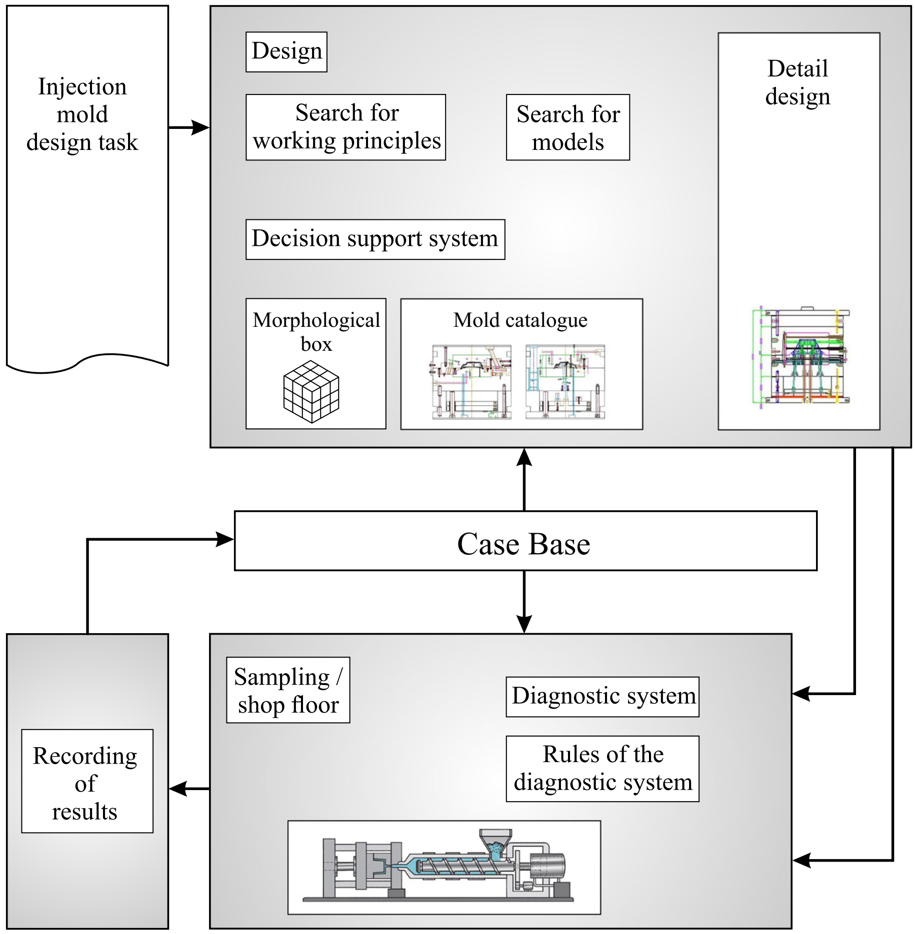

Fig. 5 An overview of a prototypical implementation, adopted from Nedess and Jacob (1997)

zation package was designed, and indexing and matching methods were applied to the database. Parts were described in terms of six attributes: shape, thickness, feature, surface, assembly type, and difficulty. These attributes were further sub-categorized. Semantic adjectives of the parts were utilized in case indexing, capturing relations between mold design and other functions. In case comparison and matching, all of the characteristics of a new case had to be matched one by one. The knowledge was linked and shared by memory organization which played an important role in the case-base formulation. In the knowledge capitalization cycle, exploit knowledge was reused, and decision making associated with injection mold design was accomplished in five steps. In the knowledge capitalization cycle, experts and analysts were employed as knowledge editors and problem solvers, respectively. The newly generated knowledge and ontology were used to retrieve past knowledge from the case-base library. Finally, the name card box was considered as a case study, and the system chose the closest case considering all injection mold design details. The results of that study suggested that the developed system helped to reduce the time required for mold design. At the same time, the designed new mold was based on previous applicable designs. Later, following this idea, the researcher proposed the concept of knowledge capitalization associated for injection mold design, which used for the testing phase and validated by shop floor experts (Butdee 2011).

Recently, in Li et al. (2018) redesign of injection mold is facilitated by CBR approach. In this regard, nearest neighbor is used to achieve the retrieval. In detail, the designer can request a retrieval, so a new transaction block can be created, and after validation can be added to the transaction blockchain. By the applied system it is claimed that the implemented system is secure to realize the knowledge sharing.

CBR in fault diagnose

In work (Mikos et al. 2007) CBR was used for solving nonconformity problems in injection molding. According to the definition of ISO 9000:2005, nonconformity is non-fulfillment of a requirement. The proposed system was organized into three main blocks: situation, solution, and outcome. Each of these main blocks had several attributes in different categories. Researchers implemented a prototype based on the Java Agent Development (JADE 2006) and also used the jCOLIBRI CBR framework as a core engine.

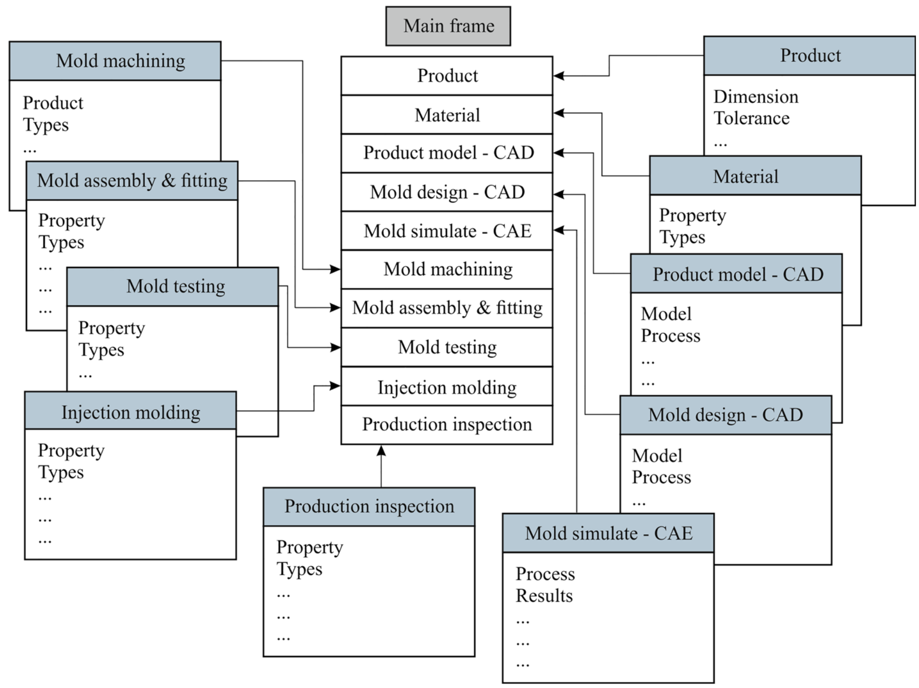

Fig. 6 Frame based representation and relations adopted from Butdee (2010)

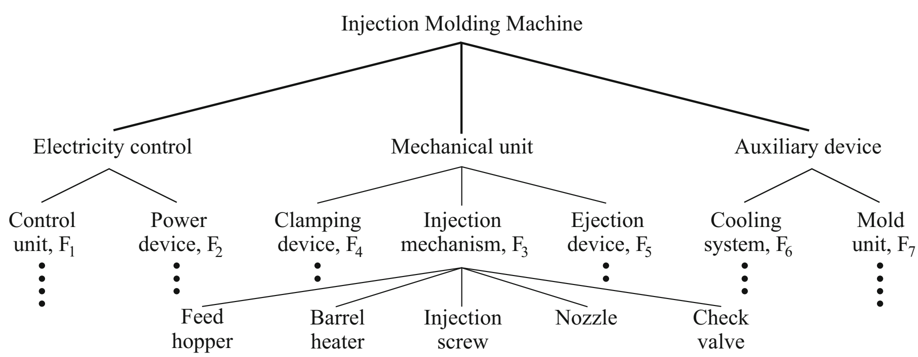

Fig. 7 Hierarchical structure of the possible faults for an IMM (Tsai 2009)

One advantage of the proposed system was the possibility of user-mediated adjustment of weights. The relative weights signaled the importance of the attributes; thus, the ability to adjust weights enabled the users to adjust global similarity. As a case study, the problem of fabricating electrical parts by injection molding was considered. Owing to its feasibility and conceptual perspective, the approach was deemed to be appropriate for solving nonconformity problems in injection molding.

In Tsai (2009), CBR was used for diagnosis of faults during the maintenance of an injection molding machine. The developed system enabled web-based fault diagnosis (see Fig. 7), using which the downtime of the analyzed injection molding machine was reduced. Fault tree analysis, information flow analysis, and symptom attributes were used for deep analysis of system fault levels and for determining the causes of faults. Researchers developed a case-retrieval algorithm from the algorithm that was proposed in Kolondor (1993), and weights were determined based on the correlation matrix. In that system, each case described one particular condition, and all cases were independent. The most similar case was selected and adaptation was performed. For the first case of diagnosis, the Active Server Pages (ASP) programming language was used, and cases were saved in a Microsoft Access database. As a case study, a part of a compact disc manufacturing system was considered by the study authors, and the developed CBR-based system enabled quick fault diagnosis.

More recently, Khosravani et al. (2019b) presented a case-based fault detection system for drippers. The studied drip irrigation tapes were produced by Semnan Polyethylene Pipe and Fitting Co. (SP&F 2018), a specialist in design and manufacturing of polyethylene products such as water pipes, gas pipes, pressure irrigation systems, and drip irrigation fittings. The mentioned drip irrigation tapes were made from polyethylene pipes and drippers. In Khosravani et al. (2019b), twenty-one features in six categories were considered based on the concerns of domain experts in injection molding; these features included temperature, pressure, time, speed, and size. The accuracy of the system with respect to determining fault sink marks, jetting, and burn marks for drippers was 90%, 78%, and 71%, respectively. Therefore, by utilizing the weights that were defined by domain experts, the accuracy of the system as a whole increased by 33% and reached 80%.

Regrading to the reviewed researches we summarized that retrieval process and case matching are the significant phases in CBR applications. In deed, the quality of the results mainly depends on the similarity measurements which used to retrieve the similar cases, and adaptation mechanisms used to recommend the proposed solutions. Table 1 presents the similarity measurements which have used in previous researches since 1997.

The user acceptance rate is high for CBR application in injection molding, where selected solutions correspond to real experience and can be explicitly presented to the user. Cases also contain descriptions of failures, the causes, and the determined injection molding parameters, and are independent of one another and readily available to users or even non-experts. In addition, CBR can recommend solutions based on incomplete problem descriptions. Moreover, the quality control is a topic of ongoing research in injection molding process. Two important factors are associated with difficulty of in-line monitoring in the quality control of process conditions in injection molding. The first factor is a large number of associated factors, and the second one is the restrictions on time. This approach reduces the down time by avoiding the repetition of past faults and errors. In the reuse phase of injection molding, usually, only little adaptation is necessary, which does not significantly affect the quality of the suggested solution. If the proposed solutions do not satisfactory and are not matched to the target case, then the revision procedure is needed. Therefore adaptation mechanisms should be applied in case-based systems. Here, utilized adaptation mechanisms in the reviewed studies are presented in Table 2. Finally, for knowledge maintenance in CBR, users can efficiently add, modify and remove new and old cases.

Despite of benefits, CBR also has some disadvantages with respect to its application in injection molding. Cases may not provide full coverage of the field, and scenarios that are stored in the case library can be limited, which can negatively affect the effectiveness of this approach. Most suitable cases still require adaptation, and revise of knowledge. According to the use of CBR in injection molding, the lack of graphical description of the presentation of cases is another limitation of the CBR approach. There are some solutions to these disadvantages, e.g., by hybridizing CBR with the other AI methods like rule-based reasoning, cases can provide better coverage of the field scenarios can be modified, which one good example is Nasiri and Khosravani (2019). Ontologies can support CBR for presenting the graphical description of the cases, like (Guo et al. 2012), and frames were chosen for data analysis presentation (see Fig. 6 Butdee 2010).

Hybrid intelligent systems utilizing CBR

Similar to other AI techniques, hybrid intelligent systems are also used in injection molding. In a hybrid intelligent system, two or more AI methods are combined to overcome the limitations of the individual constituent methods. In other words, hybrid intelligent systems are computational systems that integrate different smart approaches associated with their components. The use of hybrid systems in injection molding, without CBR, has been documented in the AI literature. For instance, in Mok et al. (2001b) and Shen et al. (2007) ANNs and GAs were used to construct a hybrid intelligent system in order to determine injection molding parameters.

In work Mok et al. (2001b) a hybrid intelligent system was implemented for determining initial process parameters. The obtained results showed that the developed system could be used to define processing parameters, resulting in the production of high-quality parts. As another example, a hybrid neural network system was developed to predict process parameters. Two critical parameters, injection time and injection pressure, were predicted using the developed system (Yarlagadda and Khong 2011). Researchers used data from flow simulations as training data, and the obtained results demonstrated the capability of the developed system to predict injection time when presented with previously unseen operation conditions. More recently, in Gao et al. (2018) expert systems methods and also data fitting and optimization methods which are used in injection molding process are briefly reviewed. The researchers concluded that reduced demand for experiments is an advantage of the expert systems in this field.

Although the CBR approach is not new and dates back to the 1980s, there have not been many applications of CBR in hybrid systems that are used in injection molding. Some researchers built hybrid intelligent systems that combined CBR with other AI techniques. CBR is used in hybrid intelligent systems for different reasons. For instance, in a hybrid system with CBR presentation of sub-problems is significantly simpler compared with hybrid systems that do not use CBR. In addition, avoidance of high knowledge acquisition efforts, handling of unexpected or missing inputs, the weighted learning process, knowledge representation and consideration of uncertainties, retrieval processes and local similarity measures, revision of solutions, and adaptation are additional important advantages that favor utilization of CBR in hybrid intelligent systems. A contribution of reviewed

Table 1 Similarity measurements of CBR applications in injection molding domains

Ref.	Applied system	Domain	Similarity
Kwong et al. (1997), Jin and Zhu (2000)	CBR	PP	$1-\frac{\sum_{i=1}^{n} w_i \times \frac{\lvert f_{oik}-f_{nik}\rvert}{f_{nik}}}{\sum_{i=1}^{n} w_i}$
	Hybrid (ANN)		w_i: important of index i
			f_{oik}: value of index i of the old case
			f_{nik}: value of index i of the new case
Nedess and Jacob (1997)	CBR	QC	k-nearest neighbor and if-then rules
Malek et al. (1998)	CBR	FD	$sim(P_i, C_j) = \frac{1}{\sqrt{\sum_{k=1}^{l} W_k^2 (p_{ik}-c_{jk})^2}}$
			W_k: weight related to each injection parameters
Kwong (2001), Kwong and Smith (1998), Mok and Kwong (2002)	Hybrid (RBS), (Blackboard), (ANN-FL)	PD,PP	$Sim(case^1(C_n), case^2(C_m)) =$
			$1/\sqrt{\frac{1}{k} * \sum_{j=1}^{k} w_j^2 [case_j^l(C_n) - case_j^2(C_m)]^2}$
			W_j: importance of jth attribute [4cm]
Mikos et al. (2007)	CBR	FD	$sim(C_{new}, C_{base}) = \frac{\sum_{i=1}^{n} sim(f_i^{new}, f_i^{base}) \times w_i}{\sum_{i=1}^{n} w_i}$
			$sim(f_i^{new}, f_i^{base}) = 1 - (\lvert f_i^{new}, f_i^{base}\rvert \div l_i)$
			w_i: importance of the i attribute
			f_i^{new}: values of the i attribute in the new case
			f_i^{base}: values of the i attribute in the case base
			l_i: range values of the i attribute
Tsai (2009)	CBR	FD	$\sum_{j=1}^{8} W_{ij} \times (1 - \frac{s_j^I - s_j^R}{2})$
			W_{ij}: weight set
			s_j: assessed level of symptoms
Butdee (2010)	CBR	PD	$sim(X_k, Case_{t,k}) = 1 - [\sum_{k=1}^{n} W_k Case_{i,k}]$
			W_k: weight of the condition k
			X_k: given value
			$Case_{i,k}$: retrieved value of the case i to k
Butdee (2011)	CBR	PD	$\beta_i = \sum_{k=1}^{n\beta} W_k \times [1 - \lvert \frac{X_k, Case_{i,k}}{Range_k} \rvert]$
			$\gamma_i = 1 - [\sum_{i=1}^{N} \sum_{k=1}^{n_\gamma} W_k \times R_{i,k}], sim(X_k, Case_{i,k}) = \frac{\beta_i + \gamma_i}{\sum W}$
			β_i: numeric similarity and γ_i: text similarity
			$n\beta$ and $n\gamma$: lists of numeric data and text data
			x_k: expected value of the k
			$R_{i,k}$: relation between Xk and case i of the characteristic k
Mok et al. (2001c)	CBR	PP	$SI_i = \frac{\sqrt{\sum_{i=1}^{N} (W_i \times d_{ij})^2}}{\sum_{j=1}^{N} (W_j)}$
			SIi: similarity index of the ith case
			wj: importance weighting of the attribute j and N: number of attributes
			dij: normalized distance of jth attribute of case i and input problem

CBR systems integrated into hybrid intelligent components which employed in injection molding is illustrated in Fig. 8.

Similar to the CBR applications, here we present the hybrid intelligent systems which developed in injection molding based on four described categories.

Hybrid systems in processing parameters

In Sheleshnezhad and Siores (1997), CBR was combined with a RBS for injection molding. The implemented system had four main parts: CBR, flow analysis sub-system, post-processor system, and RBS. Researchers used CBR for optimization of process parameters. In this regard, several

Table 1 continued

Ref.	Applied system	Domain	Similarity
Wang et al. (2003)	CBR	QC	Nearest neighbour (NN) algorithm
Sheleshnezhad and Siores (1997)	Hybrid (RBS)	PP	if-then rules
Hu and Masood (2002)	CBR	PD	$S_i = \frac{\sum_{k=1}^{T} W_{ik} W_k}{\sqrt{\sum_{k=1}^{T}(W_{ik})^2 \sum_{k=1}^{T}(W_k)^2}}$ $W_{ik} = \frac{F_{ik} Log(n_K/N)}{\sqrt{\sum_{j=1}^{N}(F_{ij} Log(n_f/N)^2}}$ W_k: weight of the kth term in query W_{ik}: weight of the k^{th} term in case i F_{ik}: number of occurrences of term k in case i
Tong et al. (2001)	Hybrid (FL)	PP	$Sim = \frac{\sum_{i=1}^{k} W_i \times sim(X_{ij}, X_{in})}{\sum_{i=1}^{k} W_i}$ W_i: weight of feature i $sim(X_{ij}, X_{in}) = 1 - ((X_{ij} - X_{in})/\text{variable range})^2$ X_{ij}: value for feature i in the old case j X_{in}: value for feature i in the new case n
Lou et al. (2004)	Hybrid (ANN)	PD	$S = \sum_{i=1}^{n} W_i M_i$ W_i: attribute i's weight M_i: attribute i's mating value
Zhou et al. (2007)	Hybrid (FL)	PD	$s = \frac{g(0) \times \sum_{i=1}^{4}(W_i \times (f(i))}{\sum_{i=1}^{4} W_i}$ $f(i) = 1 - \frac{\lvert x_{obj} - x_{src} \rvert}{x_{obj}}$ $g(0) = \frac{v_i \times \varphi(i)}{\sum_{i=1}^{3} v_i}$ W_i: importance of $f(i)$ $f(i)$: similarities of the part
Mok et al. (2008)	Hybrid (RBS)	PD	if-then rules
Guo et al. (2012), Guo et al. (2013)	Hybrid (FL)	PD	$Sim(T, S) = \frac{\sum_{i=1}^{n} w_i \times Sim(T_i, S_i)}{\sum_{i=1}^{n} w_i}$ w_i: weight of requirement T_i, S: whole source cases set
Khosravani et al. (2019b)	CBR	FD	$SIM(F, IF) = \sum_{i=1}^{n} w_i sim_i(F_i, IF_i)$ n: number of features, w_i: weight of i^{th} feature, $IF = if1, if2, \ldots, if19$
Nasiri and Khosravani (2019)	Hybrid (FL)	FD	$w_{f_i} = \sum_{j=1}^{m} FO_{f_i} \times Crisp(\tilde{\mu}_{f_i}^{Relationship}(PR_{ji}))$ w_{f_i}: fuzzy weight for i^{th} feature, FO_{f_i}: occurrence weight of i^{th} feature $\tilde{\mu}_{f_j}^{Relationship}(PR_{ji})$: relationship of j^{th} parameter and feature i

parameters, such as the type of material, cavity geometry, and flow type, were considered. On the other hand, the flow analysis sub-system was used for determining the nozzle parameters, such as the pressure drop and temperature. Meanwhile, molding parameters were converted to machine settings parameters using the post-processor. Finally, the RBS derived changes in the process parameters and was used for dealing with possible variations, for optimization of parameters. To provide strong cases for the case-library, finite element method was used and "IF-Then" rules were utilized to reveal similarities between the new problem (that required solution) and stored solved problems. Simulation of human expert strategies and reduced optimization time were the main advantages of the implemented system. In addition, the hybrid system was linked to the simulation program, and dependence on human experts was reduced.

Design of injection molding processes is accomplished in several steps. The most important steps are selection of

Table 2 Presentation of applied adaptation mechanisms

Ref.	Applied system	Domain	Adaptation
Kwong et al. (1997)	CBR	PP	$P_{c2} = PA_2 \,.\, IP_c \frac{P_a}{PA_I \,.\, IP_I}$
			P_{c2}: clamping pressure of the input case
			PA_2: project area of the input case
			IP_2: injection pressure of the input case
			P_a: actual clamping pressure of reference case
			PA_I: project area of the reference case
			IP_I: injection pressure of the reference case
Malek et al. (1998)	CBR	FD	$Modif_{param} = \sum_{i=1}^{m} \frac{E_i \times V_i \times S_i}{m}$
			E: effect
			V: value of the modification
			S: solution
Kwong (2001)	CBR	PD	For each attribute (i)-value (i) pair in the new problem,
			set the value (j) of the attribute (i) in the reference case,
			If attribute (i) is not the problem description
			Then substitute value (i) with (j)
Tsai (2009)	CBR	FD	Domain expert
Mok and Kwong (2002)	Hybrid (ANN-FL)	PP	neuro-adaptation
Zhou et al. (2007)	Hybrid (FL)	PD	RBR
Mok et al. (2008)	Hybrid (RBS)	PD	Domain expert

the injection molding machine, production scheduling, mold design, and determination of process parameters. In Kwong and Smith (1998), a blackboard-based expert system with CBR was built for determining all of the above-mentioned process design steps. Because the expert system was not able to identify injection molding parameters, the CBR approach was combined with a blackboard-based expert system to provide this capability. Details of blackboard architecture can be found in Nii (1986a) and Nii (1986b) and it is a global database that supports inputting problem-related data and extraction of common and partial solutions. In Kwong and Smith (1998), a control module was used to monitor the changes on the blackboard and to make a decision about the required action. The control module was used to control information to determine the focus of attention and to determine the next task. Researchers organized the case library as a combination of the hierarchical organization of cases and a linear list. Two methods were proposed for indexing. The first method was based on the checklist that was provided by the system designer, while the second method was based on the explanation of the reason for selecting the indexes. To increase the accuracy, a two-level similarity analysis was conducted. In the first level, matching of the basic complexity index, tolerance, and surface finishing index was considered to determine the closest matching batch of the case. In the second level, similarity analysis was applied to the batch of the cases in the matching of the other cases. The implemented system was used to design the process of fabrication of box-shaped plastic parts. The optimal model of the injection machine, mold base parameters, and production scheduling were successfully determined. Later, in Jin and Zhu (2000) and Mok and Kwong (2002), hybrid intelligent systems were developed using CBR and fuzzy logic for determining the process parameters of injection molding. In Jin and Zhu (2000), several defects such as short shots, shrinkage, warpage, weld lines, flow marks, and voids were considered, and the implemented system was used to

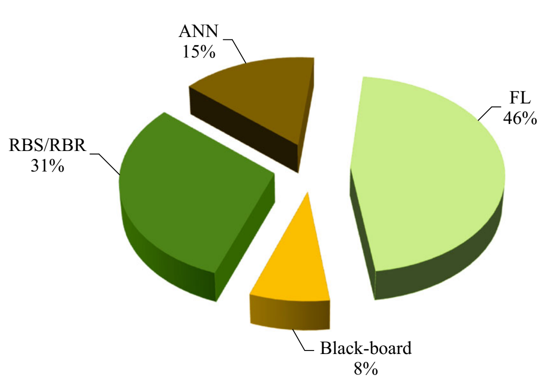

Fig. 8 Contributions of AI methods in CBR hybrid intelligent systems in IMM

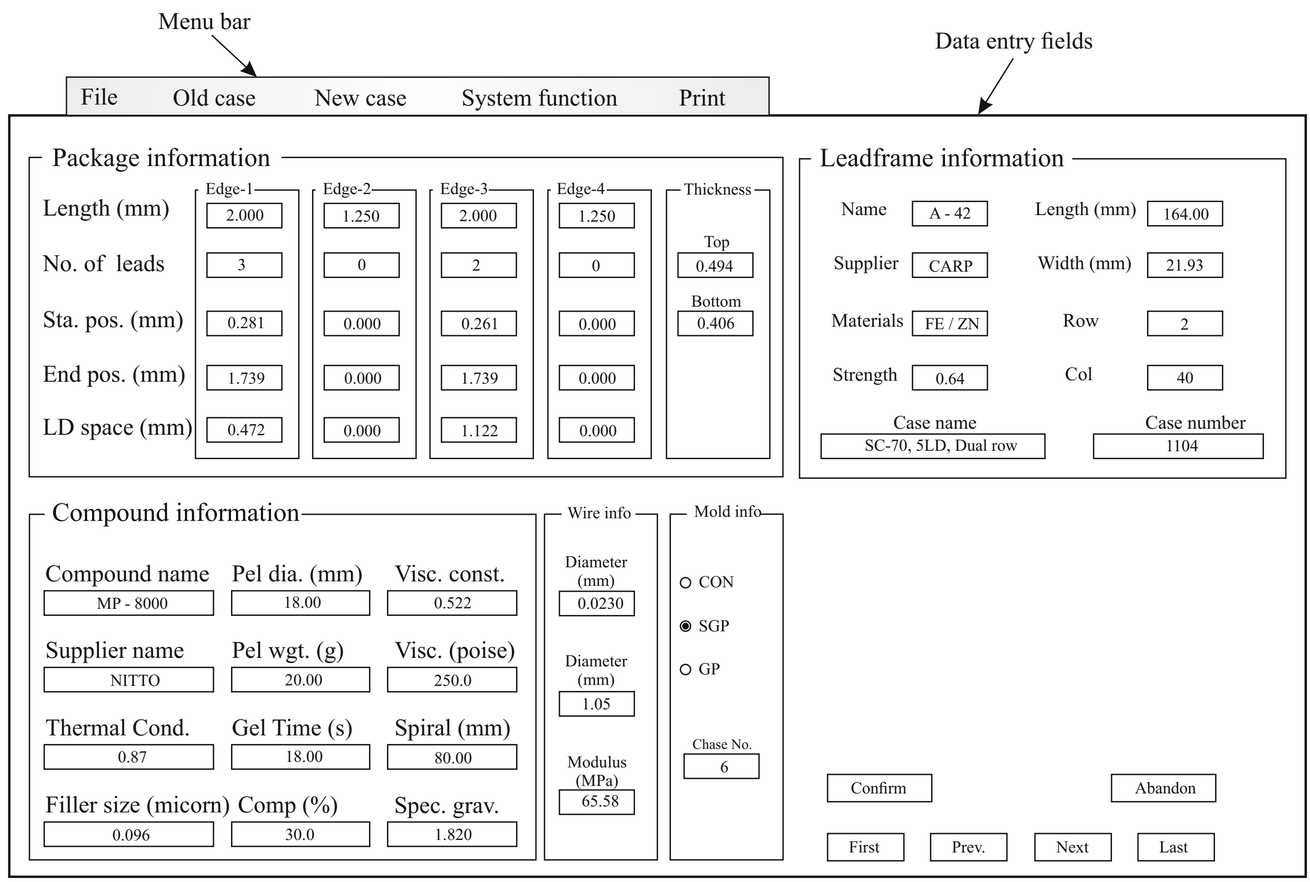

Fig. 9 User interface for the process parameters generated from the system (Tong et al. 2001)

obtain the process parameters experimentally. Although testing proved that the hybrid system is able to reduce defects, the weights in the fuzzy relationship matrix depended on the mold design and machine type, which are determined by experience. Similarly, in Mok and Kwong (2002), fuzzy logic was utilized for case indexing and similarity analysis of CBR, and a hybrid intelligent system was constructed for determining the process parameters of injection molding. Moreover, an ANN was used for case adaptation. The hybrid system was implemented in the Visual Basic programming language, and the study authors conducted two validation tests using a mold flow simulation package. The obtained results were not found to violate quality criteria; this suggests that hybrid systems can help increase the quality of fabricated parts. In study (Tong et al. 2001) CBR approach is utilized in a hybrid intelligent system for setting of process parameter, which its user interface is illustrated in Fig. 9. The researchers considered forty real cases in the case library and defined the features. Then, fuzzy theory is used for multiple indexing of a case on a single feature. After utilizing nearest neighbor algorithm for similarity measurement, the system performs case adaptation by three methods: (a) based on the first principle and rule of thumb, (b) based on previous successful cases, and (c) derived from the results of previous research. For instance, clamping force, mold temperature and curing time are adapted by the mentioned methods, respectively. For the validation of the proposed system, the authors conducted test based on a real industrial case, and claimed that the obtained values are acceptable by molding experts.

Several years later, a hybrid intelligent system was used for determining injection molding process characteristics in Zhou et al. (2007). The proposed hybrid system combined CBR and fuzzy inference to determine initial process parameters in injection molding. When the process parameters were determined by CBR, the fuzzy system addressed defects and adjusted the process parameters. The developed hybrid system was validated on a case study. The primary process parameter was determined and uploaded to the injection machine. The molded part of the first trial was shown and a particular defect was detected. Then, the fuzzy system adjusted the settings and the process repeated until ensuring that the fabricated part has no defects. The advantage of this system is that it allowed online optimization of process-related parameters.

Hybrid systems in quality control and cost

Injection pressure and temperature play important roles in determining the quality of the product; thus, different sensors are commonly used in the internal components of molding, to predict the quality of molded parts before opening the mold. In this case, according to the sensor type and information about the locations of the molded parts, careful determination should be performed. With regard to human experts, three main parameters, which are the maximal wall thickness of the mold cavity, the number of cavities, and the maximal flow length, are considered as input data. Based on these parameters and also on different types of defects, a list of sensor types and their locations in the mold are determined. It should be noted that misplaced sensors could result in the mold replacement, which is very expensive. In Pinyol et al. (2012), a hybrid intelligent system that featured CBR and RBS was proposed for determining and using a minimal set of sensor types and locations, for quality control. Researchers related the above-mentioned input and output data using a knowledge-based system. The implemented system compared the defined new mold to the case base, and the most similar case was selected. After that, rule-based reasoning (RBR) was used to modify the parameters, to obtain the most appropriate result. In the case of limited availability (or complete unavailability) of case database, RBR was used to create a new case. Both parts of knowledge-based systems were accessible through the web and it was claimed that experts validated the implemented system. The proposed system significantly saved time, and reduced the dependence on human experts.

Hybrid systems in process design

Hybrid intelligent systems were also utilized in the area of mold design in injection molding (Lee et al. 1997; Mok et al. 2001a). In the design of mold, several parameters should be considered, but the principles and rules of the cavity layout design can be presented in the form of knowledge and use of KBSs. In work Hu and Masood (2002), an intelligent system for the cavity layout design was developed as a reasoning engine based on CBR. Similar to the process parameters in injection molding, the cavity layout design also depends on human knowledge (designer knowledge), skills, and experience. Researchers classified this knowledge into five different categories, and used object-oriented presentation. They used the CBR approach for fast determination of suitable solutions. The results were presented in a graphical form and indicated that the developed system can be used for the cavity layout design, which contributes to automatization of the injection mold design process. Lou et al. (2004) developed an integrated knowledge-based system for mold design. In the developed system, product modeling and knowledge representation with frame-rule structure technologies were used. In addition, the system featured an ANN and CBR. Successful design cases were saved in the mold case library. This case library presented cases for CBR and also fed information to the ANN. Researchers tested the system in a mold factory and based on the test results suggested that, by utilizing the system, engineers can focus on designing the product. In addition, the system was capable of improving design efficiency by creating a design environment with field knowledge. The study authors concluded that the developed system demonstrated the possibility to incorporate computer-aided technologies into knowledge-based systems.

In Mok et al. (2008), a hybrid intelligent system was used for injection mold design. Because in the field of design the CBR approach cannot cover the entire domain, in Mok et al. (2008) KBS was combined with CBR, allowing to use the advantages of the KBS and CBR approaches. In particular, when a designer answered questions, the implemented system made an index code that described parts and molds. In the retrieval process, the cases with all attributes were marked for future consideration. Differences between the selected case and the new problem were determined during the adaption process. In this process, a knowledge base module was used and it featured generalized domain-independent knowledge that could be presented in different formats, such as rules and design constraints. This format helped the designer to choose among some proposed solutions. Researchers provided access to the standard mold base for designers, allowing to change/edit the standard mold base and/or components library. The implemented system was time-efficient because it avoided unnecessary steps in design.

In work Guo et al. (2012) the CBR approach is used in a hybrid system to response the questions in the field of mold design. In this regard, mold design of a plastic grip is considered as a case study. In system development, the researchers claimed that two grades of retrieval strategy are used: (i) ontological semantic retrieval, and (ii) measuring fuzzy numerical similarities of structure parameters. It is reported that obtained results indicated performance of the system. In the subsequent year, the same researchers used CBR in their researches in a hybrid intelligent system for injection molding process (Guo et al. 2013). In this respect, an ontological case-base is presented, which contained many past design cases and provided useful insights and guidance for developing novel concepts, based on the semantic similarity measure. Moreover, because the studied design cases were characterized by many numerical features, the study authors used numerical measurement methods and effectively reused appropriate cases.

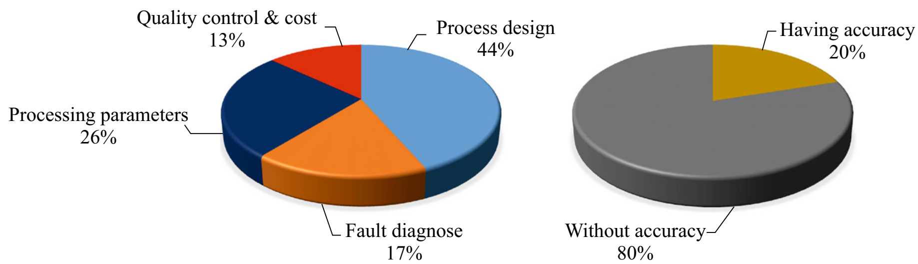

Fig. 10 Contribution of CBR applications in IMM from 1997 to the present (left) and obtained accuracy of the reviewed CBR systems (right)

Hybrid systems in fault diagnose

CBR was also used for detection of faults in injection molding machines, utilizing the information retrieved from troubleshooting guidelines (Nasiri et al. 2017). One such case-based fault detection system used fuzzy sets based on the relationship between the process parameters, parts, and molds discussed in Mok and Kwong (2002), to define the weights of features that were found to be associated with faults. The system also utilized the presence weights of features based on the troubleshooting guidelines to capture problems in injection molding, and to provide recommendations for fixing these problems. The case database of fifteen common faults was defined based on twenty features of injection molding. More recently, Nasiri and Khosravani presented a fuzzy CBR fault detection system (Nasiri and Khosravani 2019). In this work, the fuzzy CBR system is implemented for the fault detection of produced drippers in an injection molding machine. The proposed system utilizes fuzzy sets in the definition of the essential features' weight in occurring faults. These important features play big roles in injection molding which are classified into five categories: (i) temperature, (ii) pressure, (iii) speed, (iv) size, and (v) time. Moreover, 21 faults are considered which occurred in the production line, e.g., sink marks, jetting, short shots, and cracking. The fuzzy weights are determined by a domain expert based on the strength relationship of quality control, parts, mold, and process parameters. Their obtained results proved capability and accuracy of the proposed system in detection of faults. The system is much faster than traditional method and indicates a stable product quality. The author claimed that the proposed system can also be adapted for other complex products in the injection molding process.

Although hybrid AI systems are reliable for use in injection molding, applications remain somewhat limited. In this regard, HORIZON 2020 funded EU researchers in the plastic injection molding industry for developing and validating AI-based systems that would allow to increase productivity and to reduce the cost and time of production; one example is project Des-MOLD (Project ID: 314581, Funded under: FP7-NMP) (Horizon2020 2015). It utilizes AI techniques such as CBR and computational arguments to optimize the design time and the geometries of parts and molds according to the chosen features, and to derive process control variables that will be observed during production. Because this production method should satisfy several criteria, all intelligent systems should be developed by considering these criteria. In the following section, concluding remarks and some suggestions for future work are presented.

Concluding remarks and future work

Successful product design requires advanced manufacturing technology, well-developed strategy, and team effort. Technologies which have been used in injection molding process, can be borrowed from various branches of science, which often leads to higher-quality products. Existing methods are mostly concerned with increasing the speed of injection molding, but faults and failures during production remain unavoidable. Detection of faults, process design, diagnosis of failures, process optimization and quality control of injection molding are areas of interest to researchers. In Fig. 10 contribution of the reviewed systems in four described categories and their achieved accuracies are shown.

Injection molding teams consist of different engineers, such as designers, material suppliers and mold makers. The quality of the final product in injection molding is significantly affected by the process parameters and conditions. Highly skilled operators determine these parameters, which requires significant experience. Currently, the capability of AI and knowledge-based systems to attain high levels of performance with regard to troubleshooting in injection molding has become evident. A problem-solving strategy based on the similar past experiences help the operators to exploit the useful details to a particular similar case. For manufacturing businesses to gain such skills, a very thorough understanding of their production processes is required. This issue is equally valid for different production lines and injection molding. Although experimentation provides remarkable opportunities for the manufacturers to generate and record the knowledge about their specific product processes, the experimental approach is not cost-effective. CBR can be suitably used in robust product development for injection molding-based production. In this regard, CBR systems can support the process of knowledge creation, documentation, and trans-

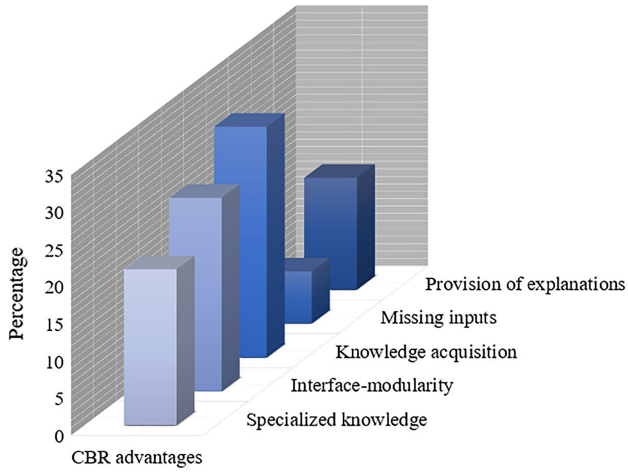

Fig. 11 Quantitative comparison of the CBR advantages for reviewed applications of injection molding

fer. Because knowledge that is obtained from experiments should be saved for later reuse, CBR systems can also keep and use previous knowledge about different phases, such as design and fault detection, which increases the robustness of product development. CBR is able to enhance online visibility of production data in injection molding, can be used for task automatization, and for intelligent control of process and parameters.

In practice, numerous human expert competencies are experience based, so developing knowledge based systems can be leads to learning systems which provides consultations for the clients. The main advantages of applied CBR systems in injection molding process are categorized as follows: (i) Expression of specialized knowledge, (ii) Interface-modularity, (iii) Knowledge acquisition, (iv) Unexpected/missing inputs, and v) Provision of explanations. The classification of reviewed injection molding CBR applications based on these advantages are illustrated in Fig. 11.

Recommendations and suggestions

The following suggestions can be used to increase product performance and improve various manufacturing stages in injection molding:

1. The overall energy consumption associated with the product can be reduced by using different intelligent systems. In this regard, CBR can be used to reduce the production time of high-quality products, accordingly reducing the cost. The suggestion is to utilize CBR in IMM to recommend process parameters of each product when they need readjustment, to bring the product quality back to the acceptable state.
2. Although in-line monitoring of process conditions is a difficult task, this technique is needed for increasing productivity. Because in-line systems can improve the rate of production, any investment in in-line systems will yield big benefits for operators, and will quickly increase the quality and quantity of the final product. The systems that have implemented by CBR approach offer a specific solution. Therefore, more practical in-line systems based on this approach should be developed for real-world applications in IMM.
3. Injection molding is affected by many parameters. Results that were obtained by different researchers in different studies indicate that classification of parameters into various groups of units in injection molding can improve performance. In this regard, process parameters of injection molding could be classified into three categories: (a) parameters that are related to the injection unit, (b) parameters which that are related to the clamping unit, and (c) parameters that are related to other functional units. According to the role of each parameter in the task accomplished by its unit, there is a possibility to evaluate the impact of individual parameters on the quality and efficiency of production.
4. Because injection molding consists of different phases, several monitoring and control tools are required. These controls are process control, machine control, and quality control. Appropriate hybrid CBR methods can be proposed and used to present and connect the mentioned different controls. As the product quality in injection molding is essentially difficult to predict in the design phase, comprehensive reasonable quality control programs without any human intervention remain among the most desired features in injection molding. In this regard, allocation of intelligent control systems to different control levels based on particular intelligent methods is very much needed for development of control methods in injection molding. According to the previous researches, integration of fuzzy logic into CBR methodology brings considerable advantages.
5. To be able to examine the accuracy and efficiency of implemented AI-based systems, careful analysis of manufacturer's data is very much required. In this respect, CBR systems that use previous similar case(s) can determine a set of initial process parameters quickly by retrieving, reusing, and revising new cases (problems/solutions), thus increasing the process efficiency. Therefore, hybrid CBR systems can generate more accurate solutions in shorter time (see Fig. 10).

Future opportunities

As noted previously, the CBR approach has been used in different fields, and in the last few years as a branch of AI it has come to play an important role in several aspects of product and intelligent manufacturing. One of the future research area for application of CBR could be cost estimation in injection molding process. There are three approaches toward analyzing the cost of plastic injection, which consider factors that affect the cost of plastic injection (Wang et al. 2013). The first approach involves research and development, the second approach involves mold manufacturers, which helps to reduce the cost of fabrication by determining the number of cavities based on different parameters (e.g., mold materials and weights). Finally, the third approach involves the injection molding plant, and amounts to calculating the cost of maintenance and end product.

Moreover, according to the Hu and Masood (2002) two types of cost reduction (Cost Reduction = (previous cost-current cost)/previous cost) can be expected: (i) theoretical cost reduction which obtained in the design of injection molds, and (ii) practical cost reduction that is related to each of parameters in injection molding. One of the open research area in this field is focusing more cost reduction in injection molding via CBR. In this case, cost reduction attributes can be defined and stored in the case base. Thus, each case has its own cost reduction attribute which calculate the overall cost based on the user's requirements.

Application of CBR in production processes such as injection molding has several important implications for future research and development of intelligent systems. Although compared with other branches, injection molding has somewhat fallen behind in terms of applicability of AI methods, CBR systems have demonstrated a variety of significant benefits and opportunities for use in this manufacturing process. The contribution of reviewed intelligent system based on CBR applications, suggests that we are likely to witness a steady increase in the number of applications of CBR in fault detection and quality control in injection molding.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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