An Intelligent System for the Determination of Initial Process Parameter Setting for Injection Moulding

By

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Abstract of thesis entitled **An Intelligent System for the Determination of Initial Process Parameter Setting for Injection Moulding**

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The global competition that demands high quality plastic products and short time-to-market has made the current trial and error practice in the determination of initial process parameters for injection moulding become inadequate. According to the nature of the problem in initial process parameter setting for injection moulding, case based reasoning (CBR) is deemed to be a promising technique to handle the experience-based problems. In this research, a hybrid neural network and genetic algorithm (NN-GA) approach was introduced to complement the CBR approach in the determination of initial process parameters for injection moulding, from which a Hybrid System for Injection Moulding (HSIM) was developed. In the system, initial process parameters of injection moulding are generated in two attempts. In the first attempt, initial process parameters are generated based on CBR approach. If there is no workable solution to be obtained from the first attempt, the second attempt in the generation of initial process parameters for injection moulding is performed based on hybrid NN-GA approach.

HSIM was validated by using a commercial simulation package for injection moulding. Results of the system validation indicate that HSIM can generate a set of initial process parameters for injection moulding that can lead to the production of good quality moulded parts. Implementation of HSIM has also demonstrated that the time for the determination of initial process parameters for injection moulding can be greatly reduced, daily experience of moulding personnel in initial process parameter setting can be captured, and self-learning capability can be facilitated.

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1. **Mok, S.L.**, Kwong, C.K. and Lau, W.S., "Review of research in the determination of process parameters for plastic injection molding", *Advances in Polymer Technology*, Vol.18, no.3, pp. 225-236 (1999)
2. **Mok, S.L.**, Kwong, C.K. and Lau, W.S., "An intelligent hybrid system for initial process parameter setting of injection moulding", *International Journal of Production Research* (accepted for publication)
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4. Kwong, C.K., **Mok, S.L.**, and Tam, S.M., "Case based reasoning approach to concurrent design of low power transformers", *International Journal of Production Economics* (submitted for publication)

Conference Papers:

5. **Mok, S.L.**, Kwong, C.K. and Lau, W.S., "The determination of process parameters for plastic injection molding: case based reasoning approach", *Proceedings of the 3rd Annual International Conference on Industrial Engineering Theories, Applications and Practice*, Hong Kong, 28-31 Dec. 1998, on CD-ROM (1998)

6. **Mok, S.L.**, Kwong, C.K. and Lau, W.S., "An intelligent hybrid system for initial process parameter setting of injection moulding", *Proceedings of the 15th International Conference on Production Research*, Ireland, 9-13 Aug. 1999, pp.185-190 (1999)
7. Kwong, C.K., **Mok, S.L.**, and Tam, S.M., "Case based reasoning approach to concurrent design of low power transformers", *Proceedings of the 15th International Conference on Production Research*, Ireland, 9-13 Aug. 1999, pp.227-232 (1999)

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CHAPTER ONE - INTRODUCTION

1.1 Process Design of Injection Moulding

Plastic industry has been growing rapidly in recent years. The growth will be accelerated by the tendency of substituting plastics for metal, which is appearing throughout the world. Injection moulding is the most common and versatile process for mass production of complex plastic parts with good dimensional tolerance. It is a process by which plastic pellets are melted and injected into a cavity to form a complex three-dimensional part in a single operation. Approximately 32% by weight of all plastic parts are made by injection moulding [C-MOLD 1997]. Injection moulded plastic parts can be found easily in a number of consumer products such as mobile phones, electronic dictionaries and notebook computers.

Primary goal of injection moulding is to produce moulded parts with acceptable quality. To achieve this goal, various design and engineering activities including product design, process design and process control have to be involved. Process design of injection moulding is one of the crucial activities in the development of plastic products. Good process design can minimise the possible production problems, shorten the time-to-market, reduce product development cost and improve the quality of moulded parts. Process design of injection moulding involves a series of activities which mainly include the selection of injection moulding machines, injection mould design, cost estimation and determination of process parameters for injection moulding.

Basically, a proper injection moulding machine should provide sufficient shot size, plasticising rate, injection pressure and clamping force for the moulding application as well as allow the injection mould to be mounted on the machine platen.

Injection mould design involves a number of activities such as determination of cavity layout, design of side pulls/ internal lifters/ unscrewing devices, selection of mould base, runner and gating system design, cooling system design and ejection system design. In the current practice, injection mould design is mainly done by mould designers and the quality of the design is dependent totally on their knowledge and experience. Recently, more and more companies attempt to use computer-aided engineering (CAE) analysis packages in injection mould design in order to maintain or even enhance the quality of mould design even if no well experienced mould designer can be recruited.

Cost estimation for injection moulding can be divided into three components, which are tooling cost estimation, processing cost estimation and material cost estimation. Tooling cost is related to the cost involved in producing the injection mould(s). Processing cost involves the cost in production. Material cost refers to the cost of polymer material used in the injection moulding process.

Once proper moulding machines were selected and the injection mould was manufactured and installed in the moulding machine, trial-run of moulding can be performed to determine a proper set of process parameters for producing defect-free moulded parts. Process parameter setting of injection moulding involves two types of activities: initial process parameter setting and process parameter resetting. Initial process parameters for injection moulding are usually determined based on the guidelines provided by resin suppliers and/ or experience of moulding personnel. Since injection moulding is a highly complex process where a large number of factors are involved, it is difficult to produce good quality/ defect-free moulded parts based on the initial process parameter setting obtained from the previous methods. Therefore, process parameter resetting is required many times in order to reduce or eliminate the defects of moulded parts.

1.2 Statement of Problem

This research is focused on the determination of process parameters for injection moulding which is one of the critical activities in the process design of injection moulding. Once the moulding material has been selected and the required injection mould has been designed and produced, quality of moulded parts largely depends on the setting of process parameters. Improper parameter setting could lead to various types of moulding defects in moulded parts, such as voids, burn marks and crazing. Many experimental works were carried out to investigate the influence of the injection moulding parameters on the quality of moulded parts [Cox 1986, Hsiung 1990, Lee 1994] and the occurrence of moulding defects [Liou 1990, Kurosaki 1992, Hamada 1996, Yoshii 1996]. The experimental findings have indicated that moulding parameters have significant influence on the quality of moulded parts. For example, increasing both the holding pressure and holding time could reduce sink marks of moulded parts, while decreasing injection speed could eliminate flow marks for the case of amorphous polymer.

As mentioned in Section 1.1, process parameter setting of injection moulding involves the determination of initial process parameters and process parameter resetting. Determination of initial process parameters for injection moulding generally is done by moulding personnel. Setting these initial process parameters is a highly skilled job and based on skilled operator's "know-how" and intuitive sense acquired through long-term experience rather than a theoretical and analytical approach. They often recall their previous works to find out the design of a moulded part that is similar to the current one. The corresponding tested moulding parameters with intuitive adjustments and modifications are then used as a start for the new moulding application. Therefore, effectiveness of initial process parameter setting is largely dependent on the experience of moulding personnel.

Due to the complexity of injection moulding process, the process parameter resetting is required many times in order to obtain good quality/ defect-free moulded parts. This resetting process is repeated until the quality of moulded parts is found satisfactory. Length of the time required to perform the process parameter resetting is much dependent on the experience of moulding personnel. Unfortunately, plastic industry has been facing a serious problem that the growing demand of experienced moulding personnel far exceeds the supply. Moulding personnel typically needs 10 to 20 years' experiences to become an expert. Shortage of experienced moulding personnel has been resulted in the need for a new solution.

Although some suppliers of thermoplastic material have provided guidelines to assist moulding personnel in setting process parameters of injection moulding for a particular thermoplastic material, the information provided is mainly empirical in nature and only provides the general guidelines for parameter setting. Besides, several computer aided engineering (CAE) tools are commercially available in market for injection moulding such as C-MOLD from AC Technology Co. [C-MOLD 1998] and MoldFlow from MoldFlow (AUST) Pty Ltd. [MoldFlow 1995]. The CAE tools can provide satisfactory prediction of moulding quality based on input process parameters. However, if the initial input process parameters for the CAE analysis are improper, a lot of time may be required to iterate the analyses in order to obtain a satisfactory result.

Quite a few number of injection moulding machine manufactures such as Chen Hsong, TMC, Kawaguchi and DongShin have employed database technology to help machine operators in the setting of moulding parameters. Normally, database systems are built into their machines which allow moulding personnel to input successful moulding parameters and results. The parameters and results are stored in the system and can be recalled and reused for the next production of identical moulded parts. The database systems mainly deal with the case of exact-matching and some may handle very limited partial matching. Some injection moulding machine manufactures such as Niigata and Mitsubishi have used database technology combining with mathematical equations in the determination of initial machine setting for a new application. To determine the machine parameter setting, information and data are required to be input to the systems which include type of resin, part weight and thickness, gate thickness and mould thickness. However, some parameters that could largely affect the setting of initial moulding parameters such as part complexity, runner type and size, and projected area of moulded parts are not considered in their database system.

Facing with the global competition with emphasis on the high quality plastic products and short time-to-market, the current practices in the determination of process parameters for injection moulding seem to be inadequate. More efficient approaches and techniques to the determination of process parameters are necessary to be explored.

1.3 Research Scope and Objectives

This research is focused on the area of initial process parameter setting for injection moulding. According the nature of the problem in initial process parameter setting for injection moulding, Case-based reasoning (CBR) approach [Riesbeck 1989] is deemed to be a promising artificial intelligence (AI) technique to handle the experience-based problems. However, a poor solution or even no solution is resulted, if there is no relevant case found from the case library of a CBR system. To make up the deficiency, a hybrid neural network [Picton 1994] and genetic algorithm [Goldberg 1989] (NN-GA) approach is introduced in this research to complement the CBR approach in the determination of initial process parameters for injection moulding.

The major objective of this research is to explore the effectiveness of combined CBR and hybrid NN-GA approach in the determination of initial process parameters for injection moulding. It is expected that the proposed approach not only mutually strengthens the three artificial intelligence (AI) techniques, but also avoids their weak aspects. Based on the combined approach, a computer-aided system can be developed for the determination of initial process parameters for injection moulding. The major purpose of the system is to provide a set of initial process parameters for injection moulding that could lead to the production of good quality moulded parts in very short time without relying heavily on experienced moulding personnel.

During the past two decades, numerous attempts have been made to develop various injection moulding processes to produce moulded parts. These efforts have resulted in a number of processes, including co-injection (sandwich) moulding, injection-compression moulding, gas-assisted injection moulding etc. In this research, the injection moulding of thermoplastic materials with employing the reciprocating-screw injection machines is considered, as it is the most popular manufacturing process in Hong Kong manufacturing industry.

1.4 Thesis Outline

In Chapter Two, a general review of research in process design of injection moulding is firstly presented. It is then followed by a comprehensive review of research in the determination of process parameters for injection moulding. The potentials and limitations of individual approaches to the determination of process parameters for injection moulding are discussed in the end of the chapter. The issues of design and development of the proposed system are discussed in Chapter Three. System implementation and validation are described in Chapter Four. Discussion of this research is given in Chapter Five while conclusions and future works of this research are presented in the last chapter.

CHAPTER TWO - LITERATURE REVIEW

2.1 Introduction

In this chapter, a general review of research in process design of injection moulding is firstly presented in Section 2.2. In the section, five approaches for supporting the process design of injection moulding including computer-aided engineering (CAE), knowledge-based systems, case based reasoning (CBR), neural networks (NNs) and structured models are briefly described. It is then followed by a comprehensive review of research in the determination of process parameters for injection moulding. In Section 2.3, researches based on various approaches to the determination of process parameters for injection moulding, including mathematical models, numerical simulation, process window, design of experiments (DOE), knowledge-based systems, neural networks (NNs), case based reasoning (CBR) and genetic algorithms (GAs), are described. Finally, the potentials and limitations of individual approaches to the determination of process parameters for injection moulding are discussed in Section 2.4.

2.2 Review of Research in Process Design of Injection Moulding

Process design of injection moulding involves a series of design and engineering activities which mainly include the selection of injection moulding machines, injection mould design, cost estimation and determination of process parameters. A general review of research in the process design of injection moulding is presented in this section. The review does not cover the area of the determination of process parameters for injection moulding, which will be described in details in Section 2.3. In the following, five approaches for supporting the process design of injection moulding, computer-aided engineering (CAE), knowledge-based systems, case based reasoning (CBR), neural networks (NNs) and structured models, are described.

2.2.1 Computer-aided engineering (CAE)

Computer-aided engineering (CAE) is the most common approach to perform the process design in injection moulding which is the use of computer simulation to acquire engineering process insights. Currently, CAE tools are well developed at different levels of sophistication to aid the process design of injection moulding. More than half a dozen CAE analysis packages for injection moulding are commercially available in market such as C-MOLD from AC Technology Co. [C-MOLD 1998] and MoldFlow from MoldFlow (AUST) Pty Ltd. [MoldFlow 1995]. The process behaviour of injection moulding predicted by the CAE analysis packages can help moulding personnel determine whether plastic parts are manufacturable and economically viable at the early design stage. With the analysis results, moulding personnel can make "early" process design decisions with more understanding of the possible defects of moulded parts.

Several efforts have been made in injection mould design based on the results of CAE analyses such as runner system design [Beaumont 1989, Bunch 1992], gating design [Payne 1994, Picarsic 1994] and cooling system design [Himasekhar 1992]. Bourdon K. [Bourdon 1989] developed a computer program for the selection of moulding machines and process parameter setting of injection moulding. In his study, a weighting system was developed for the machine selection in which an order of rank of potential machines is determined based on the results of machine capacity utilisation assessment. Some process windows are established to determine the process parameter setting for injection moulding. Wang K.K. [Wang 1997] proposed an implementation plan to integrate all main functions in producing injection moulded parts into a unified system called IMS (Integrated Moulding System). The IMS is intended to make full use of existing CAD/CAM/CAE tools and to develop new necessary software and technologies.

In order to reduce the human intervention in the use of CAE tools, quite a few attempts have been made to incorporate the CAE analysis with an optimisation theory for facilitating injection mould design. The work involves the determination of gate location [Pandelidis 1990a, Lee 1996a], runner sizing and balancing [Jong 1990, Lee 1996b] and cooling system layout [Zou 1992, Tang 1998]. In their work, an objective function is established to represent the quality of mould design. Numerical optimisation techniques, such as hill-climbing techniques and simulated annealing, are applied to adjust the mould design variables such as the gate location and runner diameter for running the CAE analyses. A number of analyses are usually required in order to obtain a near-optimal/optimal solution.

2.2.2 Knowledge-based systems

Technological advances in computer engineering, especially in artificial intelligence (AI), have boosted the development of compute-aided systems for the process design of injection moulding. One popular AI technique being employed is knowledge-based systems. Knowledge-based systems are software programs designed to simulate the human reasoning process by applying specific knowledge and inferencing. The domain knowledge can be represented in a number of ways such as semantic networks, production rules, decision tables, frames and objects.

Rule based reasoning is the most common approach to develop a knowledge-based system. In the rule-based systems, the knowledge is represented as a set of production rules, which are usually extracted from a number of domain experts. These rules are constructed in the form of condition-action pairs, which can be read as "IF condition are satisfied, THEN performs actions". Rule-based systems solve problems by taking an input specification and then "chaining" together the appropriate set of rules from the rule base to arrive at a solution.

Rule-based systems have been used in the process design of injection moulding such as the selection of injection moulding machines [Elsayed 1992], mould making planning and injection mould cost estimation [Chin 1995]. In order to handle the numerous decision factors in mould cost estimation, Chin K.S. et al. [Chin 1996a] considered decision tables as a logic representation method in the development of a knowledge-based system called DTMOLD-1 for mould cost estimation. Some efforts have also been made in the use of object-oriented programming and rule-based reasoning to encode mould design knowledge in the knowledge base. This knowledge representation method allows an easy expansion of the knowledge base due to their modular structures. Based on the rule-based and object-oriented approach, Ong S. K. et.al. [Ong 1995] developed a knowledge-based system called CADFEED for gating design. Chin K.S. et al. [Chin 1996b] and Lee R.S. et al. [Lee 1997] also developed two prototype knowledge-based systems to generate major parameters for injection mould design. In fact, quite a few rule-based systems have been developed to determine the process parameters for injection moulding. Details of them are described in Section 2.3.5.

Recently, a research project was conducted in the National University of Singapore which is to develop a computer-aided system for injection mould design. In the project, a knowledge-based system named IMOLD was developed and commercialised [Lee 1996c, IMOLD 1999]. IMOLD consists of a number of modules, such as filling design, mould base selection, cooling design and ejecting design. The object-oriented paradigm (OOP) was utilised in the development of IMOLD, in which knowledge about the product is encapsulated in a special product model.

Kwong C.K. et al. [Kwong 1998] employed blackboard architecture to organise the multi-disciplinary knowledge into a single knowledge-based system called CSPD in order to perform concurrent process design of injection moulding. CSPD firstly derives the process solution, including the selection of injection moulding machine and mould base, tooling and processing cost estimation and production scheduling, based on the blackboard-based expert-system approach. It is then followed by the determination of initial process parameters for injection moulding based on case based reasoning approach.

2.2.3 Case based reasoning (CBR)

In the middle of the 1980s, Riesbeck C. K. and Schank R. C. [Riesbeck 1989] pioneered case based reasoning (CBR) techniques as an alternative to the more traditional rule-based reasoning technique. The basic idea of CBR is that a case based reasoner solves a new problem by adapting solutions that were used to solve the old problems. The new problem is matched against the cases in the case library and one or more similar cases are retrieved. The most similar one is then repaired to yield the solution.

Recently, CBR has been applied in the development of computer-aided systems for process design of injection moulding. Nedebb C. et al. [Nedebb 1997] and Hu W. G.

[Hu 1998] employed CBR approach to develop CBR systems for injection mould design. The systems aim to aid mould designers in the determination of the major parameters of mould design such as type of spure, cavity layout and type of demoulding. Garman T.B. [Garman 1996] also employed CBR concept to develop a system to reduce the time in the preparation of drawings for new standard mould frames. Regarding the cost estimation of injection moulds, Filz P. F. et al. [Filz 1997] developed a system called Moldcalc based on the fact that similar moulds generally give rise to similar costs. Some CBR systems were developed to determine initial process parameters of injection moulding. Details of them are described in Section 2.3.6.

2.2.4 Neural networks (NNs)

Neural networks (NNs) are an information processing technique that emulate the neural reasoning behaviour of biological neural systems [Picton 1994]. A NN consists of several interconnected layers of non-linear processing units. An input layer accepts scaled input values and passes these values along to a series of hidden layers and finally to an output layer. A NN must be trained by methodically examining sets of input values and their associated outputs. A trained NN system has the ability to transform non-linear mathematical modelling into a simplified black-box structure that is capable of generalisation over the set of previously learned instances.

Lee B.H and Kim B.H [Lee 1996a] applied NN approach in the determination of optimal gate location(s) of injection mould. In their study, a trained NN was employed to perform a nonparametric functional mapping between ten thermomechanical properties such as bulk temperature, shear stress and volumetric shrinkage (inputs), and

Izod impact strength (output). The predicted Izod impact strength is treated as one of the evaluation criteria to evaluate quality of several gating plans (gate locations). Rawin R. and Venkat A. [Rawin 1997] also developed a model based on the NN approach for the computation of injection mould complexity. In the model, inputs are the fourteen cost drivers of manufacturing an injection mould such as moulded part size, number of cavities per mould, mould base type and mould material while output is a numerical index which describes the degree of mould complexity. Due to the fact that the higher complexity of mould normally leads to higher mould cost. The mould complexity index obtained from the model can be used to estimate the mould cost. Some NN based models were developed for the determination of process parameters for injection moulding. Details of them are presented in Section 2.3.7.

2.2.5 Structured models

Some efforts were made in the development of structured models for estimating costs in injection moulding. Boothroyd G. and Dewhurst P. [BDI 1993] developed operation-based cost models for injection moulded parts in their commercial Design for Manufacture (DFM) software package. Along with providing the component cost of an injection moulded part, the software provides the estimation of mould cost, processing cost and materials cost for the part. Some process parameters, such as fill time, cooling time and cycle time, can also be estimated by the software. Group technology (GT) was applied in the mould cost estimation by Poli C. et al. [Poli 1992]. They conducted a research to develop a coding system based on the group technology which is used to evaluate the part/mould complexity and estimate the mould cost.

2.3 Review of Research in the Determination of Process Parameters for Injection Moulding

Determination of process parameters for injection moulding is one of the crucial activities in the process design of injection moulding. An appropriate set of process parameters can effectively shorten the time in initial set-up and moulding trials, and improve quality of moulded parts. The process can be split into two subtasks: initial process parameter setting and process parameter resetting. In the following, research based on various approaches to both the initial process parameter setting and process parameter resetting are described which include mathematical models, numerical simulation, process window, design of experiments (DOE), knowledge-based systems, neural networks (NNs), case based reasoning (CBR) and genetic algorithms (GAs).

2.3.1 Mathematical models

Quite a few mathematical models for describing the physical process of injection moulding were developed based on the first principle. Kamal M.R. et al., [Kamal 1972], Wu P.C. et al. [Wu 1974] and Stevenson J.F. [Stevenson 1978] developed the mathematical models to describe the filling in a centre-gated disc. Besides, Williams G. et al. [Williams 1975] developed the mathematical models to describe the filling in a circular tube and rectangular cavities. These filling models all are limited to one-dimensional geometry. Network flow approach [Krueger 1978] and branching flow approach [Richardson 1980] were attempted to develop the filling models for multi-cavity layout. The filling models could be used to estimate the filling time and injection time. Regarding the mould cooling, White J.L. [White 1983] derived a mathematical model for cooling time estimation in which the cooling time is defined as a simple approximation for defining the transfer of heat within the moulded part during the cooling process in injection moulding. Another mathematical model for the estimation of cooling time was recommended by Kwon T.H. et. al. [Kwon 1987] in which the cooling time is defined as the time needed for the average melt temperature to reach the ejection temperature.

Some of the mathematical models were combined with the other techniques in the determination of process parameters for injection moulding. Tan K.H. et al. [Tan 1996] developed a computer-aided system for deriving initial process parameter setting for injection moulding. In their system, the initial processing condition including melt temperature, melt pressure, mould temperature and filling time is determined by fuzzy reasoning. The fuzzy inferencing is used to quantify the qualitative relationship between the process parameters and mould geometry. Once the initial processing condition is determined, the corresponding machine setting, such as nozzle temperature, injection pressure, coolant temperature and injection speed, can be calculated by using mathematical models. Tan K.H. et al. [Tan 1997a] also developed a simplified analytical model for the injection moulding process in which the process parameters of injection moulding, such as the filling pressure, cavity force, shear stress, shear rate and temperature at different time and locations, can be calculated.

2.3.2 Numerical simulation

Typical numerical simulation models are developed based on the combination of mathematical models, numerical methods and user interface programming. Quite a few numerical simulation models were developed to simulate the process behaviour of injection moulding in the filling, postfilling and cooling stages. Hieber, C. A. et al.

[Hieber 1980] and Wang, V. W. et al. [Wang 1986] employed a finite-element/finite difference scheme for simulating filling of thin cavities of general planar geometry. These models were implemented based on the generalised Hele-Shaw flow for an inelastic, non-Newtonian fluid under non-isothermal conditions. Chiang, H. H. et al. [Chiang 1991] developed a unified simulation model for the filling and postfilling stages based on hybrid finite-element/finite difference numerical solution of the generalised Hele-Shaw flow for the compressive viscous fluid under non-isothermal conditions. Himasekhar, K. et al. [Himasekhar 1992] developed a numerical simulation model for three-dimensional mould heat transfer during the cooling stage. Some of the achievements in simulating the injection moulding process were commercialised in CAE analysis packages as described in Section 2.2.1.

2.3.3 Process window

Since the quality of moulded parts is greatly affected by the conditions under which it is processed, there are several attempts that aim to determine a feasible process zone for injection moulding. This process zone is always referred as a process window. The process window as shown in Figure 2.1 is represented by a set of boundaries that define a window-like shape. It indicates the influence of injection pressure versus melt temperature. If the melt temperature is too low, higher injection pressure is required to deliver the melt polymer into the cavities. If the melt temperature is too high, material degradation may occur. On the other hand, if the injection pressure is too low, a short shot may be resulted. If the injection pressure is too high, flash may occur. The initial process parameters usually are defaulted as the centre of the process window.

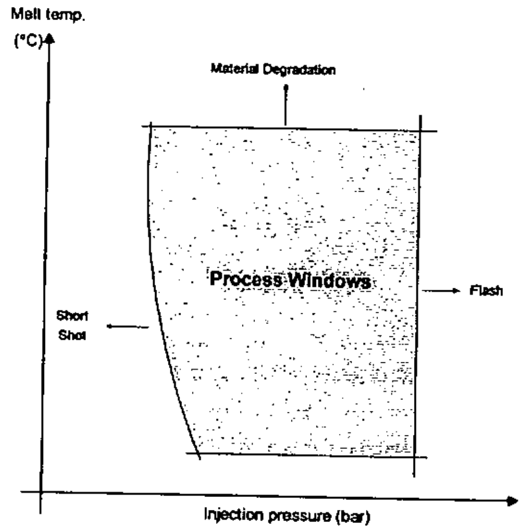


Figure 2.1 A typical process window (injection pressure vs. melt temperature)

There are various techniques that were introduced in the development of a process window for injection moulding. Quite a few researches [Bourdon 1989, Nagarsheth 1989, Pandelidis 1990b] developed a process window through a number of simulation trials with different combination of process parameters for injection moulding. Their simulation trials normally are based on a specific material and the machine capability as well as the approximated geometry of moulded parts. Murakami, T. et al [Murakami 1993] employed constraints processing method and the simulation results in the development of process windows. The thermal analysis, named Thermogravimetric Analysis (TGA), was also used to develop a process window for injection moulding [Hutchins 1995].

To obtain optimal / near-optimal parameter setting from a process window, quite a few techniques have been employed. Nagarsheth, P.S. [Nagarsheth 1989] formulated the linear quadratic model by regression analysis of the simulated data for the optimisation of one dependent variable. Pandelidis I. et al. [Pandelidis 1990b] quantified the quality as a function of flow simulation outputs and constituted this objective function that must be minimised. Murakami T. et al. [Murakami 1993] proposed to use constraints processing method based on knowledge or operators' experience for optimising the moulding conditions.

2.3.4 Design of experiments (DOE)

When injection moulding is studied, an experiment is traditionally conducted in which only one process parameter is varied at a time until the quality of moulded parts is found satisfactory. Such a method ignores the effect of interactions among the process parameters in injection moulding. In fact, the process parameters involved in injection moulding are interacting with each other. Design of experiments (DOE) techniques are attempted to obtain the understanding of injection moulding process [Skourlis 1997]. Among the various DOE techniques, Taguchi method was widely used to determine optimal process parameters for injection moulding. Figure 2.2 shows the typical processes of using DOE techniques in the determination of optimum process parameters for injection moulding.

Researches were done on the optimisation of the injection moulding conditions by using Taguchi parameter design [Kyle 1990, Bourdon 1991, Vaatainen 1994, Blyskal 1994, Dillman 1996]. Their studies show that Taguchi experiment design can uncover subtle interactions among process variables with minimum number of test runs. Furthermore, analysis of the experimental results could help to develop a model of injection moulding process, which allows the prediction of part characteristics as a function of process conditions. Such a model can then be used to find the optimal setting of process parameters.

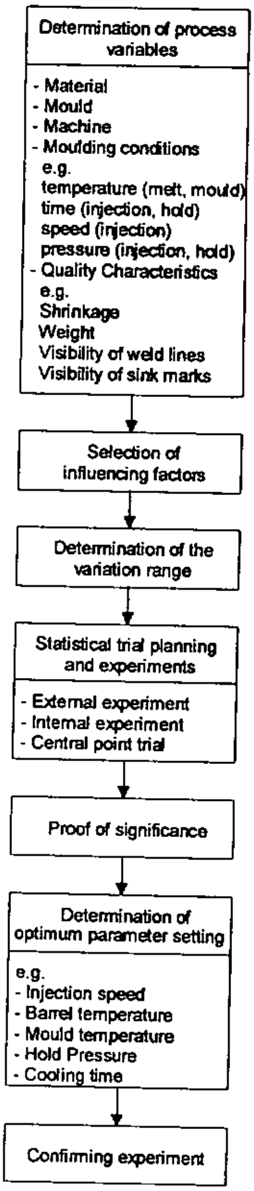


Figure 2.2. Procedural steps of DOE techniques for process analysis and optimisation

To improve the effectiveness of the DOE, other techniques were incorporated with the use of Taguchi method. Yeung W.S. et al. [Yeung 1997] attempted linking Quality Function Deployment (QFD) with DOE to establish a prioritisation mechanism for the setting of selected parameters with respect to the quality characteristics. This could allow the best trade-off among the customer satisfaction, significance of control parameters, and the response for quality control. Kuhmann K et al. [Kuhmann 1996] combined the Taguchi method and the Shainin method to improve the robustness of injection moulding process.

2.3.5 Knowledge-based systems

Quite a few rule-based systems were developed to recommend the qualitative correction instructions [Luong 1997] and/or the quantitative change of moulding parameters [Jan 1992, Jan 1993, Tan 1995, Catic 1996, Jong 1997] in response to the input moulding defects. Figure 2.3 shows the block diagram of a typical rule-based system for injection moulding defect correction. It consists of two major elements, a knowledge base and an inference engine. The knowledge base contains facts and heuristics about the domain and the relationships between them. Inference engine may be described as a control mechanism that organises the correct sequence of heuristic activation. Its function is to access and manipulate the knowledge base according to the specific problem data contained in the working memory.

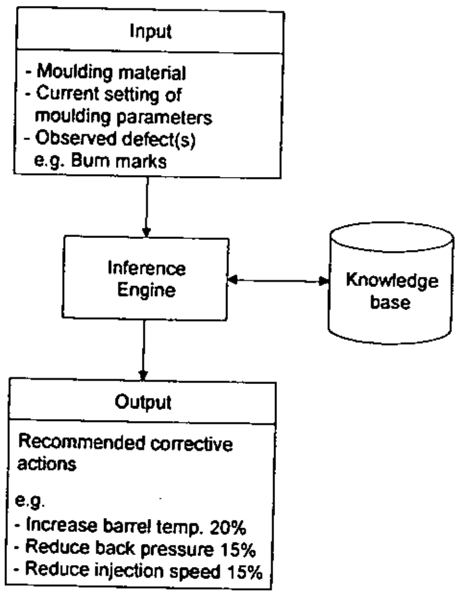


Figure 2.3 A typical expert system for injection moulding defect correction

Initially, the system prompts users to input information about the material to be processed, the current setting of moulding parameters and the moulding defects being observed. After the inputs, the knowledge base is inferenced and then the corrective actions are recommended.

Various techniques have been attempted in the development of rule-based systems for injection moulding defect correction. Jan T.C. et al. [Jan 1992, Jan 1993] developed an algorithm to calculate the decision indexes that show the likelihood of the influencing variables being responsible for defects. Normally, the corrective action with the highest value of the decision index is firstly recommended. Certainty factors were introduced in the development of rule-based expert systems for injection moulding [Jong 1997, Catic 1996]. They are used to specify the assurance of possible remedies for the given injection moulding problems. Propositional logic and fuzzy logic [Tan 1995a, Tan 1995b] were applied in the development of a rule-based expert system, which can recommend the quantitative change of moulding parameters. Another technique, the Multi-dimensional Matrix, was applied to develop a rule-based expert system called ESIM to realise the skilled operators' inference procedures into the system [Kameoka 1993]. The ESIM does not generally use a single countermeasure that is considered best, but prepare plural potential countermeasures from past experiences at the same time.

2.3.6 Case based reasoning (CBR)

CBR was widely applied in different engineering applications such as assembly planning, building design and system diagnosis. For process design, CBR approach has been applied in the determination of parameters for die casting process [Price 1993, Price 1995] and grinding process [Rowe 1996]. Recently, CBR approach has also been attempted in the determination of initial process parameters for injection moulding. Kwong C.K. et al. [Kwong 1997] developed a CBR system called CBRS to obtain proper initial process parameters for injection moulding based on the old solutions. The basic algorithm of reasoning in the CBRS is shown in Figure 2.4.

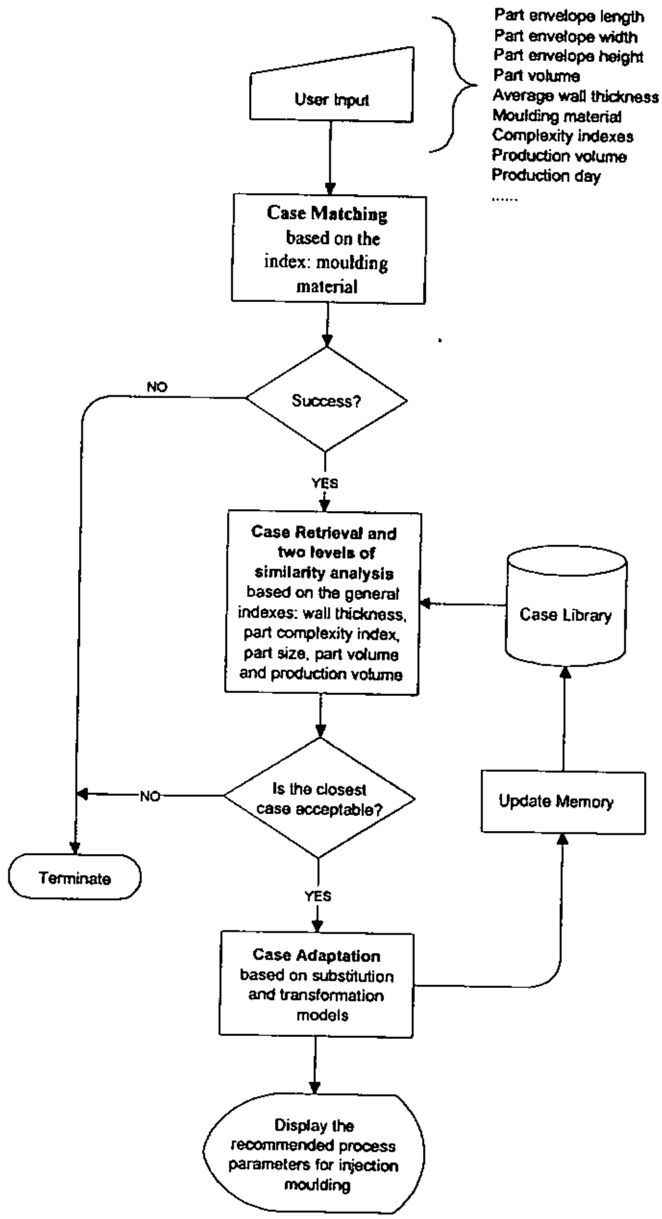


Figure 2.4. Basic algorithm of reasoning in the CBRS

The cases of CBRS are stored in case library in a structured manner. Each case is assigned with the indexes to facilitate the case retrieval. In the CBRS, the critical indexes are the moulding material and wall thickness. The input problem is then matched against the cases in the case library. Some potential cases are retrieved and similarity analysis is applied to find out the most similar case. Adaptation models are then used to perform the repairing on the most similar case.

Shelesh-Nezhad K. et al. [Shelesh 1997] also applied the CBR approach in deriving the initial process parameter setting of injection moulding. Unlike the CBRS, their CBR system only derives the optimum magnitude of the process parameters in the cavity based on the linear relationships between the operating conditions and the dimensions of moulded parts. The other required magnitudes of parameters are determined by a mould flow analysis sub-system.

2.3.7 Neural networks (NNs)

Neural network approach had been applied in building a process model for quality control in injection moulding [Souder 1994, Smith 1996, Hausler 1996a]. Inputs to the networks are the process parameters of injection moulding and the outputs are the quality characteristics. After supervised learning, these process models can project the process parameters onto the quality characteristics for on-line quality forecast or quality control. Figure 2.5 shows the structure of a NN for the quality prediction of moulded parts.

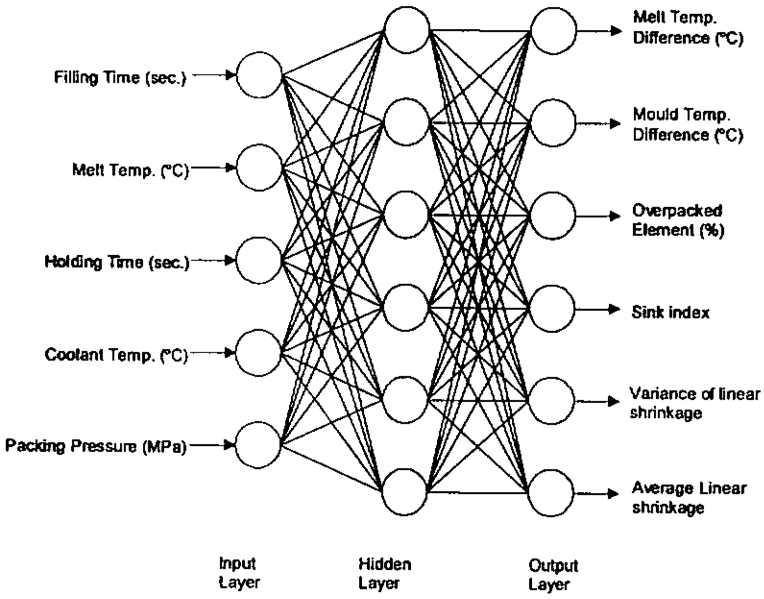


Figure 2.5. Structure of neural network for moulded part quality prediction.

To obtain the optimal parameter setting for injection moulding, Choi G.H. et al. [Choi 1994] quantified the part quality in terms of a performance index which is essentially a function of two geometrical characteristics of a moulded part, namely variance of linear shrinkage and sink index. A set of optimal process parameters can be obtained by minimising the performance index.

Some efforts have been made in incorporating fuzzy logic with neural networks to develop an intelligent system for process parameter resetting [He 1998]. The theory of fuzzy logic provides mathematical strength to capture the uncertainty, ambiguity and vagueness associated with the process of parameter resetting. In the system, inputs are the common injection moulding defects and the "fuzzified" dimensional parameters of the part while outputs are the recommended adjustments of process parameters. The trained neural network was treated as a fuzzy inference system to provide better outputs.

2.3.8 Genetic algorithms (GAs) and evolutionary strategies

More and more artificial intelligence (AI) techniques are being developed from the observation of nature. Two of them are genetic algorithms (GAs) [Goldberg 1989] and evolutionary strategies [Schwefel 1995]. Both of them draw inspiration from the natural search and selection processes leading to the survival of the fittest individuals. The principal difference between them is that evolutionary strategies use mutation as the primary search mechanism, while genetic algorithm relies on crossover to locate better solutions.

GA approach has been applied in the development of a system for the optimisation of the process parameters for injection moulding based on the results of flow simulation [Kim 1996]. The behaviour of GAs can be subtle, but their basic construction and execution cycle are straightforward. Figure 2.6 shows a typical process flow for the optimisation of process parameters for injection moulding based on GA approach.

In the system, initial process parameters of injection moulding are randomly chosen within the feasible search space and evaluated by a mould flow simulation package. The quality of moulded parts is quantified by a fitness function. The process iterates until an optimal or near optimal process parameter setting of injection moulding is found.

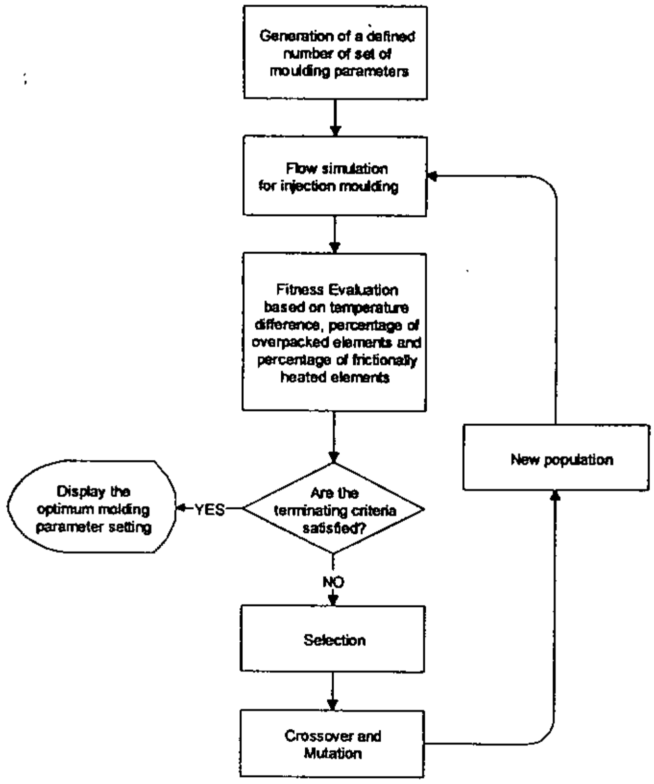


Figure 2.6. Typical process flow for the optimisation of the injection moulding parameters based on GA approach

Since the optimisation of process parameters for injection moulding is not a static process, an optimisation system called Ibos-Pro has been developed based on evolutionary strategy approach for on-line optimisation of the process parameters [Haupt 1989, Offergeld 1992]. In the system, the calculated working point from off-line optimisation or the empirical data provided by machine operators is used as the starting value. Optimisation is performed on the real process by automatically interrogating the input values such as holding pressure, holding time and metering stroke through the master computer interface. The output values such as cycle time, flash formation and part weight are analysed by the optimisation system. The derived operating point setting is then transferred to injection moulding machines.

2.4 Discussions

In Section 2.2, five approaches to the process design of injection moulding including computer-aided engineering (CAE), knowledge-based systems, case based reasoning (CBR), neural networks (NNs) and structured models were briefly discussed. CAE is the most common approach to perform the process design of injection moulding. The CAE analyses can provide useful information about part design as well as process design of injection moulding. The process behaviour predicted by the CAE analyses can help novice engineers overcome the lack of experience in injection moulding and assist experienced engineers in pinpointing factors that may otherwise be overlooked. Several efforts had been made in the selection of injection moulding machines and injection mould design such as runner system design, gating design and cooling system design based on the results of CAE analyses.

Most of the CAE analysis packages are based on the mathematical modelling of plastic melt flow during injection process. To reduce the degree of complexities in solving the governing partial differential equations of conservation of mass, momentum and energy, some assumptions and simplifications were used in the development of mathematical models of filling mould cavities. For example, Hele-Shaw model was generally assumed in the filling of thin cavities, in which the flow in the thickness direction of cavities was neglected and only 2-D flow in the plane of the cavities was considered. Batch G.L. [Batch 1993, Batch 1994] reported that the assumption of the Hele-Shaw flow was reasonable for large thin-wall parts, but could lead to numerically inaccuracy for small ones.

In addition, a mid-plane finite element mesh (FEM) model must be created before running any finite element analysis (FEA) in the CAE analysis packages. The preparation of a FEM model can take a considerable amount of time. The meshing size can profoundly affect the accuracy of the analyses and the processing time [Ni 1997]. Coarse meshing could cause an unacceptable result, while too fine meshing of course could lead to more accurate results but requires excessively long computing time. Based on the FEM model, users are required to evaluate alternative design and to interpret the analysis results correctly and intelligently until the solution reaches the requirements of users. Therefore, effectiveness of the approach relies heavily on the proficiency of users. A novice moulding personnel could perform a number of CAE analyses without getting any useful information.

Application of artificial intelligence (AI) techniques in engendering knowledge-based systems in the process design of injection moulding could abate some of the problems associated with the CAE tools. Rule based reasoning is the most common approach to develop a knowledge-based system. Quite a few rule-based systems were developed for the injection mould design, mould cost estimation and the selection of injection moulding machines. The rule-based systems are found suitable for use in injection moulding because of the large amount of on-the-job experience and empirical knowledge that are always involved. They can provide assistance to moulding personnel in the process design of injection moulding. However, in the domain of process design of injection moulding, the domain experts including mould designers, mould makers and moulding personnel rely heavily upon their experiences rather than upon explicit-stated rules. Their experience probably exceeds their understanding of the technology and sometimes it is hard for them to explain the reason for actions that they have taken. Since the nature of the experience is fragile and not well structured, it may not be acquired easily or readily transformed into rules format.

CBR is an alternative to the rule-based reasoning. Some CBR systems were developed for injection mould design and mould cost estimation. This approach eliminates the knowledge elicitation bottleneck which is inherent in rule-based systems. Instead of generalising knowledge into rules, CBR represents the knowledge as individual problem solving episodes. In CBR, knowledge elicitation becomes a task of gathering case histories. However, effectiveness of a CBR system depends largely on the size of case library, effectiveness of indexing and the relevance of old cases stored in the case library.

Some NNs were also employed to handle the complex relationship among the parameters involved in the process design of injection moulding. Unlike some other techniques such as non-linear regression, NNs do not require any prior assumption of the function such as linear, first-order polynomial and logarithmic to form the process models. They can derive their "knowledge" of the processes from examining sets of input data and their corresponding outputs. Therefore, this approach is found suitable to deal with the process design of injection moulding where quite a large amount of knowledge is fragile and ill-structured. However, there is no defined methodology available which could help users design a NN for a given problem domain. Network builders have a high degree of freedom to define the structure of a NN. They need to determine the number of nodes, the connectivity between nodes, and the number of layers of nodes in a network in order to identify a network structure. The process is trial-and-error in nature and could be quite time consuming.

In Section 2.3, researches based on various approaches to the determination of process parameters for injection moulding, including mathematical models, numerical simulation, process window, design of experiments (DOE), expert systems, neural networks (NNs), case based reasoning (CBR) and genetic algorithms (GAs), were described. The literature review shows that there are quite a few mathematical equations available for the determination of initial process parameters for injection moulding. The initial process parameters can be derived from the mathematical models in very short time. However, a general comprehensive mathematical model describing the actual filling process is not yet available because of the complexity of the mould filling process and difficulties in obtaining an accurate rheological description of the actual material being processed. Nedess C. et. al. [Nedess 1992] reported that the different mathematical models for injection moulding give vastly different results even for identical operating conditions. The problem could be alleviated by the introduction of CAE analysis packages. However, this approach involves creating a FEM model and running a number of CAE analyses in order to obtain the acceptable process parameters for injection moulding. As the time required to run a mould flow analysis of a plastic part, such as a casing of mobile phones, could take an hour or even more, it may not be practical to perform CAE analyses in shop floor production environment.

Several attempts have been made in utilising the CAE analysis results to determine a set of process parameters for injection moulding. Some tend to define a defect-free moulding region or process window for injection moulding. Some applied DOE techniques to define an acceptable parameter setting. The process parameters of injection moulding can be obtained easily from process windows. Normally, an acceptable result of injection moulding can be yielded based on the process window approach. However, development of a full set of process windows would be very difficult because of the large number of process parameters involved and the number of possible interactions among the parameters. Moreover, development of process windows is by means of a number of mould flow analyses or test-runs of injection moulding. It could be a time consuming and costly process in the production environment. The DOE approach requires a certain measure of expert knowledge of both statistics and processes in experiment planning. If the properties of experiment plans are not fully understood, it is possible that interaction between two factors could bring out pseudo effects on other parameters, thus leading to incorrect interpretation. Therefore, moulding experts need to be involved in the determination of importance of individual process parameters for injection moulding during the DOE process. Moreover, during the experiments, production generally has to be interrupted for setting the experiment points and quantifying the target variables.

Some artificial intelligence (AI) techniques such as knowledge-based systems, neural networks (NNs), genetic algorithms (GAs) and case based reasoning (CBR) have been attempted in the determination of process parameters for injection moulding. Some knowledge-based systems could provide useful information to moulding personnel in process parameter resetting. However, a typical symbolic knowledge-based system is not easy to be implemented in the area of the process parameter resetting due to its incomplete integration of qualitative and quantitative reasoning [He 1998].

NNs have been shown to be an effective technique for modelling complex non-linear processes which enables NNs to be an effective technique in handling the problem of initial process parameter setting of injection moulding. In order to obtain an optimal set of initial process parameters of injection moulding, NNs must be incorporated with some optimisation techniques. On the other hand, NNs cannot communicate their working to users so that it may be difficult to see what they are going wrong. As a consequence, users cannot gain the understanding of process through the NNs.

With the aid of the GAs and evolutionary strategies, optimal/near-optimal process parameter setting of injection moulding could be obtained even without knowledge of injection moulding process. If a dynamic optimisation is carried out, any disturbance occurring in moulding can be compensated. Effectiveness of the GAs and evolutionary strategies is much dependent on the choice of the operating range of process parameters and design of a fitness function which is used to quantify the quality of moulded parts. If a poorly defined fitness function and improper operating range are adopted, the optimisation process may either converge prematurely to a sub-optimal solution or become an inefficient random walk through the solution space. Therefore, experienced moulding personnel need to be involved in system development stage. Besides, the control parameters of GAs and evolutionary strategies such as population size, crossover rate and mutation rate must be properly defined. Otherwise, exploitation and exploration could not be balanced due to the poor setting of these control parameters.

CBR systems can determine a set of initial process parameters for injection moulding quickly based on the pervious successful case(s) without relying heavily on expert moulding personnel. A self-learning capability can be incorporated into the CBR systems that enable expertise in setting of moulding parameters to be easily embodied. However, the performance of the CBR systems is limited by the size of case library and the relevance of old cases stored in the case library. On the other hand, their effectiveness is dependent on the design of case retrieval algorithm, adaptation models and indexing method.

CHAPTER THREE - SYSTEM DESIGN AND DEVELOPMENT

3.1 System Architecture of an Intelligent System for the Determination of Initial Process Parameter Setting for Injection Moulding, HSIM

In this research, a hybrid neural network and genetic algorithm (NN-GA) approach was firstly proposed to complement case based reasoning (CBR) approach in the determination of initial process parameters for injection moulding. Based on the combined CBR and hybrid NN-GA approach, a Hybrid System for Injection Moulding (HSIM) was developed to the determination of initial process parameters for injection moulding. Figure 3.1 shows a basic architecture of HSIM that mainly consists of an user interface, a case based reasoning (CBR) module and a hybrid neural network and genetic algorithm (NN-GA) module.

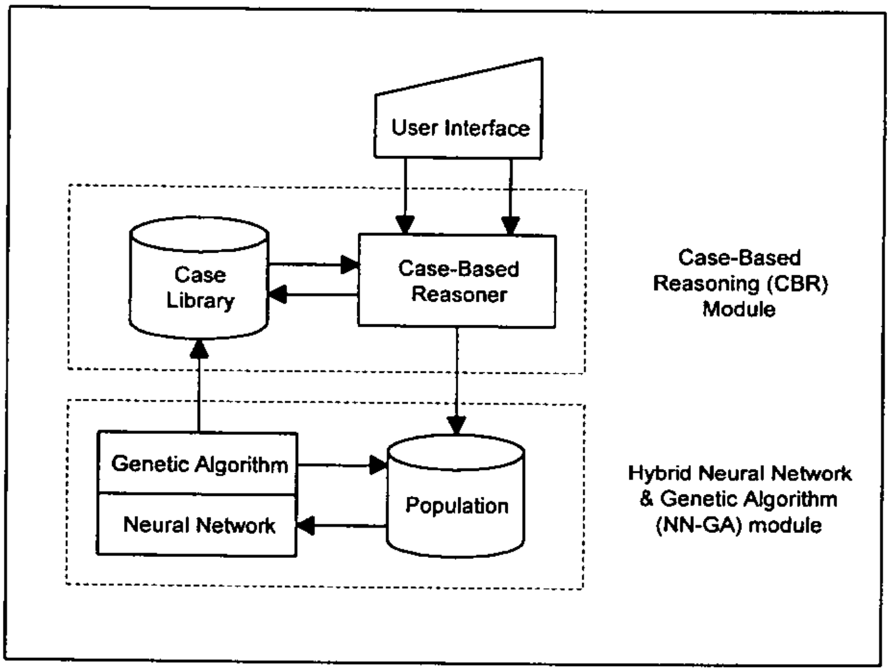


Figure 3.1. Basic Architecture of HSIM

The user interface allows system users to input required information and data to the system. The CBR module composes of two elements, a case library and a case-based reasoner. The case library stores the old cases in a structured manner, while the case-based reasoner performs the case indexing, case retrieval and case adaptation to generate initial process parameters of injection moulding for an input problem. The hybrid NN-GA module is used to generate and optimise initial process parameters of injection moulding within a pre-defined searching space if there is no relevant case found in the CBR module. The initial process parameters recommended by HSIM could be used in CAE analyses or actual trial-run of moulding. Once the parameters are validated, they can be stored in the case library through the user interface for future reference.

In the next section, basic algorithm of reasoning in HSIM is depicted. The issues of design and development of the CBR module and the hybrid NN-GA module are discussed in Section 3.3 and Section 3.4 respectively.

3.2 Basic Algorithm of Reasoning in HSIM

Figure 3.2 shows the basic algorithm of reasoning in HSIM which mainly involves the following processes:

a. Problem input

Firstly, production requirements including production volume, allowable working days, number of shifts per day, reject rate and machine utilisation, and parameters of part design including moulding material, part envelope size, projected area, part volume, wall thickness and part complexity are required to be input. The input data and information will form the description of a problem. Some of them will be identified as the indexes for case matching.

b. Matching of critical indexes

Some input data and information are identified as critical indexes to filter out irrelevant cases. By matching the critical indexes, a cluster of potential cases are retrieved for further evaluation.

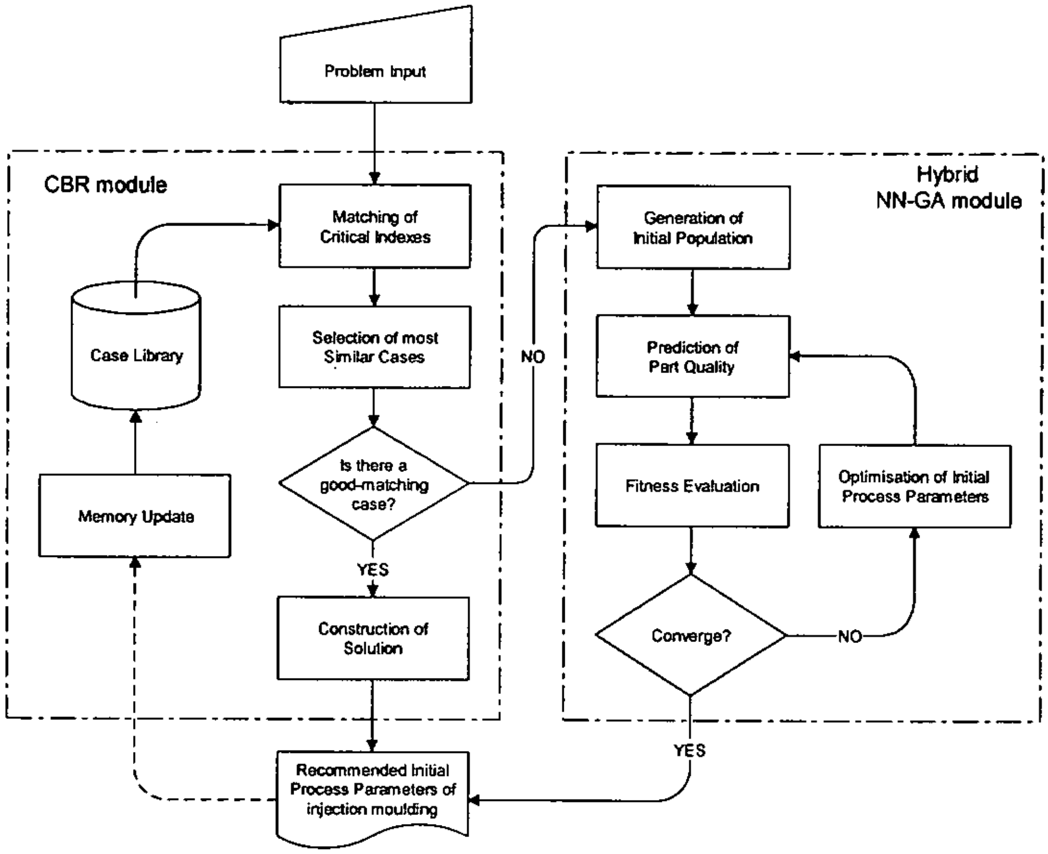


Figure 3.2 Basic algorithm of reasoning in HSIM

c. Selection of the most relevant cases

In this process, similarity analysis is performed on the potential cases and a small batch of the most similar cases are identified.

d. Construction of solution

This process looks for prominent differences between the similar cases obtained in process (c) and the input problem, and then applies some adaptation techniques to take those differences into account. The adapted case, which contains a set of initial process parameters for injection moulding, is recommended to system users as a starting condition for performing CAE analyses or actual trial-run of moulding.

e. Generation of initial population

If no good matching case is retrieved in process (c), the hybrid NN-GA module will be invoked to determine the initial process parameters of injection moulding. An initial population is required to be generated first.

f. Prediction of part quality

Once the initial population has been generated, each string stored in it will be fed into a trained neural network for the quality prediction of moulded parts. Outputs from the neural network are quality measures of a moulded part.

g. Fitness Evaluation

A fitness function is used in this process to evaluate the fitness of the strings based on the quality measures obtained in process (f).

h. Optimisation of process parameters

This process aims to generate optimal/ near optimal initial process parameters of injection moulding within a pre-defined searching space. The optimisation process is terminated if an optimal solution is obtained. Otherwise, a new population is generated and the processes (f), (g) and (h) are repeated.

i. Memory update

The recommended solution, either obtained from the CBR module or from the hybrid NN-GA module, will be executed in real-world environment. After the execution, a real-world solution, which probably deviates from the system solution, is stored into the case library so as to solve similar problems in future.

3.3 Case Based Reasoning (CBR) Module

In HSIM, the role of the CBR module is twofold. Firstly, if there are good matching cases in the case library, the CBR module will generate a set of initial process parameters of injection moulding for the input problem based on the past successful cases. Secondly, if no good matching case is retrieved from the case library, the CBR module will retrieve a number of partially matched cases as a part of the initial population for performing GA based optimisation in the hybrid NN-GA module.

In the design and development of the CBR module, four important issues have to be addressed and settled before any implementation attempts, which are the case library design, case indexing, case retrieval and case adaptation. Individual issues are described in subsequent sections.

3.3.1 Case library design

The case library stores a number of old cases in an organised structure. Contents of each case stored in the case library are basically a description of the previously solved problem. In the CBR module, each case is made up of three components: a problem description, a stored solution and an outcome. Structure of each case can be represented as follows:

$Case\ \{P_i,\ S_i,\ O_i\}$

where P_i is the problem descriptions of the i-th case, S_i is the solution of the i-th case and O_i is the outcomes of the i-th case

The problem descriptions are referred to the features in a case that are used to describe a problem. As shown in Table 3.1, a problem depicted in this research is described by the information and data of production requirements, moulded part design, injection mould design and injection moulding machines. In HSIM, parameters of injection mould design to be studied are limited in the runner and gating system design. It is because runner and gating system largely affects the mould filling process, and thus the quality of moulded parts as well as the process parameter setting of injection moulding [Menges 1993].

Aspects of Description	Features
Production Information	– Production Volume
	– Allowable Working Days
	– Number of Shifts per Day
	– Reject Rate
	– Machine Utilisation
Part Design Information	– Moulding Material
	– Part Envelope Size
	– Projected Area
	– Part Volume
	– Wall Thickness
	– Part Complexity
Mould Design Information	– Number of Cavities
	– Runner Type and Size
	– Runner Layout
	– Flow Length
	– Gate Type and Size
	– Number of Gates
Machine Information	– Machine Model Number

Table 3.1 Features of problem description

The solution states the derived solution to an input problem specified in the problem descriptions. As shown in Table 3.2, a solution of the system contains a set of initial process parameters of injection moulding for an input problem. The outcome is the remarks of the case, which could describe the yield of moulding, part defects etc.

Contents of Solution	Unit
– Nozzle temperature	°C
– Barrel temperature (Rear)	°C
– Barrel temperature (Middle)	°C
– Barrel temperature (Front)	°C
– Injection pressure	bar
– Holding pressure	bar
– Back pressure	bar
– Clamping force	ton
– Screw rotating speed	rpm
– Fill time	sec.
– Holding time	sec.
– Cooling time	sec.
– Cycle time	sec.

Table 3.2 Contents of a solution

Contents of cases can be represented in a number of ways, such as attribute-value pairs, text, object-oriented representation, graphs and multimedia representations [Maher 1995]. In the CBR module, attribute-value pairs representation is employed to represent the cases, in which each case stored in the case library is described by a set of features and each feature takes on a value. The features define the vocabulary for describing the cases, and the values identify the information specific to one case. An example of the attribute-value pairs representation is shown in Figure 3.3.

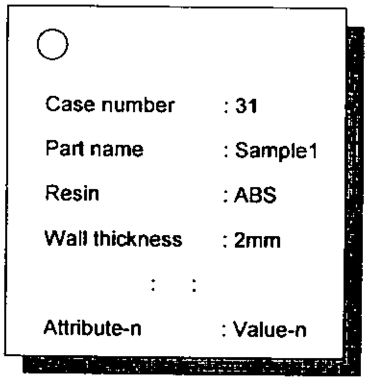


Figure 3.3 An example of attribute-value pairs representation

The attribute-value pairs representation follows the common practice of documentation of machine setting in injection moulding shop floor. The representation paradigm is generic and does not imply any specific forms of knowledge. Of course, attribute-value pairs representation is not the only way to make cases people-readable. For the prototype system development, however, the attribute-value pairs representation has been shown to be quite adequate.

Another major consideration of the case library design is case organisation. The case library should be organised in a manageable structure that supports efficient search and retrieval methods. The case library can be organised in various forms such as flat structure, feature-based structure, hierarchical structure or a combination of all these forms. Figure 3.4 shows the organisation of the case library of the CBR module, which organises the cases in a combination of feature-based structure and flat structure. Although the organisation structure may not be an optimal one, it is still effective to reduce the searching space.

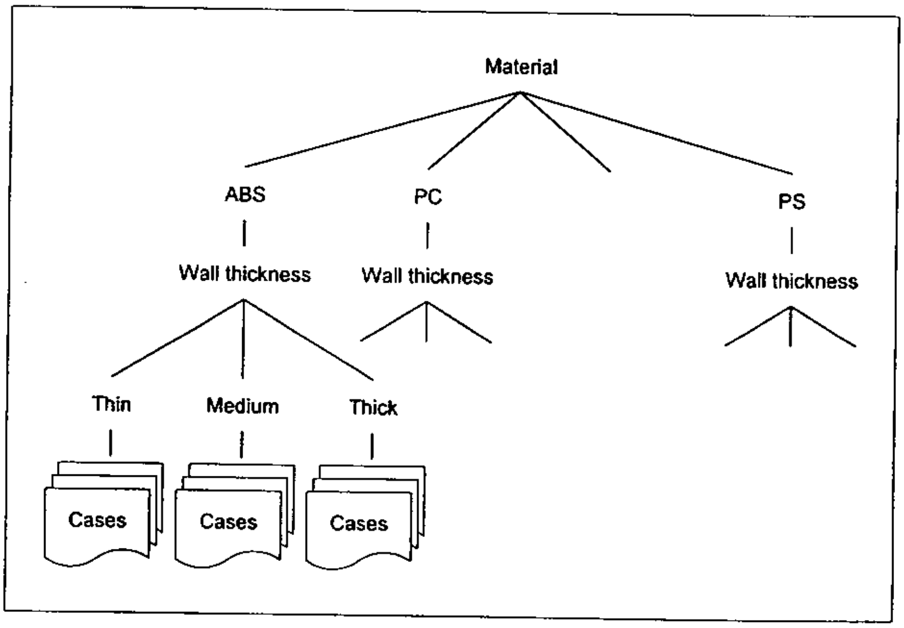


Figure 3.4 Organisation of case library

Effectiveness of the feature-based structure is greatly dependent on the key features that are used to differentiate cases. In HSIM, two features, moulding material and wall thickness, are employed to form a shared-feature network. Identification of these two features for the construction of the shared-feature network will be discussed in Section 3.3.2. In a flat structure, cases are organised in a sequential data structure, such as a list. The cases stored in the case library are decomposed into three chunks in order to reduce the size of stack memory being used and improve the computing efficiency. As shown in Figure 3.5, the chunks are indexed independently from the large case to which they physically belong.

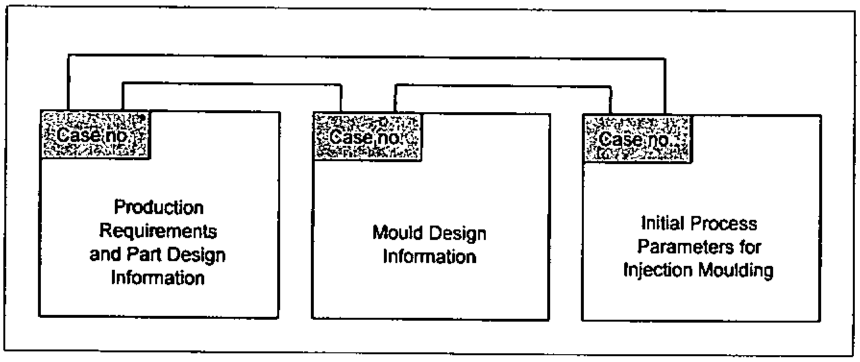


Figure 3.5 Structure of a case

3.3.2 Case indexing

A case library may contain a large number of cases. Cases need to be assigned with labels to guide their retrieval under the appropriate circumstances in order to retrieve cases in an appropriate amount of time. These labels are usually refereed as indexes of individual cases. In general, there are two kinds of heuristic methods for index selection, which are explanation-based technique [Barletta 1988] and checklist-based indexing [Kolodner 1993]. Explanation-based technique determines relevant features of each case. This method analyses each case to find which features are predictive ones. Cases are then indexed by those features. In checklist-based indexing, the problem domain is analysed and the features that tend to be predictive across the entire domain are identified. These features are then put in a checklist and used as indexes to judge the appropriateness of an old case to a new situation. This kind of index selection method is used in this research.

Kwong C.K. et. al. [Kwong 1997] had used the checklist-based indexing to identify the critical indexes. In their study, a relationship diagram was constructed to uncover the relationship between part design parameters and initial process parameters of injection moulding. Degree of influence of part design parameters on initial process parameter setting of injection moulding was described by using a crisp value with the scale from 1 to 10. The critical indexes were then identified based on the sum of the crisp values. The method is simple and easy to be implemented. However, there are two drawbacks of their work. Firstly, the significance of individual process parameters to the quality of moulded parts was not considered, which could affect the accuracy of indexing. Secondly, their work did not deal with the fuzziness in the determination of the degree of influence of part design parameters on initial process parameters of injection moulding.

In this research, a relationship diagram (process parameters of injection moulding versus moulding defects) as shown in Table 3.3 was constructed based on the work of Lau Y.K. [Lau 1996] to determine the relative importance of individual process parameters to the quality of moulded parts. In the diagram, "0" means that the corresponding process parameter has no or insignificant effect on the reduction of the corresponding moulding defect, while "1" means that the corresponding process parameter has significant effect on the occurrence of the corresponding moulding defect.

Process Parameters of Injection Moulding / Moulding Defects	Short Shot	Warpage	Mould Flash	Brittleness	Excessive Shrinkage	Sink Marks	Voids	Mould Sticking	Drooling	Splash	Jetting	Odor	Lower Gloss	Weak Weldlines	Unmelted Granules	Orange Peels	Discoloration	Brown Stains	Screw Slippage	Burn Marks	Total	Normalised Importance Weighting
Barrel Temperatures	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	18	1.0
Nozzle Temperature	0	1	0	1	1	1	1	0	1	1	1	1	0	0	1	0	1	1	0	1	13	0.7
Injection Pressure	1	1	1	1	1	1	1	1	0	0	1	0	1	1	0	0	0	0	0	0	11	0.6
Holding Pressure	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	6	0.3
Back Pressure	0	0	0	1	0	1	1	0	1	1	0	0	0	0	1	0	0	0	0	0	6	0.3
Clamping Force	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0.1
Screw Rotating Speed	0	0	0	1	0	0	0	0	1	0	0	1	0	0	1	0	1	0	0	1	6	0.3
Holding Time	1	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	7	0.4
Cooling Time	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	3	0.2
Fill Time	1	0	1	0	0	1	1	0	0	1	1	0	1	1	0	1	1	1	0	0	11	0.6

Table 3.3 A relationship diagram (process parameters of injection moulding versus moulding defects)

The relationship diagram reveals the correlation between the process parameters of injection moulding and the twenty common moulding defects. For example, improper setting of barrel temperature could cause 18 moulding defects, such as short shot, warpage, mould flash and so on. In other words, proper setting of barrel temperature is critical to produce moulded parts with good quality. The normalised values as shown in the last column of Table 3.3 are used to indicate the relative importance of individual process parameters for injection moulding. Higher normalised value indicates that more importance of the corresponding process parameters in producing moulded parts with good quality.

Once the relative importance of individual process parameters for injection moulding is determined, another relationship diagram (process parameters of injection moulding versus parameters of part design and injection mould design) as shown in Table 3.4 was constructed in order to identify and classify the indexes. The diagram was completed with the help of experienced moulding personnel, in which the degree of influence of the parameters of part design and injection mould design on initial process parameters of injection moulding is represented by using four linguistic terms, strong, moderate, weak and very weak.

Relationship :
- ⊙ Strong
- ● Moderate
- O Weak
- △ Very Weak

Process Parameters of Injection Moulding / Parameters of Part Design and Injection Mould Design	Importance	Moulding Material	Part Size	Wall Thickness	Part Complexity	Part Volume	Projected Area	Runner Type	Runner Size	Gate Type	Gate Size
Barrel Temperatures	1.0	⊙	O	O	●						
Nozzle Temperature	0.7	⊙	O	O	●						
Injection Pressure	0.6	⊙	△	⊙	⊙	O	△	O	●	⊙	⊙
Holding Pressure	0.3	⊙	⊙	⊙	⊙	●	⊙	O	●	⊙	⊙
Back Pressure	0.3	△									
Clamping Force	0.1		O				⊙		●		●
Screw Rotating Speed	0.3	●	O	△	△	△	△				
Holding Time	0.4	⊙	⊙	⊙	●	⊙		●	⊙	⊙	⊙
Cooling Time	0.2	●	△	●		△	△				
Fill Time	0.6	●	△	⊙		△	△	⊙	⊙	⊙	⊙

Table 3.4. A relationship diagram (process parameters of injection moulding versus parameters of part design and injection mould design)

Critical indexes can be identified based upon the normalised technical importance (NTI) ratings [Cole 1990]. Conventionally, the symbols used in the relationship matrix are substituted with crisp values (e.g. ⊙ = 9, ● = 7, O = 4 and △ = 2) in the calculation of NTI ratings which can be computed by using the following equations:

$$\mathrm{IDR}_i = \sum_{j=1}^{m} IFR_{ij} \bullet X_j, \; i = 1 \ldots n \tag{3.1}$$

$$\mathrm{NTI}_i = \mathrm{IDR}_i / \mathrm{IDR}_{max} \tag{3.2}$$

where NTI_i and IDR_i is the normalised technical importance rating and the individual rating of the i-th part design parameter or mould design parameter respectively, IDR_{max} is the maximum individual rating, m is the number of process parameters to be studied, n is the number of parameters of part design and injection mould design to be studied, IFR_{ij} is the degree of influence of the i-th part design parameter or mould design parameter on the j-th process parameter and X_j is the normalised importance weighting of the j-th process parameter.

In order to deal with the ambiguousness in the determination of the degree of influence of the parameters of part design and injection mould design on the initial process parameter setting, triangular fuzzy numbers (TFNs) [Khoo 1996] as shown in Table 3.5 are employed to represent the semantic of the linguistic terms. Table 3.5 shows the linguistic valuables and their corresponding TFNs.

Linguistic variable		Fuzzy number
⊙	Strong	[0.70, 0.90]
●	Moderate	[0.50, 0.70]
○	Weak	[0.30, 0.60]
△	Very Weak	[0.10, 0.30]

Table 3.5. Definition of linguistic variables [Khoo 1996]

Mathematically, the TFNs can be expressed as:

$$A_{ij} = [\alpha_{1ij}, \alpha_{2ij}] \tag{3.3}$$

where A_{ij} is a symmetrical TFN represented by the interval $[\alpha_{1ij}, \alpha_{2ij}]$.

The scalar multiplication of TFN and the sum of two symmetrical TFNs can be represented as follows [Kaufmann 1985]:

$$\lambda \bullet [\alpha_1, \alpha_2] = [\lambda \bullet \alpha_1, \lambda \bullet \alpha_2] \tag{3.4}$$

$$[\alpha_1, \alpha_2] + [\beta_1, \beta_2] = [\alpha_1 + \beta_1, \alpha_2 + \beta_2] \tag{3.5}$$

where λ is the scalar quantity and $[\alpha_1, \alpha_2]$ and $[\beta_1, \beta_2]$ are the intervals of two symmetrical TFNs respectively.

Based on equation (3.4) and (3.5), representation of individual rating can be expressed as:

$$\mathrm{IDR}_i = \sum_{j=1}^{m} A_{ij} X_j \,,\ A_{ij} = [\alpha_{1ij}, \alpha_{2ij}] \,,\ i = 1 \cdots n \tag{3.6}$$

where A_{ij} is the degree of influence of the i-th part design parameter or mould design parameter on the j-th process parameter.

The individual rating and NTI rating of each index can be calculated by using equation (3.6) and (3.2) respectively. For example, the individual rating of wall thickness can be calculated as follows:

$$\begin{aligned} \mathrm{IDR}_{wt} &= 1.0[0.30, 0.60] + 0.7[0.30, 0.60] + 0.6[0.70, 0.90] + \\ &\quad 0.3[0.70, 0.90] + 0.3[0.10, 0.30] + 0.4[0.70, 0.90] + \\ &\quad 0.2[0.50, 0.70] + 0.6[0.70, 0.90] \\ &= [1.97, 2.96] \end{aligned}$$

$$\overline{IDR_{wt}} = 2.47$$

Based on the value of NTI ratings, the indexes can be divided into two classes: critical index and general index. Table 3.6 shows the calculated individual rating and NTI rating of individual parameters, and the classification of indexes. The critical index implies that the index has significant influence on the determination of initial process parameters for injection moulding. The general index is to reflect that the index has substantial influence on the determination of initial process parameters for injection moulding. As shown in Table 3.6, the indexes, moulding material and wall thickness, are identified as the critical indexes which are used to perform "exact-matching" in the case retrieval process.

Parameters of part design and injection mould design	Individual rating	Mean	NTI rating	Classification
Moulding Material	[2.68, 3.56]	3.12	1.00	Critical index
Part Size	[1.26, 2.31]	1.79	0.57	General index
Wall Thickness	[1.97, 2.96]	2.47	0.79	Critical index
Part Complexity	[1.71, 2.37]	2.04	0.65	General index
Part Volume	[0.72, 1.26]	0.99	0.32	General index
Projected Area	[0.57, 1.05]	0.81	0.26	General index
Runner Type	[0.89, 1.36]	1.13	0.36	General index
Runner Size	[1.20, 1.60]	1.40	0.45	General index
Gate Type	[1.33, 1.71]	1.52	0.49	General index
Gate Size	[1.38, 1.78]	1.58	0.51	General index

Table 3.6 Individual rating of parameters of part design and injection mould design

In this research, the wall thickness is classified into different classes or sets which are "thin", "medium" and "thick" so as to facilitate the case matching process in qualitative manner. Conventionally, the classification is determined by clear defined boundaries or crisp sets, in which an element either belongs or does not belong to a crisp set. This binary issue of membership can be represented mathematically with the following indicator (characteristic) function.

$$\chi_A(x) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{if } x \notin A \end{cases}$$

where the symbol $\chi_A(x)$ gives the indication of an unambiguous membership of element x in crisp set A.

Since the classification method does not differentiate different degrees of membership, some marginal cases could be ignored in the case retrieval process. In order to alleviate this problem, fuzzy set theory is introduced in this research. A key difference between crisp and fuzzy sets is their membership function. A crisp set has a unique membership function, while a fuzzy set can have an infinite number of membership functions to represent it.

A fuzzy set is a set containing elements that have varying degrees of membership in the set. Elements of a fuzzy set are mapped to a universe of membership values using a function-theoretic form. This function maps elements of a fuzzy set to a real numbered value on the interval 0 to 1, where the endpoints of 0 and 1 conform to no membership and full membership and the infinite number of values in between the endpoints can represent various degrees of membership for an element in some set on the universe. For example, if an element in the universe, say x, is a member of fuzzy set $\underset{\sim}{A}$, then the functional mapping is given below:

$$\mu_{\underset{\sim}{A}}(x) \in [0,1]$$

where $\mu_{\underset{\sim}{A}}$ (x) is the degree of membership of element x in fuzzy set $\underset{\sim}{A}$. Therefore, $\mu_{\underset{\sim}{A}}(x)$ is a value on the unit interval that measures the degree to which x belongs to fuzzy set $\underset{\sim}{A}$.

Since membership values can reflect the degree that an object belongs to a set, marginal cases can be handled properly in the case retrieval process. Table 3.7 shows the recommended wall thickness of three common thermoplastic materials, ABS, PC and PS. In this research, the wall thickness is classified in three fuzzy sets which are "thin", "medium" and "thick". Figure 3.6 shows the membership functions of individual fuzzy sets for wall thickness.

Recommended wall thickness (mm)					
ABS		PC		PS	
Min.	Max.	Min.	Max.	Min.	Max.
1.0	3.5	1.0	3.8	0.85	3.8

Table 3.7. Recommended wall thickness (ABS, PC and PS)

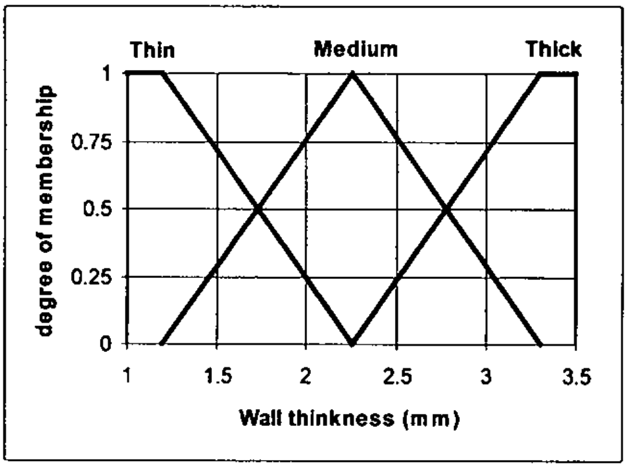


Figure 3.6 Membership functions of wall thickness for ABS

The membership functions are represented in a series of equations in the CBR module. For example, the membership functions of wall thickness for ABS can be expressed below:

$\mu_{thin}(x)$	$= 1$	if $x < 1.2$	(3.7)
	$= (2.25 - x) / 1.05$	if $1.2 < x < 2.25$	(3.8)
$\mu_{medium}(x)$	$= (x - 1.2) / 1.05$	if $1.2 < x < 2.25$	(3.9)
	$= 1$	if $x = 2.25$	(3.10)
	$= (2.25 - x) / 1.05$	if $2.25 < x < 3.3$	(3.11)
$\mu_{thick}(x)$	$= (x - 3.3) / 1.05$	if $2.25 < x < 3.3$	(3.12)
	$= 1$	if $x > 3.3$	(3.13)

where x is the wall thickness in mm

In this research, an object belongs to a set if its membership value is equal to or greater than a hurdle value called α-cut. For example, if the moulding material of an input problem is ABS and the wall thickness of the plastic part is 1.74 mm, it can be fuzzified as (thin/.49, medium/.51, thick/0) based on the membership functions as shown in Figure 3.6. If the α-cut is set as 0.45, the wall thickness of the part is classified as "thin" and "medium" and thus the matching indexes of the input case will be ABS_ TN and ABS_ME.

3.3.3 Case retrieval

In the CBR module, the retrieval process involves three main steps as shown in Figure 3.7. They are the matching of fuzzy indexes, first level of similarity analysis and the second level of similarity analysis.

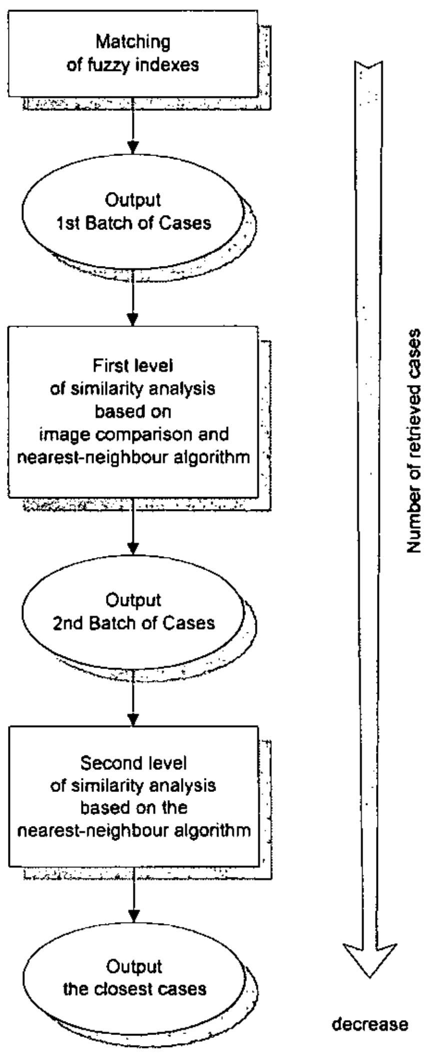


Figure 3.7 Retrieval process of HSIM

The retrieval process starts with matching the fuzzy indexes identified in Section 3.3.2. After the matching, a number of cases can be retrieved. Similarity analysis is then performed on the retrieved cases to determine the degree of similarity between the retrieved cases and the input problem. The retrieved cases are then ranked in descending order according to their similarity values. The top several cases are retrieved for further processing. Unlike the conventional CBR systems, two levels of similarity analysis are employed in the HSIM in order to speed up the selection process and improve the accuracy of matching [Adalier 1992]. The first level of similarity analysis is based on the part complexity. Part complexity is described as the complexity of moulded part design in terms of basic complexity, subsidiary complexity and surface finish/ tolerances requirements. In this research, part complexity is determined by the quantitative assessment based on the Poli's coding method and the nearest neighbour algorithm, as well as the qualitative assessment based on the image comparison. The second level of similarity analysis is based on the matching of the indexes including the wall thickness, part envelope size, part volume, projected area and the hydraulic diameters of gates and runners. Detailed discussions of individual processes are given below.

3.3.3.1 Case matching

As mentioned in Section 3.3.1, the case library is organised in a combination of feature-based structure and flat structure as shown in Figure 3.8. Therefore, the search of cases involves depth-first search and serial search algorithm.

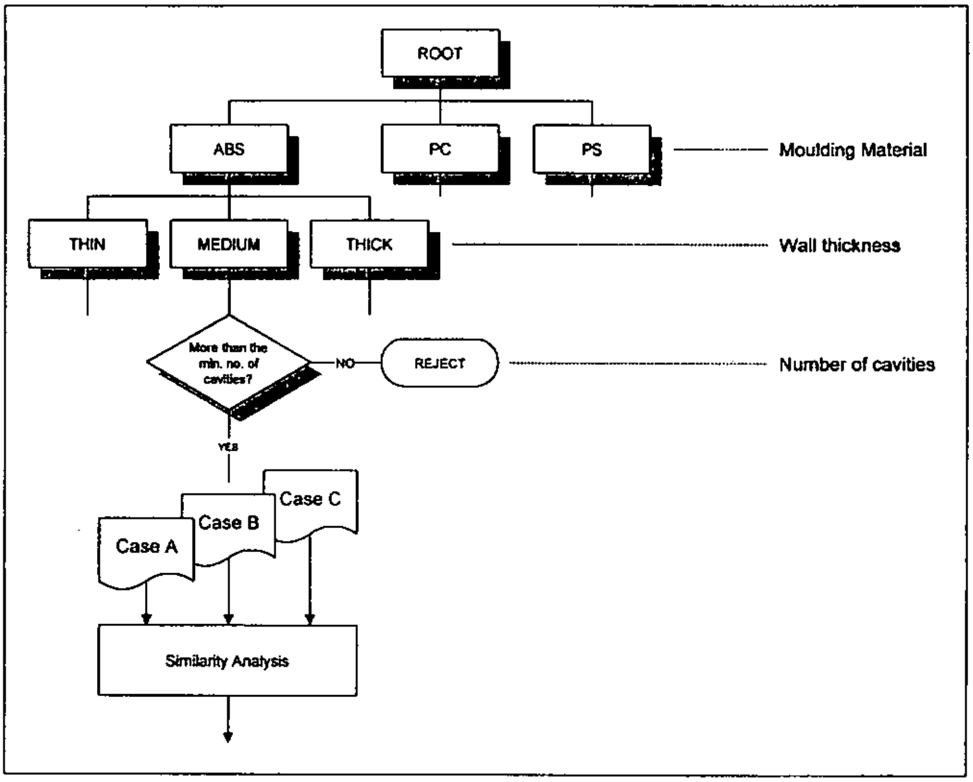


Figure 3.8 Case matching in HSIM

Once the value of the wall thickness of an input problem is fuzzified, the fuzzified wall thickness combining with the type of moulding material is used to retrieve a cluster of potential cases. Besides, the number of cavities of the retrieved cases must be equal to or larger than the required number of cavities of the input problem in order to fulfil the production requirements. For those less than the required number of cavities will not be selected. Derivation of the mathematical model for the calculation of the required number of cavities is given in Appendix A. The cluster of retrieved cases are then stored in a flat structure. Similarity analysis is performed on them in order to determine the most similar case.

3.3.3.2 First level of similarity analysis

The first level of similarity analysis is based on the matching of the part complexity which is obtained by using the quantitative and qualitative assessment. To determine the part complexity quantitatively, a coding system developed by Poli E. et al. [Poli 1992] in the University of Massachusetts, Amherst, for the description of part complexity is adopted in this research. The coding system was developed based on the group technology (GT) based complexity rating approach, in which the complexity is described by three measures: basic complexity (BC), subsidiary complexity (SC), and surface finish / tolerances requirements (ST).

The basic complexity is a function of part envelope size, the presence of features such as external undercuts and internal undercuts, and whether or not the parting line is a planar or non-planar surface. The subsidiary complexity refers to the cavity details and the complexity of external undercut. The effects of the surface finish and tolerances of parts are accounted for the determination of measure of surface finish and tolerance complexity. Based on the features of moulded parts, the measures of BC, SC and ST can be determined from the rating tables as shown in Appendix B. Once these measures are available, degree of matching on the part complexity can be calculated based on the nearest-neighbour algorithm [Zhang 1992] and denoted as SI^{i}_{qn}. Detailed descriptions of the algorithm are given in Section 3.3.3.2.

The coding system provides a consistent and systematic method for analysing the complexity of moulded parts and has been successfully used in tooling/mould cost estimation. However, in the determination of process parameters of injection moulding, the quantitative assessment method may provide inaccurate results in some circumstances. For example, part A and part B as shown in Figure 3.9 and Figure 3.10 respectively have identical envelope size, and same number and size of bosses. The part complexity of them is calculated based on Poli's method and shown in Table 3.8.

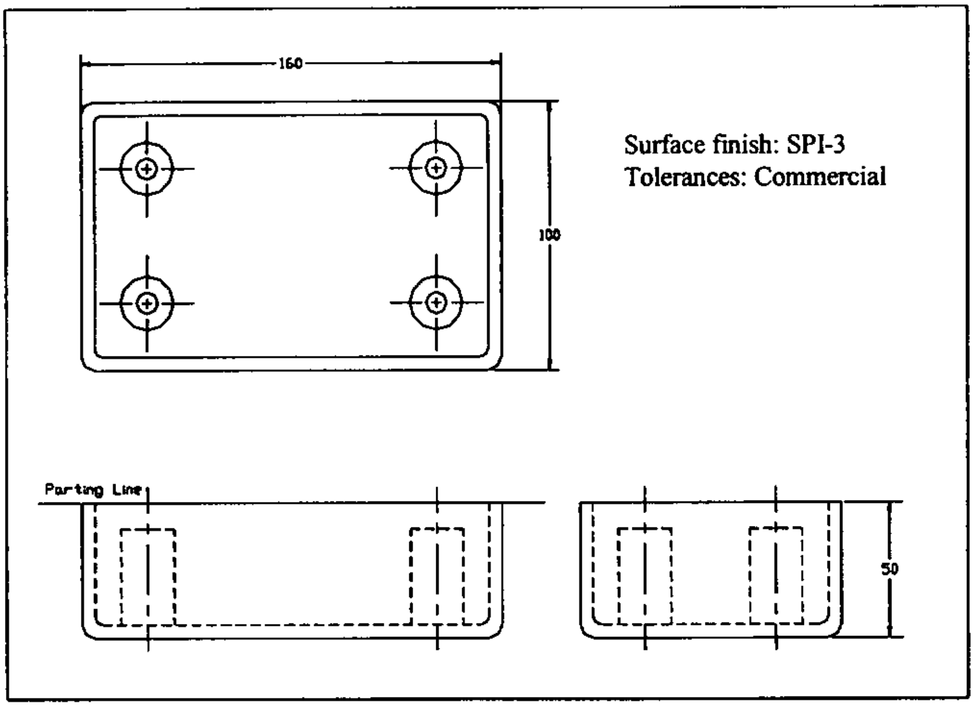


Figure 3.9 Moulded part "A"

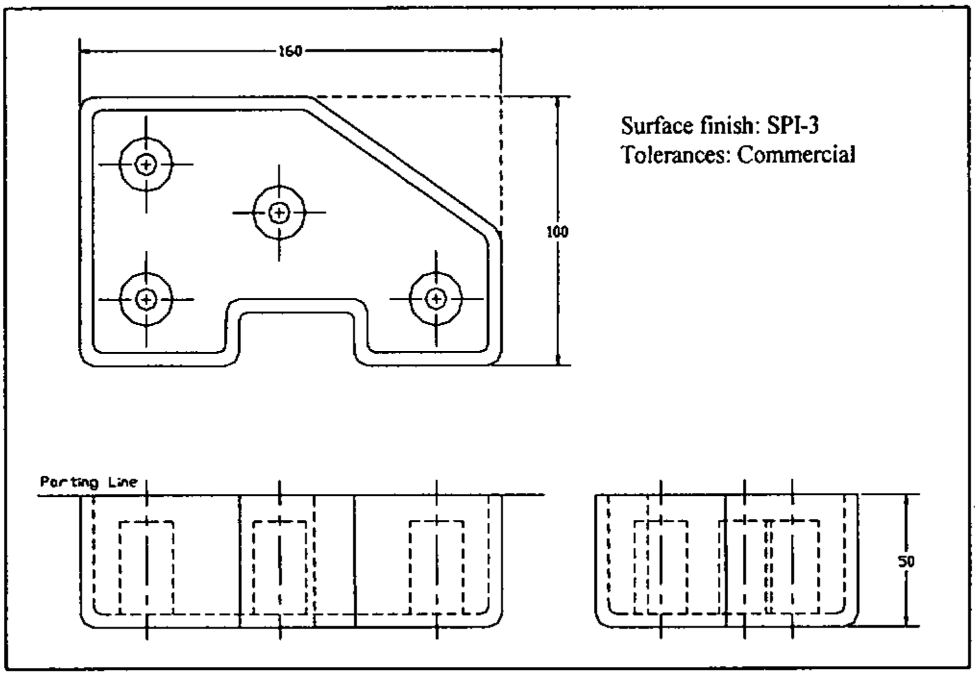


Figure 3.10 Moulded part "B"

Part Complexity	Part A	Part B
Basic complexity (BC)	1.64	1.64
Subsidiary complexity (SC)	1.00	1.00
Surface finish / tolerances requirements (ST)	1.00	1.00

Table 3.8 Part complexity indexes of two cases

It can be found that the values of part complexity of them are identical. However, two parts obviously have different mould flow characteristics which would lead to different process parameter setting of injection moulding. In this research, image comparison between retrieved cases and input problem based on triangular fuzzy numbers (TFNs) [Khoo 1996] was firstly introduced to improve the accuracy of part complexity calculation. Three geometric features, part shape, internal surface details, and external surface details, are used to define the degree of similarity. Part shape refers to the external profile of moulded parts. Internal surface details refer to the study of features on the internal surface of moulded parts including their types and locations. External surface details refer to the study of features on the external surface of moulded parts including their types and locations.

Degree of similarity between the part image of retrieved cases and the part image of an input problem is described by using the qualitative descriptors: {Very similar, Similar, Medium, Different, Very Different}, which is assigned by system users. The descriptors are represented in triangular fuzzy numbers (TFNs) as shown in Table 3.9 in order to facilitate the similarity analysis in quantitative manner.

Descriptor	Fuzzy number
Very Similar	[0.8, 1.0]
Similar	[0.5, 0.9]
Medium	[0.3, 0.7]
Different	[0.1, 0.5]
Very Different	[0.0, 0.3]

Table 3.9 Fuzzy numbers for five descriptors

To determine the weighting of the part shape, internal surface details and the external surface details in the initial process parameter setting, a pairwise comparison matrix was constructed based on Saaty's matrix [Saaty 1980] which can be generalised as shown below:

$$
A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{ij} & \cdots & a_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ a_{n1} & a_{n1} & \cdots & a_{nn} \end{bmatrix} = \begin{bmatrix} \frac{w_1}{w_1} & \frac{w_1}{w_2} & \cdots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & \frac{w_2}{w_2} & \cdots & \frac{w_2}{w_n} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \cdots & \frac{w_n}{w_n} \end{bmatrix}
$$

where A is Saaty's matrix of pairwise comparisons, n is the number of features to be studied, a_{ij} is the relative importance between the i-th feature and the j-th feature based on a nine-point intensity scale as shown in Table 3.10 and w_i is the weighting of the i-th feature.

If X is .... as (than) Y	then the preference number to assign is
equally important more important strongly more important very strongly more important extremely more important	1 3 5 7 9
Compromise between two adjacent judgements	2, 4, 6, 8

Table 3.10. Nine-point intensity scale [Saaty 1977]

The pairwise comparison matrix was completed with the help of experienced moulding personnel and is shown below:

$$
A = \begin{array}{c} \\ F_1 \\ F_2 \\ F_3 \end{array} \begin{array}{c} \begin{array}{ccc} F_1 & F_2 & F_3 \end{array} \\ \begin{bmatrix} 1 & 2 & 4 \\ 1/2 & 1 & 3 \\ 1/4 & 1/3 & 1 \end{bmatrix} \end{array}
$$

where A is the pairwise comparison matrix, F_1, F_2 and F_3 are the three geometric features, part shape, internal surface details, and external surface details respectively.

After the construction of the pairwise comparison matrix, eigenvector method [Saaty 1977] was applied to determine the weighting of features. In the method, eigenvectors in each row of the matrix (V_i) are firstly determined by the geometric mean as shown below.

$$V_i = \sqrt[n]{\prod_{j=1}^{n} a_{ij}} \qquad , i = 1 \ldots n \tag{3.14}$$

The eigenvectors are then normalised to obtain the weighting (w_i) of each feature to the initial process parameter setting of injection moulding.

$$w_i = \frac{V_i}{\sum_{i=1}^{n} V_i} \tag{3.15}$$

In order to reduce the inconsistency of human judgement in the completion of the pairwise comparison matrix, the consistency of the judgements has been examined by using an index called consistency ratio (CR). To calculate the consistency ratio, the consistency index (CI) is firstly determined by using the following equations:

$$v_j = \sum_{i=1}^{n} a_{ij} \qquad , j = 1 \ldots n \tag{3.16}$$

$$\lambda_{max} = \sum_{i=1}^{n} w_i v_i \tag{3.17}$$

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{3.18}$$

where v_j is the sum of relative importance values in the j-th column, λ_{max} is the largest eigenvalue and v_i is the sum of relative importance values in the i-th column.

CI divided by the random consistency number of the same size of matrix [Saaty 1980] yields the consistency ratio (CR). The human judgements are considered to be consistent if CR is less than 0.1. Otherwise, re-examination of the pairwise judgement is required. The final result of the pairwise comparison is shown in Table 3.11.

Process Parameter Setting	Part shape	Internal surface details	External surface details	Eigen-vectors (V_i)	Weightings (w_i)
Part shape	1	2	4	2.00	0.56
Internal surface details	1/2	1	3	1.14	0.32
External surface details	1/4	1/3	1	0.44	0.12
(v_i)	1.75	3.33	8	λ_{max}:	3.0056
				CI :	0.0028
				CR:	0.0050

Table 3.11 A pairwise comparison matrix (part shape, internal surface details and external surface details)

Once the weighting of individual features is determined, the degree of similarity between the i-th retrieved case and the input problem can be calculated and denoted as SI^{i}_{ql}. For example, Table 3.12 shows the results of image comparison while Table 3.13 shows the results after the mapping of fuzzy numbers. The SI^{i}_{ql} for the case 1 and the input problem can be calculated by using the equation (3.6) as shown below:

$$IDR_{c1} = 0.56[0.8, 1.0] + 0.32[0.3, 0.7] + 0.12[0.1, 0.5]$$

$$= [0.556, 0.844]$$

$$SI^{1}_{ql} = \overline{IDR_{c1}} = 0.7$$

Part Features		Case 1	Case 2	Case 3
Part Shape	(0.56)	Very Similar	Medium	Similar
Internal Surface Details	(0.32)	Similar	Very Similar	Different
External Surface Details	(0.12)	Different	Similar	Similar

Table 3.12 Results of image comparison

Part Features		Case 1	Case 2	Case 3
Part Shape	(0.56)	[0.8, 1.0]	[0.3, 0.7]	[0.5, 0.9]
Internal Surface Details	(0.32)	[0.3, 0.7]	[0.8, 1.0]	[0.1, 0.5]
External Surface Details	(0.12)	[0.1, 0.5]	[0.5, 0.9]	[0.5, 0.9]
	SI^{i}_{ql} :	* 0.70	0.65	0.57

Table 3.13 Similarity values based on the results of image comparison

After the quantitative and qualitative assessment of part complexity, the similarity indexes, SI^{i}_{ql} and SI^{i}_{qn}, can be determined. It is then followed by the combination of these two indexes into an index which can be used to describe the similarity between two parts in terms of part complexity. There are some common methods available to derive a combined index such as simple additive weighting (SAW) method and weighted product method. The underlying assumption of the methods is that the contribution of an individual attribute to the total score is independent of other attribute values. In view of the nature of the similarity indexes, SI^{i}_{ql} and SI^{i}_{qn}, their values are interdependent.

In this research, a multiple attribute decision making algorithm, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) algorithm [Yoon 1995], is used to combine the two similarity indexes into an index. TOPSIS algorithm selects the alternative based on the concept that the chosen alternative should not only have the shortest Euclidean distance to the positive-ideal solution in a geometrical sense but the longest Euclidean distance from the negative-ideal solution. In this research, the positive-ideal solution is defined as the case which is identical to the input problem while the negative-ideal solution is the case which is totally different from the input problem. Based on the TOPSIS algorithm, the indexes, SI^{i}_{ql} and SI^{i}_{qn}, are combined and a TOPSIS index can be obtained to express the similarity between two parts in terms of part complexity. TOPSIS index is defined by combining the proximity to the positive-ideal solution and the remoteness from the negative-ideal solution.

To apply TOPSIS algorithm in this work, a decision matrix (D) has to be constructed firstly as shown below:

$$D = \begin{bmatrix} S_{11} & S_{ij} & \cdots & S_{1n} \\ S_{21} & S_{22} & & S_{2n} \\ \vdots & \vdots & & \vdots \\ \vdots & \vdots & & \vdots \\ S_{m1} & S_{m2} & \cdots & S_{mn} \end{bmatrix}$$

where S_{ij} is the similarity value of the i-th retrieved case obtained from the j-th similarity assessment of part complexity, m is the number of retrieved cases to be studied and n is the number of similarity assessments of part complexity.

Then the vector normalisation is used for computing r_{ij}, which is given as:

$$r_{ij} = \frac{S_{ij}}{\sqrt{\sum_{i=1}^{m} S_{ij}^{2}}}, \; i = 1 \ldots m; \; j = 1 \ldots n \tag{3.19}$$

The weighted normalised value is calculated as:

$$v_{ij} = w_j \, r_{ij}, \; i = 1 \ldots m; \; j = 1 \ldots n \tag{3.20}$$

where r_{ij} is the normalised similarity value of the i-th retrieved case obtained from the j-th similarity assessment and w_j is the weighting of the j-th similarity assessment. Weighting of the quantitative and qualitative assessment are both preliminarily set as 0.5 and will be fine-tuned in system validation.

The separation of each retrieved case from the positive-ideal solution, D_i^+, can be calculated by using the following equation:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2} \text{ , i = 1...m} \tag{3.21}$$

where v_j^+ is the best similarity value obtainable from the j-th similarity assessment

Similarly, the separation from the negative-ideal solution, D_i^-, can be calculated by using the following equation.

$$D_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \text{ , i = 1...m} \tag{3.22}$$

where v_j^- is the worst similarity value obtainable from the j-th similarity assessment

Finally, the TOPSIS index of individual cases, TOP_i, can be calculated by using the following equation:

$$TOP_i = \frac{D_i^-}{D_i^- + D_i^+} \text{ , i = 1...m} \tag{3.23}$$

The retrieved cases, with the TOPSIS index larger than a threshold value, are considered as the potential cases. The top five most similar cases are selected to perform the second level of similarity analysis. If there is no good matched case found in the case library, the CBR module stops processing and the hybrid NN-GA module is invoked to determine the initial process parameters of injection moulding for the input problem. A pre-defined number of partially matched cases retrieved in the first level of similarity analysis are injected into the hybrid NN-GA module as a part of the initial population for performing GA based optimisation. Detailed description of the operations of the hybrid NN-GA module is given in Section 3.4.

3.3.3.3 Second level of similarity analysis

After the first level of similarity analysis, the five most similar cases are retrieved according to the values of TOPSIS index. In order to determine the closest case, second level of similarity analysis is performed on these five cases based on the matching of the indexes, wall thickness, part envelop size (length, width, depth), part volume, projected area, hydraulic diameter of runners and gates.

In the second level of similarity analysis, the similarity between an input problem and a retrieved case is assessed by using a similarity analysis function. Two common similarity analysis functions are found in the area of CBR. The first one is to assess the similarity based on the nearest neighbour algorithm [Duda 1973], while another one is based on Tversky's contrast function [Tversky 1977]. The nearest-neighbour algorithm is widely used in CBR systems. Nearest-neighbour algorithm assesses the overall similarity by a weighted linear combination of similarities along indexes. Tversky's contrast function is based on the cognitive notions of similarity that requires a contrast model. A contrast model expresses similarity among objects as a combination of their common and distinctive features. Tversky's contrast function does not include the weights associated with the indexes, in which similarity along indexes is assumed to be binary.

Since all the indexes in the second level of similarity analysis are quantitative and each index has different significance (weights) to initial process parameter setting of injection moulding, the use of nearest-neighbour algorithm is found more suitable to assess the similarity between a retrieved case and an input problem. The nearest-neighbour algorithm developed by Zhang H [Zhang 1992] is adopted in this research, in which the similarity between two cases Sim($case^1(C_n)$, $case^2(C_m)$) is defined as the inverse of the distance between these two cases :

$$\text{Sim}(\text{case}^1(C_n), \text{case}^2(C_m)) = 1 - \text{Dist}(\text{case}^1(C_n), \text{case}^2(C_m)) \tag{3.24}$$

Dist ($case^1(C_n)$, $case^2(C_m)$) is computed as the normalised Euclidean distance between the corresponding cases :

$$\text{Dist}(\text{case}^1(C_n), \text{case}^2(C_m)) = \sqrt{\frac{1}{k}\sum_{i=1}^{k} w_i^2 [case_i^1(C_n) - case_i^2(C_m)]^2} \tag{3.25}$$

where $case_j^i$ is the value of the j-th index of the i-th case, $k = |A_1 \cup A_2|$, A_i $(i = 1, 2)$ - the set of indexes of the corresponding cases, w_j is the importance of the j-th index.

To apply the nearest-neighbour algorithm in similarity analysis, weighting of individual indexes should be firstly determined. The conventional method to determine the weightings is based on human judgement. This method inherits the disadvantage of intuition and could result in poor solution to be obtained. Moreover, weighting all the indexes at the same time may impose a heavy cognitive burden on system designers.

To make up the deficiency of the intuitive method, many weighting assignment methods have been proposed such as the eigenvector method [Saaty 1977] and the weighted least square method [Chu 1979]. In this research, the eigenvector method is adopted to determine the weighting of individual indexes, which has been successfully applied in Analytic Hierarchy Process (AHP) [Saaty 1980] for various applications. The procedures of obtaining the weighting of individual indexes are same with those described in Section 3.3.3.2.

The weightings are globally assigned to individual indexes for computing the overall similarity value. The relative importance of the first and second level of similarity analysis is determined by using the mean individual ratings as shown in Table 3.6 and is calculated by using the following equations.

$$IPT_1 = \frac{S\_IR_1}{S\_IR_1 + S\_IR_2} \tag{3.26}$$

$$IPT_2 = \frac{S\_IR_2}{S\_IR_1 + S\_IR_2} \tag{3.27}$$

where IPT_1 is the weighting of the first level of similarity analysis, S_IR_1 is the sum of mean individual rating of the indexes defined in the first level of similarity analysis, IPT_2 is the weighting of the second level of similarity analysis and S_IR_2 is the sum of mean individual rating of the indexes defined in the second level of similarity analysis

Table 3.14 shows two retrieved cases and an input problem while Table 3.15 shows the results of two levels of similarity analysis and the computed overall similarity value of the reference cases.

Input features	Retrieved case 1	Retrieved case 2	Input case
Type of resin	ABS	ABS	ABS
Basic complexity	0.2	0.3	0.3
Subsidiary complexity	0.5	0.4	0.6
Tolerance & Surface finishing index	0.6	0.8	0.5
Wall thickness (mm)	1.5	1.3	1.5
Part volume (mm^3)	13944	9100	12310
Projected area (mm^2)	4754	3902	5221
Part envelope length (mm)	132	130	134
Part envelope width (mm)	48	46	54
Part envelope height (mm)	13	13	14
Hydraulic diameter (runner)	4.80	4.60	4.60
Hydraulic diameter (gate)	1.35	1.20	1.38

Table 3.14 Information and data of an input problem and two retrieved cases

The case with the highest overall similarity value is considered as the most similar case to the input problem. Two verification tests were conducted to investigate retrieval accuracy and consistency of the CBR module. Results of the verification tests as shown in Appendix C indicate that HSIM has high accuracy and consistency in case retrieval.

First level of similarity analysis

Features	Importance	Old case 1	Old case 2
Basic complexity	0.46	0.31	0.46
Subsidiary complexity	0.31	0.26	0.21
Tolerance & surface finishing index	0.23	0.18	0.09
SI^{i}_{qn}	0.5	0.75	0.76
SI^{i}_{ql}	0.5	0.8	0.74
Similarity value (first level) :		0.77	0.75

Second level of similarity analysis

Features	Importance	Old case 1	Old case 2
Wall thickness	0.2	0.20	0.17
Part volume	0.15	0.13	0.11
Projected area	0.12	0.11	0.09
Part envelope length	0.1	0.10	0.10
Part envelope width	0.08	0.07	0.07
Part envelope height	0.08	0.07	0.07
Hydraulic diameter (runner)	0.12	0.11	0.12
Hydraulic diameter (gate)	0.15	0.15	0.13
Similarity value (second level) :		0.94	0.86

Overall similarity analysis

Features	Importance	Old case 1	Old case 2
First level similarity	0.30	0.77	0.75
Second level similarity	0.70	0.94	0.86
Overall similarity value :		0.89	0.83

Table 3.15. Calculation of overall similarity value

3.3.4 Case adaptation

Case adaptation is a process that looks for prominent differences between the reference case and the input problem and then uses adaptation techniques to take those differences into account. This process can be done manually or automatically.

Traditionally, the reference case is adapted by system users. It is no doubt that this approach encourages human collaboration in decision support. However, performance of the adaptation quite relies upon the experience of system users. In HSIM, case adaptation is done automatically.

Case adaptation could be as simple as substituting one component of a solution into another or as complex as modifying the overall structure of a solution. In general, there are three kinds of adaptation in CBR: substitution, transformation and derivational replay. In this research, direct substitution was applied to derive the parameters for runner and gating design such as runner type, runner layout, gate location and gate type. Therefore, information and data of the runner and gating design for a particular reference case are directly recommended to system users. Once the runner type and the gate type of an input problem have been determined, the corresponding parameters of runner and gating design can be obtained by using the structured adaptation models as shown in Appendix D.

For example, if the recommended gate type for an input problem is edge gate as shown in Figure 3.11, the corresponding design parameters of the gate can be simply determined by using the following equations [Pye 1989]:

$$W = (n \bullet A^{1/2}) / 30 \tag{3.28}$$

$$h = n \bullet t \tag{3.29}$$

$$L = 0.5 \text{ mm (minimum)} \tag{3.30}$$

where W is the gate width in mm, h is the gate depth in mm, L is the land length in mm, t is the wall section thickness of the input problem in mm, A is the surface area of cavity of the input problem in mm^2, and n is the material constant

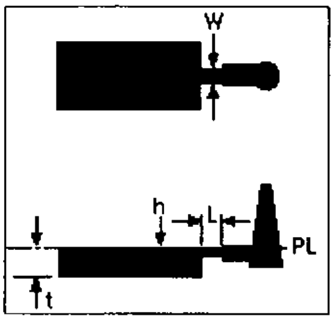


Figure 3.11. Edge gate

Regarding the adaptation of the initial process parameters for injection moulding, Kwong C.K. et. al. [Kwong 1997] developed structured transformation models for some initial process parameters of injection moulding. Further development of the structured transformation models has been done to account for the effect of runner and gating system design on the initial process parameters of injection moulding [Mok 1999]. In the both studies, the structured transformation models are used to compensate the deviations between the theoretical solution and the actual solution. It can be generalised and expressed below.

$$Sa_{new} = St_{new} \bullet \left(\frac{Sa_{ref}}{St_{ref}} \right) \tag{3.31}$$

where Sa_{new} is the solution of input problem, Sa_{ref} is the actual solution of reference case, St_{new} is the theoretical solution of input problem, St_{ref} is the theoretical solution of reference case and (Sa_{ref}/ St_{ref}) is a correction factor.

The structured transformation models can adapt a reference case to fit with a new problem in very short time. However, structured transformation models of some initial process parameters of injection moulding are not easy to be developed due to the unusual complexity of injection moulding.

Shelesh-Nezhad K. et. al. [Shelesh-Nezhad 1997] employed retrieved cases to establish a model for the adaptation of process parameters for injection moulding. In their research, three sets of linear equations are established by using the data stored in four retrieved cases such as flow length, part thickness, melt temperature, mould temperature, injection time and injection pressure. The equations can then be used to derive the melt temperature, injection pressure and the injection time for an input problem. The other process parameters including the barrel temperature, injection speed, hydraulic pressure, switch over time and plasticizing stroke are determined by using mould flow analysis. This approach makes use of the similar old cases to establish the linear relationship between the part design parameters and process parameters of injection moulding, from which initial process parameters of injection moulding for an input problem can be determined. However, injection moulding in fact is a non-linear process, in which over a dozen adjustable process parameters are involved and some of them interact with one another in subtle ways. Therefore, this approach is limited in a certain range of flow length and part thickness where the process parameters exhibit linear relationship with the flow length and part thickness.

Neural network approach was also employed in the case adaptation. This kind of adaptation, called neuro-adaptation, uses a set of similar cases obtained from the case retrieval process to train a neural network for a particular input problem. The output of the neural network is a generalised solution from the similar cases, which contains a set of initial process parameters of injection moulding for the input problem. Corchado J.M. et. at. [Corchado 1998] have attempted the neural network approach to develop an adaptation model for forecasting the behaviour of a new oceanographic environment. The behaviour of oceanographic environment is very complex, in which the underlying knowledge of the domain is not completely available, the rules governing the system are fuzzy and the sets of data samples are limited and incomplete. Results of their research have indicated that the neuro-adaptation could combine the ability of CBR in selecting similar cases and the ability of neural networks in generalising the similar cases to perform the adaptation.

In this research, the artificial neural network approach was firstly employed in the formulation of an adaptation model for initial process parameters of injection moulding. In the CBR module, a back-propagation network (BPN) is trained by the five most similar cases obtained from the case retrieval process. The trained network is used as an adaptation model to derive initial process parameters of injection moulding for the input problem. A BPN is currently the most general-purpose and commonly used neural network paradigm [Skapura 1996] which is found particularly useful in classification and pattern-recognition problems as well as the tasks that require mapping continuous input values to continuous output values. In fact, the BPNs have been widely applied in building a process model for many manufacturing processes such as abrasive flow machining (AFM) [Petri 1998] and injection moulding [Souder 1994, Smith 1996, Haeussller 1996]. The work of Hausler, J. et. al., Woll, S. et. al. and Richard, C. et.al. [Hausler 1996, Woll 1996, Richard 1994] have already proved that BPNs can provide more accurate results in quality prediction of moulded parts than other methods, such as multiple regression modelling and statistical process control, due to their ability in dealing with non-linear effects and interactions.

Figure 3.12 shows the basic architecture of a three-layer BPN which is used for the case adaptation in HSIM. The network comprises of an input layer, a hidden layer and an output layer. Number of hidden layers could be two or more which could affect the performance of networks. However, a study by Lapedes, A. and Farber, R. [Lapedes 1988] shows that networks containing more than two hidden layers offer no significant advantage over the two-hidden-layer network. In practice, BPNs with one hidden layer are usually enough to accomplish all pattern recognition and classification tasks [Souder 1994].

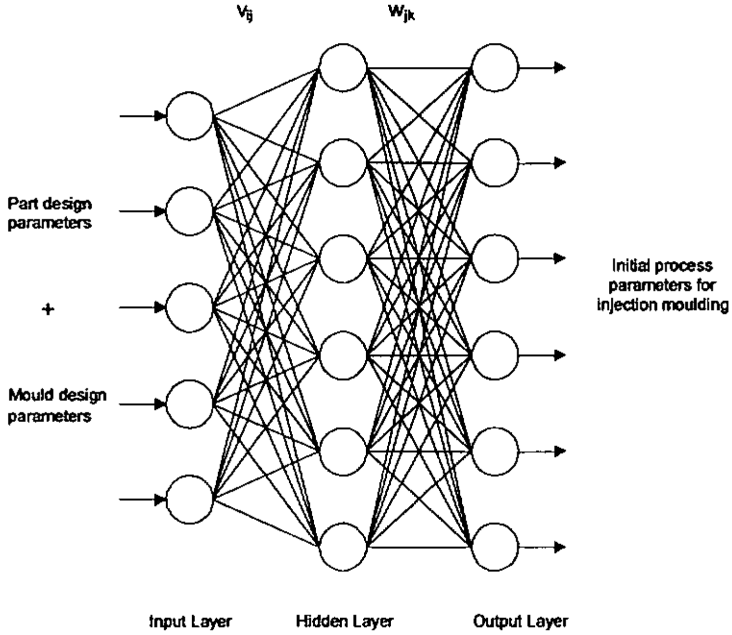


Figure 3.12. A neural network for case adaptation

As shown in Table 3.16, inputs to the network are a combination of the part design parameters and mould design parameters while outputs from the network are a set of initial process parameters for injection moulding.

Inputs	Outputs
1. Number of cavities	1. Nozzle temperature
2. Moulding material	2. Barrel temperature (Rear)
3. Part envelope length	3. Barrel temperature (Middle)
4. Part envelope width	4. Barrel temperature (Front)
5. Part envelope height	5. Injection pressure
6. Projected area	6. Holding pressure
7. Part volume	7. Back pressure
8. Wall thickness	8. Clamping force
9. Part complexity	9. Screw surface speed
10. hydraulic diameter (gate)	10. Fill time
11. hydraulic diameter (runner)	11. Holding time
12. Flow length	12. Cooling time

Table 3.16. Inputs and outputs of the neural network for case adaptation

Number of nodes in the input and output layers can be specified based on the number of inputs and outputs of the network. However, the number of nodes used in the hidden layer is dependent upon the problem itself. In this research, the number of nodes used in the hidden layer is determined by using the following equation [NeuroShell 1989]:

$$NHN = 2 \times \sqrt{Ino + Ono} \tag{3.32}$$

where NHN is the number of nodes in the hidden layer, Ino is the number of nodes in the input layer and Ono is the number of nodes in the output layer.

The derived value of NHN is rounded down to the nearest integer. Since there are 12 inputs and 12 outputs in the adaptation model, 10 hidden nodes are required based on the equation (3.32).

Two crucial steps for implementing a neural network as a computation model are pre-processing of the network inputs and post-processing of the network outputs. Pre-processing involves normalisation of inputs of a network while post-processing is to interpret the output results from a network. In general, there are two common methods for normalising the input data into the interval [0 to 1] which are range method and standardised method. Both methods would lead to the same results. In this research, the range method is used in the normalisation of network inputs because it is easier to be implemented and understood than the standardised method. In the range method, input data is normalised by using the following mapping function.

$$VI^{i}_{norm} = \frac{VI^{i}_{nomi} - VI^{i}_{\min}}{VI^{i}_{\max} - VI^{i}_{\min}} \tag{3.33}$$

where VI^{i}_{norm} is the normalised value of the i-th input of the network, VI^{i}_{nomi} is the nominal value of the i-th input of the network, $VI^{i}_{\min}$ is the minimum value of the i-th input of the network and $VI^{i}_{\max}$ is the maximum value of the i-th input of the network

For example, if the wall thickness of a ABS moulded part is 1.5 mm and the recommended maximum and minimum wall thickness of plastic parts in ABS material are 1.0 mm and 3.8 mm respectively, the normalised value of the wall thickness is:

$$VI^{wt}_{norm} = \frac{1.5-1.0}{3.8-1.0} = 0.18$$

Similarly, the normalised values of outputs of NNs can be mapped back to the nominal values by using the following mapping function.

$$VO^{i}_{nomi} = VO^{i}_{norm}(VO^{i}_{\max} - VO^{i}_{\min}) + VO^{i}_{\min} \tag{3.34}$$

where VO^{i}_{norm} is the normalised value of the i-th output of the network, VO^{i}_{nomi} is the nominal value of the i-th output of the network, $VO^{i}_{\min}$ is the minimum value of the i-th output of the network and $VO^{i}_{\max}$ is the maximum value of the i-th output of the network

In a back-propagation network, each connection between two nodes has an associated weight. As shown in Figure 3.13, each node in the network forms a weighted sum of the inputs from previous layers to which it is connected, and passes the sum through a non-linear activation function to produce an output for the node.

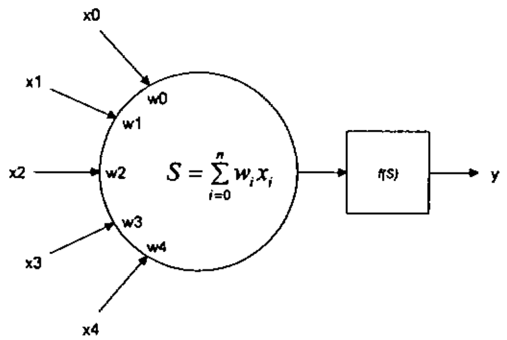


Figure 3.13 The anatomy of a node

The activation function could be square root, Π (product), log, e^x and so on. However, mathematicians and computer scientists have found that the sigmoid (Sshaped) function is particularly advantageous [Quantrille 1991]. Figure 3.14 shows a plot of a sigmoid function (logistic function), which is monotonically increasing, with limiting values of 0 (at x = $-\infty$) and 1 (at x = $+\infty$). Because of the limiting values, sigmoid functions can be considered as threshold functions.

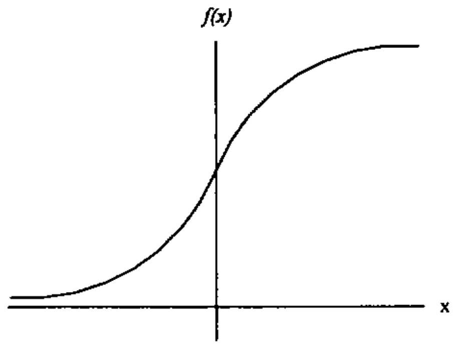


Figure 3.14 A plot of sigmoid functions

If sigmoid functions are used as an activation function, the inhibitory and excitatory effects of weight factors are straightforward. Inhibitory effect refers to $w_i < 0$ while $w_i > 0$ is called excitatory effect. Since sigmoid functions are continuous, differentiable, monotonic, and well-behaved even if x approaches $\pm\infty$, they could provide more efficient training. For this reason, the logistic function, one type of sigmoid functions, is used as an activation function in the BPN.

Responses from the nodes in the hidden layer (h_j) and the output layer (r_k) can be computed by using the following equations.

$$h_j = f\left(\sum v_{ij} x_i\right) \tag{3.35}$$

$$r_k = f\left(\sum w_{jk} h_j\right) \tag{3.36}$$

$$f(x) = \frac{1}{1+e^{-x}} \tag{3.37}$$

where v_{ij} is the weight of the connection between the i-th input node and the j-th hidden node, w_{jk} is the weight of the connection between the j-th hidden node and the k-th output node, and x_i is an input to the i-th input node. The function *f( )* is the logistic function.

Based on the input-output patterns obtained from the five most similarly retrieved cases, supervised learning can be performed. Generally, there are two types of learning algorithms applied in BPNs which are vanilla back-propagation algorithm and generalised delta-rule (GDR) algorithm. The vanilla back-propagation algorithm is a gradient-descent learning technique that minimises the error between the input and desired output. The advantage of this method is that weight changes are estimated systematically rather than arbitrarily. The main problem of the vanilla back-propagation algorithm is excessive learning time.

The GDR algorithm makes use of momentum and a bias function, which are two distinguishing features between the GDR and the vanilla back-propagation algorithm. Momentum is an extra weight added onto the weight factors when they are adjusted. It accelerates the change in the weight factors, and thus improves the training rate and prevents the network stuck in a local minimum. In the GDR algorithm, the internal thresholds become a bias function by adding a fixed number to the nodal summation. When serving as a bias function, the internal threshold values are not changed or updated as training processes. By using momentum coupled with a bias function, the GDR algorithm is found more efficient than the vanilla back-propagation algorithm [Quantrille 1991]. In this research, the GDR is adopted to perform the training of the BPN in this research. Details of the GDR algorithm used in HSIM are described in Appendix E.

In the GDR algorithm, operations of networks are affected by two factors, learning rate (η) and momentum factor (α). Learning rate is the constant of proportionality while momentum factor determines the proportion of the last weight change that is added into the new weight change. In this research, learning rate and momentum factor are set as 0.6 and 0.9 respectively, which are found to be a proper setting in most problems [NeuroShell 1989].

Once the BPN has been trained by the similar old cases, it can be used as an adaptation model to derive initial process parameters of injection moulding for an input problem.

3.4 Hybrid Neural Network and Genetic Algorithm (NN-GA) Module

The major propose of the hybrid NN-GA module is to complement the CBR module in the determination of initial process parameters for injection moulding if there is no similar case retrieved from the CBR module. As shown in Figure 3.15, the hybrid NN-GA module comprises of two units, a NN prediction unit and a GA optimisation unit.

The NN prediction unit, which is a trained neural network, is used to predict quality of moulded parts. The GA optimisation unit is used to optimise the process parameters of injection moulding within a constrained searching space. As shown in Figure 3.15, an initial population is firstly generated and then the strings stored in it are individually fed into the NN prediction unit for the quality prediction of moulded parts. The predicted quality measures of moulded parts are used to indicate the fitness of strings. Finally, the GA optimisation unit is used to find out the best combination of process parameters by applying genetic operators. The cycle is repeated until an optimal/near-optimal solution is found. In the following, issues of design and development of the hybrid NN-GA module are discussed.

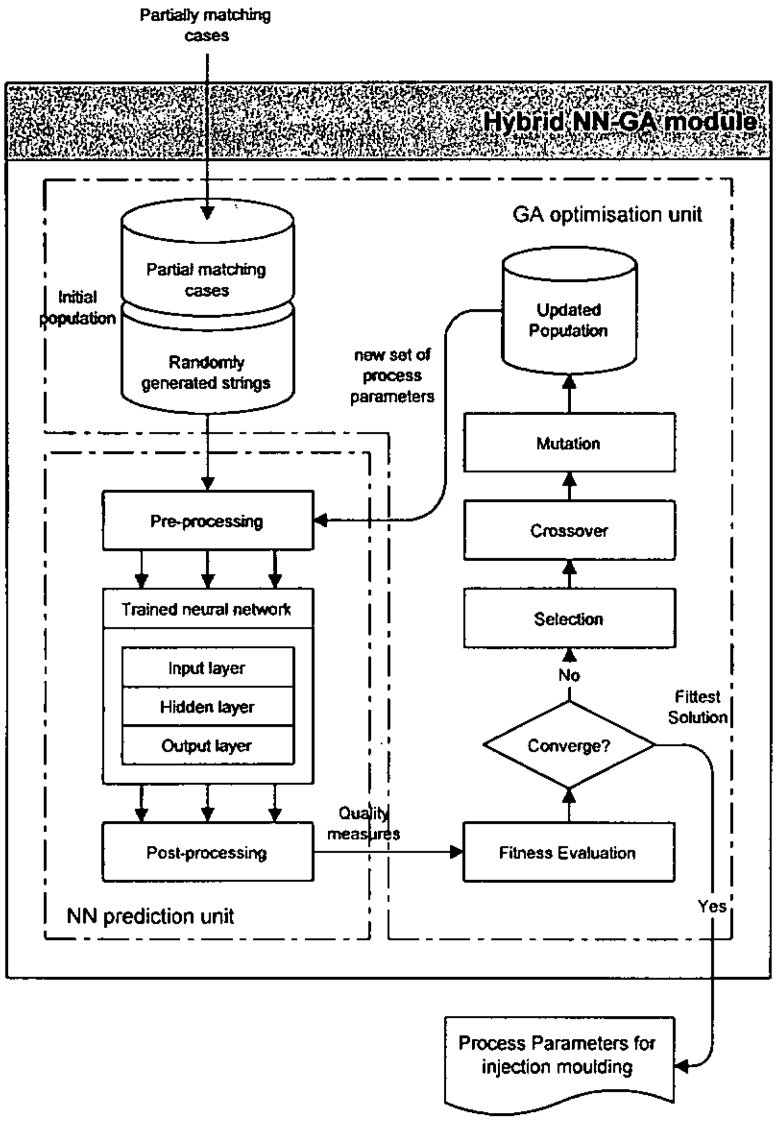


Figure 3.15 Basic architecture of hybrid NN-GA module

3.4.1 Initial population and strings

The hybrid NN-GA module is started with the generation of an initial population which contains a predefined number of chromosomes (strings). Contents of a string stored in the initial population is shown in Figure 3.16. Each string contains a set of part design parameters, mould design parameters and process parameters of injection moulding.

TR	EL	EW	EH	WT	PV	PA	PC	NC	HR	HG	ME	MO	IP	HP	BP	CF	SS	FT	HT	CT

where TR is the type of resin, EL is the envelope length, EW is the envelope width, EH is the envelope height, WT is the wall thickness, PV is the part volume, PA is the projected area, PC is the part complexity, NC is the number of cavities, HR is the hydraulic diameter of runners, HG is the hydraulic diameter of gates, ME is the melt temperature, MO is the mould temperature, IP is the injection pressure, HP is the holding pressure, BP is the back pressure, CF is the clamping force, SS is the screw surface speed, FT is the fill time, HT is the holding time and CT is the cooling time.

Figure 3.16 Contents of a string

The string can be represented / encoded in a binary string (binary-coded GA), or in a set of real numbers (real-coded GA). Binary encoding is the most common method to represent strings in GAs. This type of encoding can give many possible strings even with a small number of alleles (feature values). However, binary encoding is often not natural for many problems, such as where many real numbers are involved. In the determination of initial process parameters for injection moulding, a large number of real numbers are involved. Hence, real number encoding is found more suitable to represent the strings in the GA optimisation unit, in which each string is represented by a set of real numbers.

For example, Table 3.17 shows the information and data of design and moulding of a moulded part. Then, its corresponding string is represented as {1, 150, 48, 15, 1.5, 15000, 4800, 0.6, 1, 4.8, 2.6, 250, 80, 300, 150, 5, 50, 550, 0.5, 3, 5}.

The parameters of part design and injection mould design are directly obtained from system users through the user interface. Since these parameters are used to describe the input problem, they will not be altered during the GA based optimisation process. The process parameters of injection moulding are varied within their operating ranges in each generation in order to search for the best combination of process parameters within a constrained searching space. The operating range of the process parameters for the materials, ABS, PC and PS, can be found in Appendix F.

Attribute	Value
Type of resin	ABS (1)
Envelope length	150 mm
Envelope width	48 mm
Envelope height	15 mm
Wall thickness	1.5 mm
Part volume	15000 mm^3
Projected area	4800 mm^2
Part complexity	0.6
Number of cavities	1
Hydraulic diameter (runner)	4.8
Hydraulic diameter (gate)	2.6
Melt temperature	250 °C
Mould temperature	80 °C
Injection pressure	300 bar
Holding pressure	150 bar
Back pressure	5 bar
Clamping force	50 ton
Screw surface speed	550 mm/s
Fill time	0.5 sec.
Holding time	3 sec.
Cooling time	5 sec.

Table 3.17 Contents of a string

In this research, the population size, crossover rate and the mutation rate of the GA optimisation unit are set as 50, 0.6 and 0.001 respectively which are based on the suggestions from DeJong K.A. [DeJong 1975]. Unlike the conventional GAs, the initial population of the hybrid NN-GA module is generated by a combination of randomly generated strings and the partially matched cases retrieved from the CBR module. This combination can establish a better balance between exploration and exploitation of the searching space and hence provide a more efficient search [Louis 1997]. In the GA optimisation unit, 10% of the initial population come from the partially matched cases retrieved from the CBR module. The others are generated from random number generation. Once the initial population has been formed, each string of it is fed into the NN prediction unit for the quality prediction of moulded parts.

3.4.2 Neural network based quality prediction

The NN prediction unit was developed based on the neural network approach. A back-propagation network with sigmoid function is employed as a process model to predict the quality of moulded parts. Figure 3.17 shows the basic architecture of the 21-10-4 multi-layered BPN used in the NN prediction unit, which comprises of an input layer, a hidden layer and an output layer. Design processes of the network are very similar to those of the network which is used in the case adaptation of the CBR module.

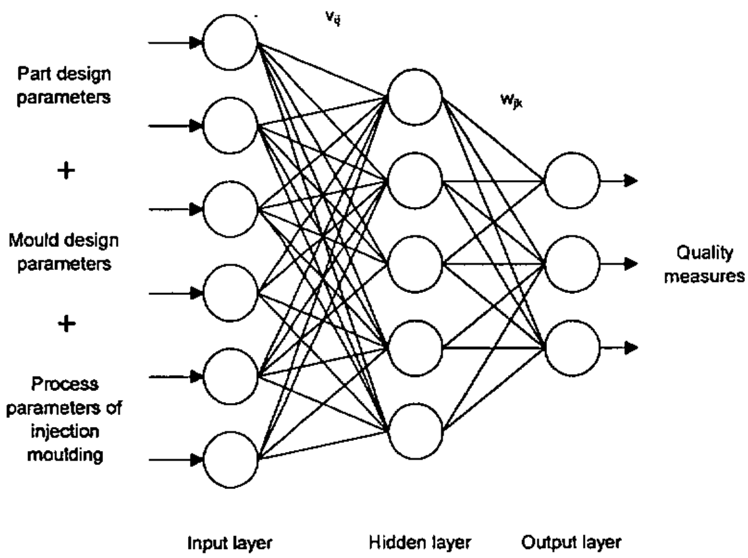


Figure 3.17 Structure of the neural network used in the hybrid NN-GA module

The input layer receives information from an external source and passes this information into BPN for processing. The input pattern to the NN prediction unit is a combination of the part design parameters, mould design parameters and the process parameters of injection moulding. The part design parameters and mould design parameters are directly obtained from the CBR module while the process parameters are generated by the GA optimisation unit.

The hidden layer receives information from the input layer, and "quietly" does all of the information processing. The hidden layer of the NN prediction unit models the relationship between the inputs and the outputs of the network. This processing step is hidden from the view.

The output layer receives processed information from the BPN and sends the results out to an external receptor. Outputs from the network are the quality measures of moulded parts including the maximum wall shear stress, maximum representative shear rate, mould temperature difference and the cycle time. The predicted cycle time is used to measure the productivity of injection moulding process. The other three quality measures are indirect type of measurement and used as an indication of possible moulding defects appearing in moulded parts.

Wall-shear stress is defined as the shear force at the mould wall per unit area and is proportional to the pressure gradient at each location. Shear stress is an indirect indication of the degree of molecular or fibre orientation. Higher shear stress would induce higher orientation, especially near the surface of the moulded part. In addition, flow instability, such as melt-fracture, has been shown experimentally to correlate directly with the shear stress level. As a rule of thumb, the maximum wall shear stress should not exceed the maximum value recommended by resin suppliers.

Representative shear rate is derived from the wall-shear stress and the fluidity. The representative shear rate can characterise the magnitude of the shear rate at any cross section. Therefore, the results can be used to identify the areas of higher shear rate and frictional heating. To establish an objective function, an average or weighted-average of the shear rate across the thickness is not desirable because a straight average would result in a misleadingly low value. As a rule of thumb, the maximum representative shear rate should not exceed the critical value recommended by resin suppliers. Otherwise, polymer degradation may occur.

Mould temperature difference is the difference between the core and the cavity mould-wall temperature. The temperature difference leads to asymmetric cooling, and thus contributes to thermal residual stresses in moulded parts. Therefore, these data can indicate the occurrence of warpage due to uneven mould cooling. Ideally, the mould temperature difference should be zero so that non-uniform shrinkage can be eliminated. As a rule of thumb, the temperature difference should not exceed 20° C.

Before the BPN can be used to predict the quality of moulded parts, it must be trained properly. To train the network, a certain number of input-output pairs must be available. In this research, the input-output pairs are obtained by performing a number of mould flow analyses. The obtained input-output pairs are then divided into a training set and a test set respectively. The network is trained with the training set and the performance of the network is tested periodically using the test set. The results of the training and the testing are shown in Appendix G.

Once the input-output pairs are available, generalised delta-rule (GDR) training algorithm with momentum term can be performed to train the BPN. During training, an input pattern is sent to the network and an output is obtained. The output is compared with the known output for the pattern and the error is propagated back through the network by adjusting the weights. This helps to minimise the error associated with the present input-output set. Details of the GDR training algorithm have been described in Section 3.3.4. If the BPN is properly trained, it not only can correctly evaluate patterns that have been trained upon but also can interpolate between these patterns to describe unfamiliar but related input patterns. The outputs from the neural network, which are the quality measures of moulded parts, are then evaluated by a fitness function.

3.4.3 Fitness function

In this research, a fitness function was established to evaluate each string in the processing population which is shown below:

$$\text{Minimise}: \quad F(X) = a\left(\frac{\tau_{max}}{\tau_{critical}}\right) + b\left(\frac{\dot{\gamma}_{max}}{\dot{\gamma}_{critical}}\right) + c\left(\frac{T_d}{T_d^a}\right) + d\left(\frac{t_{cycle}}{t_{allow}}\right) \quad (3.38)$$

Subject to : $C_1(X) : \tau_{max} \leq \tau_{critical}$ (to prevent flow instability)

$C_2(X) : \dot{\gamma}_{max} \leq \dot{\gamma}_{critical}$ (to prevent degradation)

$C_3(X) : T_d \leq T_d^a$ (to prevent warpage)

$C_4(X) : t_{cycle} \leq t_{allow}$ (to ensure productivity)

where τ_{max} is the maximum wall shear stress, $\tau_{critical}$ is the critical wall shear stress, $\dot{\gamma}_{max}$ is the maximum representative shear rate, $\dot{\gamma}_{critical}$ is the critical representative shear rate, T_d is the maximum temperature difference, T_d^a is the allowable temperature difference, t_{cycle} is the cycle time, t_{allow} is the allowable processing time, and a,b,c and d all are the weighted factors.

Minimising the fitness function implies the minimisation of moulding defects and the maximisation of productivity. In order to maintain uniformity over various problem domains, values obtained from the fitness function are normalised to a range of 0 to 1. In this research, the normalised values are considered as the fitness of a string, which are calculated by the following equation:

$$fit_i = \frac{FV_{max} - FV_i}{FV_{max} - FV_{min}} \tag{3.39}$$

where fit_i is the fitness of the i-th string, FV_i is the value of the i-th string obtained from the fitness function, and FV_{max} and FV_{min} is the maximum and minimum value obtainable from the fitness function respectively.

3.4.4 Control population

After the first generation, the strings are ranked in descending order based on their fitness value. The top ten strings are stored in a temporary population, called control population. In successive generations, the fitness value of each string stored in the processing population compares with the fitness value of each string stored in the control population. If the fitness value of a string of the processing population is better than the one with the smallest fitness value stored in the control population, the former will be copied to the control population while the latter stored in the control population will be removed. Then the strings stored in the control population are re-ranked according to their fitness values. While the iterations show declining in fitness, all the strings stored in control population will be copied to replace the ten weakest strings stored in the processing population.

3.4.5 Termination criteria

Two termination criteria, settling boundary and maximum number of iterations, are defined in the GA optimisation unit. Settling boundary is used to determine whether the population has converged, while maximum number of iterations is used to avoid excessive computer time. Settling boundary is determined based on the difference between the largest and smallest fitness value of the strings stored in the control population.

$$SB = \frac{FC_{\max} - FC_{\min}}{FC_{\max}} \times 100\% \qquad (3.40)$$

where SB is the settling boundary, and FC_{max} and FC_{min} are the largest and smallest fitness value of the strings stored in the control population respectively.

In this research, the settling boundary is defaulted as 0.1 % while the maximum number of iterations is set as 1,000. These values can be modified by system users. If the settling boundary is less than 0.1% or the pre-defined number of iterations is reached, the GA process stops and the string with the largest fitness value, which contains a set of initial process parameters for injection moulding, is recommended to system users.

3.4.6 Generation of new population

If the termination criteria have not been fulfilled, the GA operators including selection, crossover and mutation will be applied to generate a new population. Selection is an operation for the determination of the combination that performs crossover. There are quite a few selection techniques such as roulette-wheel selection, Boltzman selection, tournament selection, rank selection and steady state selection. In this research, the roulette-wheel selection and the rank selection are considered.

The roulette-wheel selection is the most common technique for selecting strings, which allocates offspring based on the ratio of string's fitness value to the population's average fitness value. There are two shortcomings in the use of this selection scheme. Firstly, in the initial generations of the genetic algorithm, a large number of offspring may be generated from a few strings with relatively high fitness values. It can cause a premature convergence. Secondly, when the variance in individual fitness values becomes small, approximately equal number of offspring may be generated from individual strings. It can deplete the driving force to promote better strings.

In rank selection, the population is sorted according to the fitness values. The fitness assigned to each string depends only on its position in the individuals rank and not on the actual fitness value. It has been proved that rank selection behaves in a more robust manner than roulette-wheel selection [Back 1991]. Hence, the rank selection is adopted in the GA optimisation unit.

After selection, strings are subjected to crossover in order to produce more adapted string (better solution). The simplest approach to perform crossover is single-point crossover. Single-point crossover is to choose a random cut point along the string of values and generate the offspring by combining the segment of one parent to the left of the cut point with the segment of the other parent to the right of the cut point. Single-point crossover has very strong positional bias, but no distributional bias. Experimental results have indicated that the combination of biases is far from optimal and has undesirable side-effects on the exploratory power of crossover [Eshelman 1989].

There are quite a few crossover methods available to overcome the shortcomings of single point crossover such as two-point crossover, multi-point crossover, segmented crossover, shuffle crossover and uniform crossover. In this research, two-point crossover and uniform crossover are considered. In the two-point crossover scheme, two crossover points are randomly chosen within the length of strings and segments of strings between them are exchanged. In the uniform crossover scheme, the bits are exchanged randomly at each string position. Therefore, uniform crossover exchanges bits of a string rather than segments.

Empirical evidence shows that uniform crossover is more suitable for small populations, while for larger populations, the less disruptive two-point crossover is better [Srinivas 1994]. Since a relatively small population is used in the GA optimisation unit, uniform crossover is adopted in order to sustain a highly explorative search in the population. Operations of uniform crossover are illustrated below:

For example, uniform crossover is performed on a pair of selected strings, string 1 and string 5, and crossover break point is set as 0.2.

String 1:	*[250,*	*70,*	*300,*	*150,*	*5,*	*50,*	*55,*	*80,*	*0.5,*	*3,*	*5,*	*90]*
String 5:	*[270,*	*85,*	*250,*	*150,*	*8,*	*35,*	*70,*	*120,*	*0.6,*	*3.5,*	*5,*	*90]*
Random no.:	*[.35,*	***.15,***	*.23,*	*.65,*	*.50,*	*.66,*	*.78,*	***.18,***	*.28,*	*.33,*	*.88,*	*.56]*

In this example, the second token and eighth token of the pair of strings have a random number smaller than the crossover break point. Therefore, these tokens will exchange and their offspring will be:

String 1:	*[250,*	***85,***	*300,*	*150,*	*5,*	*50,*	*55,*	***120,***	*0.5,*	*3,*	*5,*	*90]*
String 5:	*[270,*	***70,***	*250,*	*150,*	*8,*	*35,*	*70,*	***80,***	*0.6,*	*3.5,*	*5,*	*90]*

The number of strings selected to perform crossover in each generation can be calculated by using the following equation.

$$NC = CR \times PS \qquad (3.41)$$

where NC is the number of strings to perform crossover in each generation, CR is the crossover rate and PS is the population size.

After crossover, mutation is applied to each string. Mutation is used to increase the variability of the population by introducing a small amount of random search. During mutation, each fundamental unit (bit, position or token) in a string has a finite probability of changing. Therefore, the probability of searching any region in the problem space is never zero, which prevents complete loss of genetic material through selection and elimination. Operations of mutation are illustrated by using the following example.

If mutation rate is set as 0.01, the token to be mutated is selected as follows:

String 1:	*[270,*	*70,*	*300,*	*150,*	*5,*	*50,*	*55,*	*120,*	*0.5,*	*3,*	*5,*	*90]*
Random no.:	***[.005,***	*.422,*	*.923,*	*.645,*	*.150,*	*.066,*	*.078,*	*.106,*	*.328,*	*.343,*	*.858,*	*.546]*

......continue on other strings......

In this example, the first token of string 1 has a random number smaller than the mutation rate 0.01. Therefore, mutation is done on the token randomly within the range of it. As the first token represents melt temperature and its operating range is between 210 and 260, string 1 may be changed as follows:

String 1:	***[256,***	*70,*	*300,*	*150,*	*5,*	*50,*	*55,*	*120,*	*0.5,*	*3,*	*5,*	*90]*

The number of tokens to perform mutation in each generation can be calculated by the following equation.

$$NM = MR \times SL \times PS \tag{3.42}$$

where NM is the number of tokens to perform mutation, MR is the mutation rate, SL is the string length and PS is the population size.

The newly generated strings are then fed to the NN prediction unit for the quality prediction of moulded parts.

CHAPTER FOUR – SYSTEM IMPLEMENTATION AND VALIDATION

4.1 System Implementation

The prototype system for the determination of initial process parameters for injection moulding, HSIM, has been developed. The system which consists CBR module and NN-GA module was implemented in Visual Basic programming language based on combined case based reasoning (CBR) and hybrid neural network and genetic algorithm (NN-GA) approach. Figure 4.1 shows the overall process flow of HSIM.

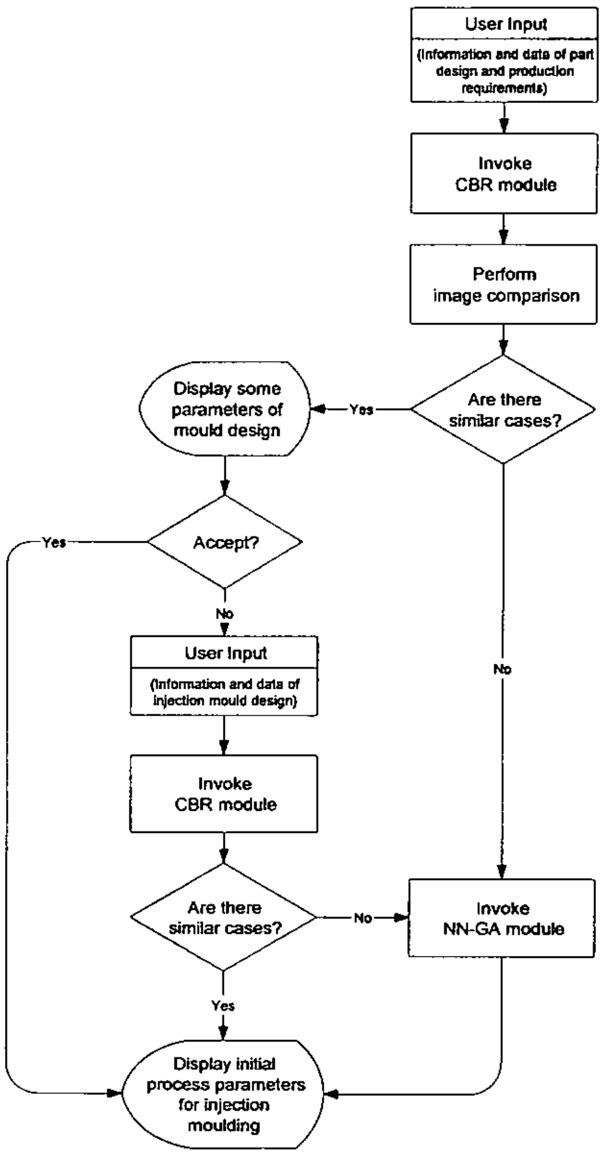


Figure 4.1 Overall process flow of HSIM

In this chapter, capabilities and operations of HSIM are described and demonstrated. Determination of initial process parameters for injection moulding of a mobile phone casing as shown in Figure 4.2 is used as an example for illustration throughout this section. The demonstrations are shown in two scenarios. In the first scenario, there are good matching cases found in the case library and the initial process parameters of injection moulding for the input problem are determined by the CBR module. In the second scenario, no good matching cases can be retrieved from the CBR module and the initial process parameters of injection moulding for the input problem are determined by the hybrid NN-GA module.

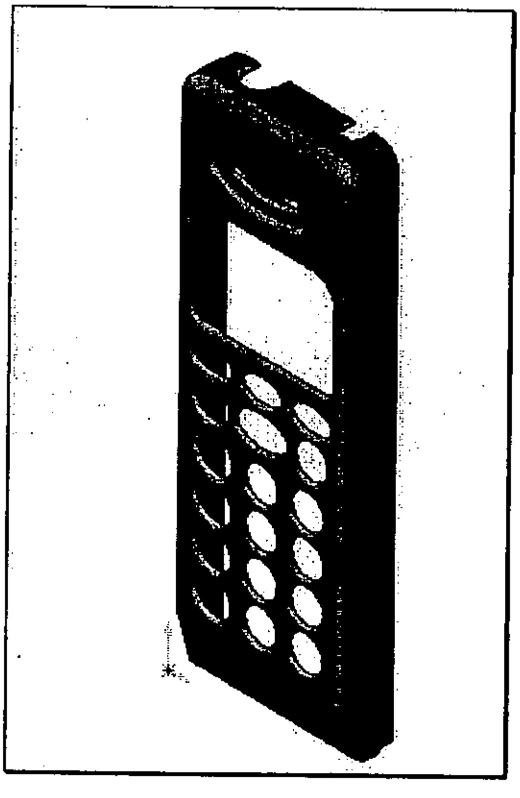


Figure 4.2 A mobile phone casing (for illustration)

4.1.1 Determination of initial process parameters for injection moulding based on CBR approach

Firstly, the part design parameters and production requirements are input to the system through the user interface as shown in Figure 4.3. Based on the production requirements of the input problem, the required number of cavities can be calculated which is one of the critical indexes for case matching.

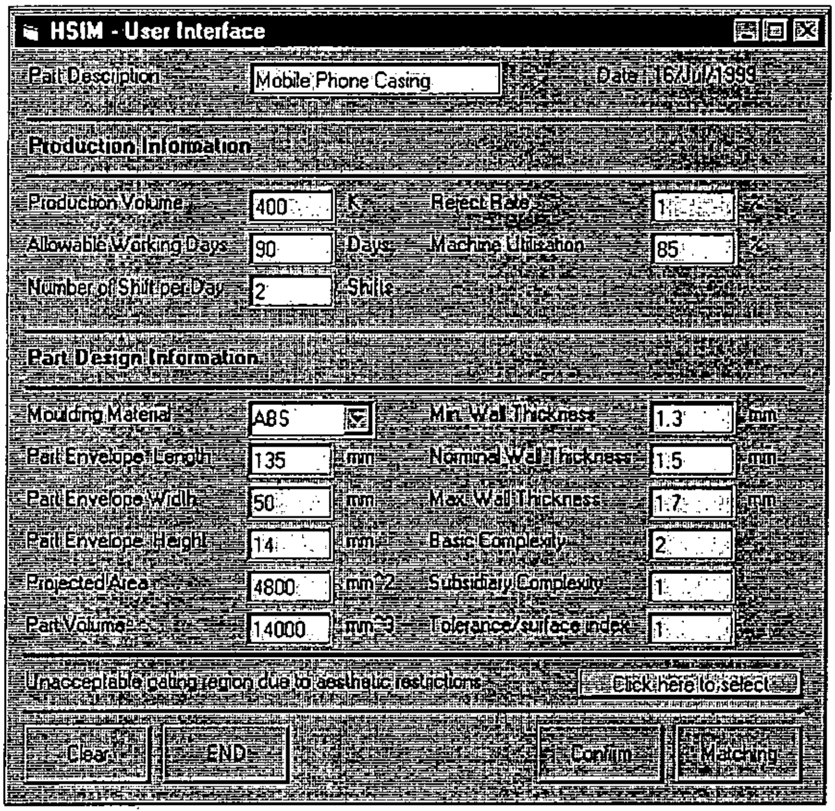


Figure 4.3 User input interface of HSIM

After the input, the CBR module is invoked to determine the initial process parameters of injection moulding. Case retrieval starts with matching the pre-defined indexes. After the matching, a number of cases are retrieved. The first level of similarity analysis is then performed on the retrieved cases based on the part complexity. The part complexity is determined by both the quantitative assessment (based on the Poli's method) and the qualitative assessment (based on the image comparison). Figure 4.4

shows the results of the quantitative assessment while Figure 4.5 shows the interface for performing the image comparison. Results of the first level of similarity analysis are shown in Figure 4.6.

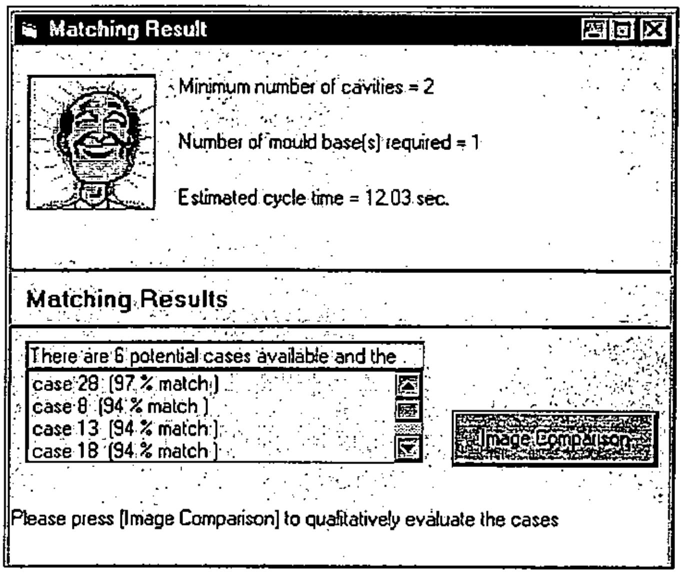


Figure 4.4 Results of quantitative assessment

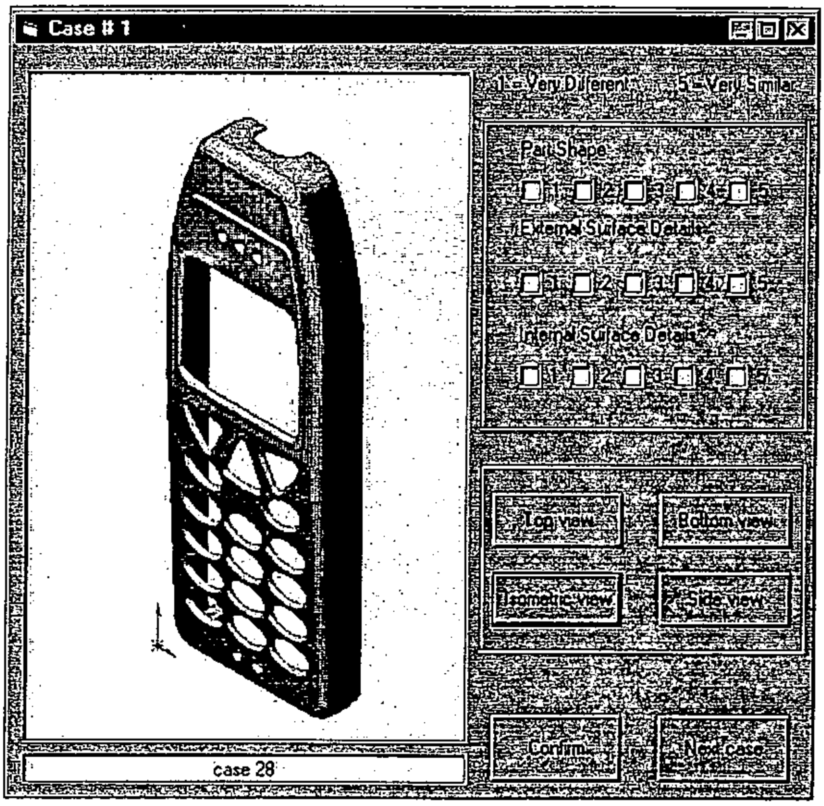


Figure 4.5 Interface for image comparison

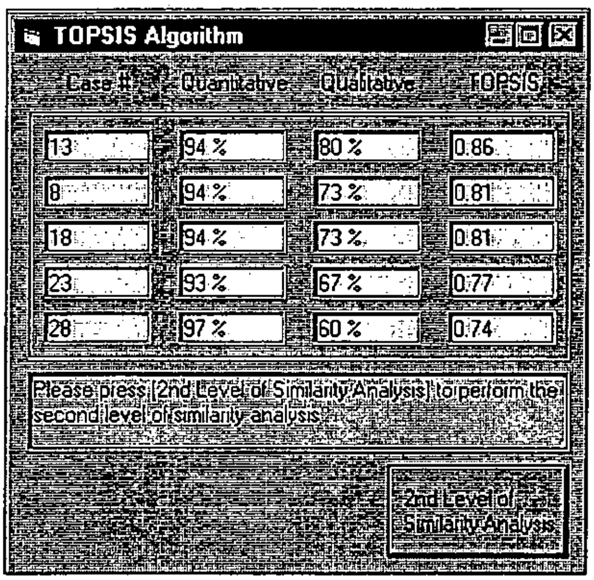


Figure 4.6 Results of first level of similarity analysis

After the first level of similarity analysis, the second level of similarity analysis is performed on the retrieved cases based on the indexes, wall thickness, part envelop size (length, width, depth), part volume, projected area and hydraulic diameter of runners and gates. Results of the similarity analysis are shown in Figure 4.7.

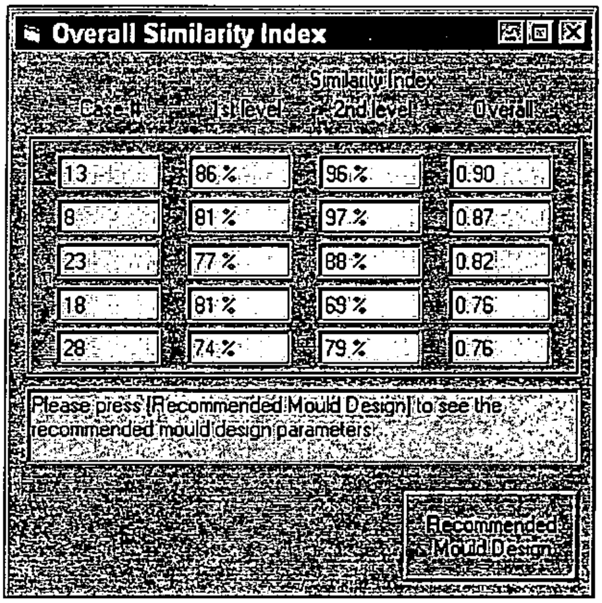


Figure 4.7 Results of second level of similarity analysis

After the two levels of similarity analysis, the overall similarity value of individual cases is obtained. The five most similar cases are used as training sets for formulating a neuro-adaptation model. The initial process parameters of injection moulding and some mould design parameters of the closest case are shown in Figure 4.8 and Figure 4.9 respectively. The mould design parameters are directly recommended to system users which could be used in the injection mould design.

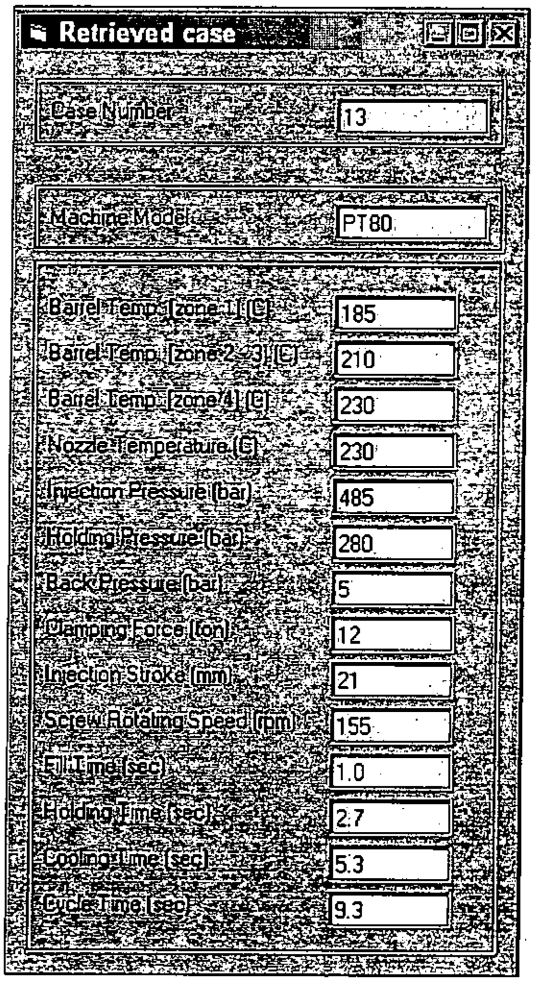


Figure 4.8 Process parameter setting of a selected case

If the recommended mould design parameters are accepted, a set of initial process parameters of injection moulding for the input problem is then output to system users as shown in Figure 4.10 after the case adaptation.

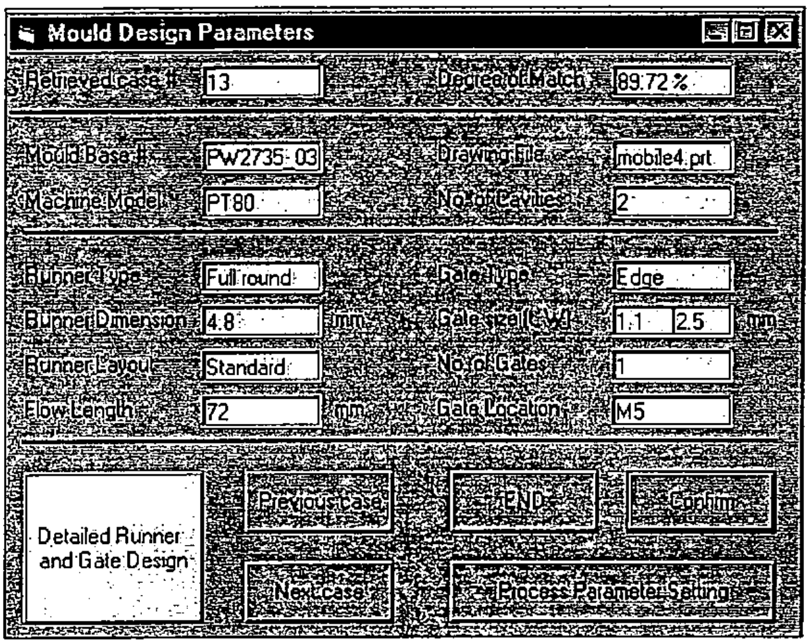


Figure 4.9 Major mould design parameters of a selected case

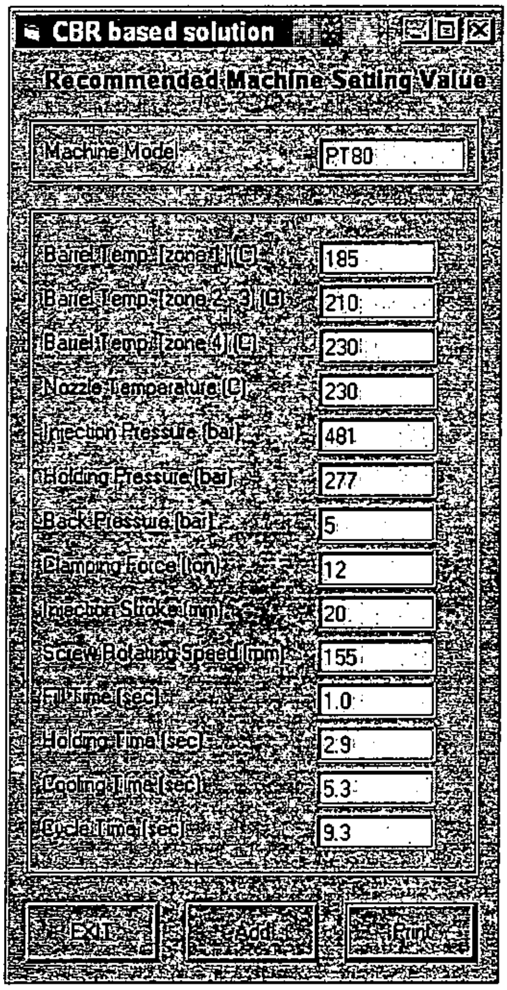


Figure 4.10 Initial process parameter setting for an input problem

If the mould design parameters recommended by the CBR module are modified, such as the change of gate size and runner size, the second level of similarity analysis is performed again in order to take the influence of the changes into account. The overall similarity values are then re-calculated. The five most similar cases are identified again to formulate an adaptation model based on neural network approach. For example, if the gate size is changed from 1.1mm × 2.5mm to 1.2mm × 3mm, a new set of initial process parameters recommended by the CBR module is shown in Figure 4.11.

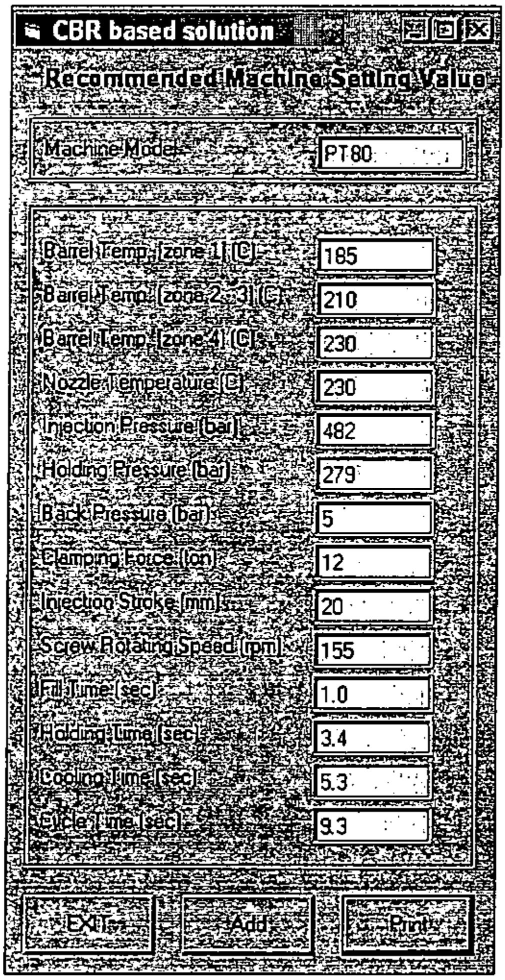


Figure 4.11 Process parameter setting of an adapted case

4.1.2 Determination of initial process parameter for injection moulding based on hybrid NN-GA approach

If the highest TOPSIS index obtained from the first level of similarity analysis is less than the threshold value (0.7) as shown in Figure 4.12, system users are required to input the mould design parameters through the user interface as shown in Figure 4.13.

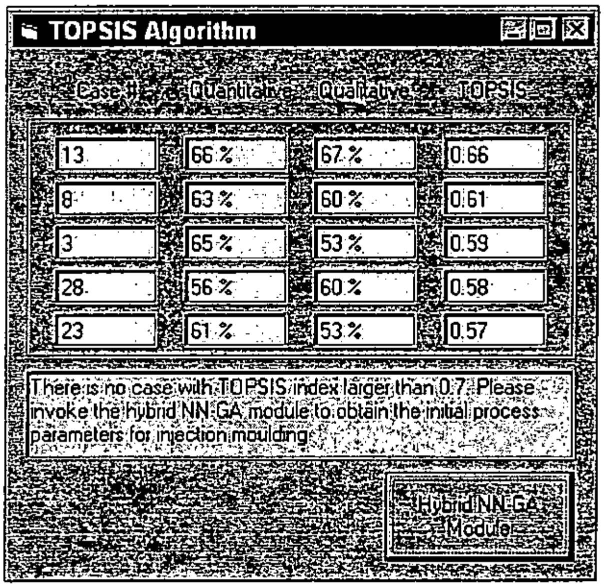


Figure 4.12 Results of first level of similarity analysis (no similar case is retrieved)

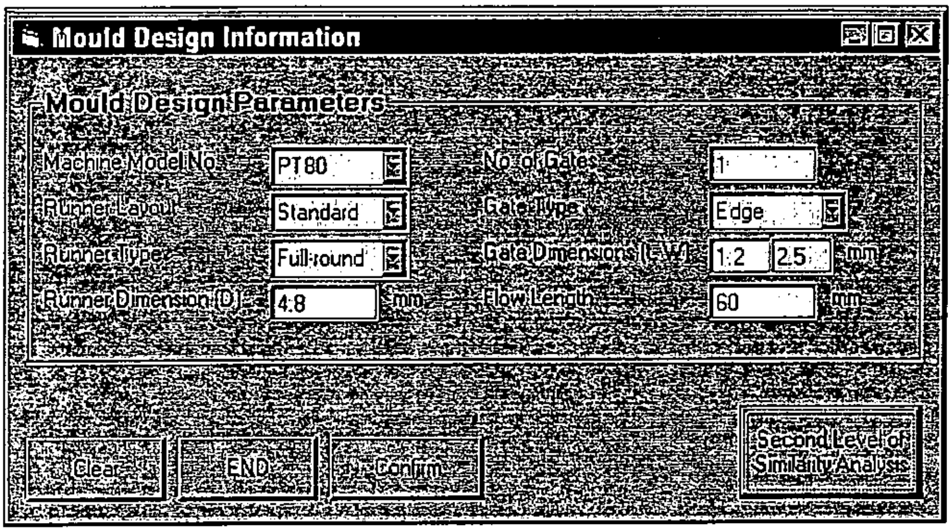


Figure 4.13 User interface for the input of mould design parameters

The second level of similarity analysis is performed to retrieve a number of similar cases. These similar cases become one part of the initial population for performing the GA based optimisation in the hybrid NN-GA module. Figure 4.14 shows the user interface of the hybrid NN-GA module, in which the GA control parameters including population size, mutation rate, crossover rate and settling boundary can be altered.

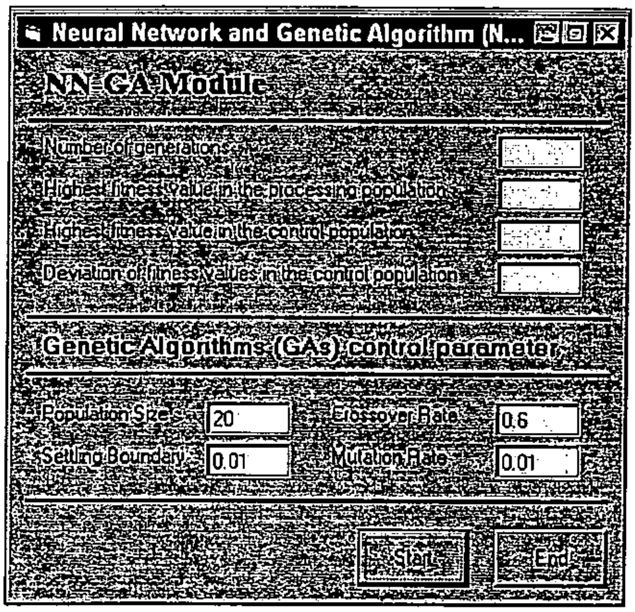


Figure 4.14 Interface of hybrid NN-GA module

The hybrid NN-GA module then applies the genetic operators to obtain an optimal solution. If the difference between the largest and smallest fitness values of the strings stored in the control population is less than 0.1% or the pre-defined number of iterations is reached, the GA process stops and the string with the largest fitness value will be recommended to system users. Figure 4.15 shows the contents of a string recommended by the hybrid NN-GA module.

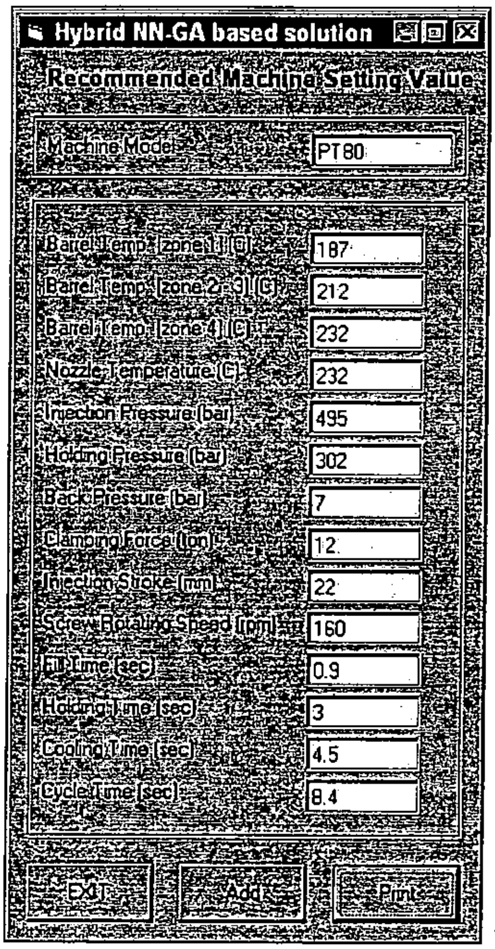


Figure 4.15 Recommended solution from the hybrid NN-GA module

4.2 System Validation

4.2.1 Methodology of system validation

Validation of HSIM can be performed in two stages. The first stage of system validation involves the investigation of the effectiveness of HSIM by using a CAE analysis package for injection moulding. The second stage of system validation involves the application of HSIM in real world environment. One or more manufacturing companies have to be involved in this stage. Since the manufacturing companies are still not identified, it seems that the second stage of system validation probably cannot be done by the end of this research. Details of the first stage of system validation is described below.

A commercial CAE analysis package for injection moulding called C-MOLD was employed in the first stage of system validation to validate the solutions generated by the HSIM. Previous applications of C-MOLD have already shown that the package can provide a good estimation of actual moulding results under quite a wide range of conditions. Solid models of mobile phone casings were created by using Pro/ENGINEER CAD software [Pro/ENGINEER 1997] and converted into mid-plane FEM models for the C-MOLD analyses.

Two validation tests were conducted in the first stage of system validation. The tests aim to investigate the effectiveness of HSIM when there are good and bad cases retrieved from the CBR module. In general, if there are good matching cases retrieved from the case library, only the CBR module is invoked to determine the initial process parameters. Otherwise, the hybrid NN-GA module is invoked. In order to investigate the effectiveness of individual modules, both modules are invoked in individual validation tests. Hence, two sets of initial process parameter setting are obtained for comparison in each test.

The initial process parameters of injection moulding for an input problem generated either from the CBR module or from the hybrid NN-GA module are used as a starting condition for running the C-MOLD analyses. The analysis results are assessed based on the quality criteria for moulded parts developed by Tan K.H. [Tan 1997b]. The quality criteria are summarised as follows:

$C_1 : \tau_{max} \leq \tau_{critical}$

$C_2 : \dot{\gamma}_{max} \leq \dot{\gamma}_{critical}$

$C_3 : \overline{VS} \leq \overline{VS}_{accept}$

$C_4 : \overline{T}_{cavity} \leq \overline{T}_{demold}$

where τ_{max} is the maximum wall shear stress, $\tau_{critical}$ is the critical wall shear stress, $\dot{\gamma}_{max}$ is the maximum representative shear rate, $\dot{\gamma}_{critical}$ is the critical representative shear rate, $\overline{VS}$ is the average volumetric shrinkage, $\overline{VS}_{accept}$ is the acceptable average volumetric shrinkage, $\bar{T}_{cavity}$ is the average cavity temperature, and $\bar{T}_{demold}$ is the material demoulding temperature.

The quality criteria are briefly explained below [Tan 1997]:

1. The first criterion is used to prevent flow instability, which is correlated to the maximum wall shear stress. Flow instability is considered to be not existed if the maximum wall shear stress is below its critical value.
2. The second criterion is used to prevent polymer degradation due to shear heating which is correlated to the maximum representative shear rate. This defect is considered to be not existed if the maximum representative shear rate is below its critical value.
3. The third criterion is used to prevent excessive linear shrinkage. Volumetric shrinkage is a qualitative indication of linear shrinkage and can be used to correlate this defect indirectly. Excessive linear shrinkage is considered to be not existed if the average volumetric shrinkage of the moulded part is below the acceptable value.
4. The fourth criterion is used to prevent warpage due to insufficient rigidity. This defect is considered to be not existed if the end-to-cool average cavity temperature is below the material demoulding temperature.

If the analysis results of a moulded part do not violate any quality criterion, the moulded part will be considered as free of the above defects and the corresponding initial process parameter setting can be considered to be acceptable. Results of the system validation are summarised in the following sections.

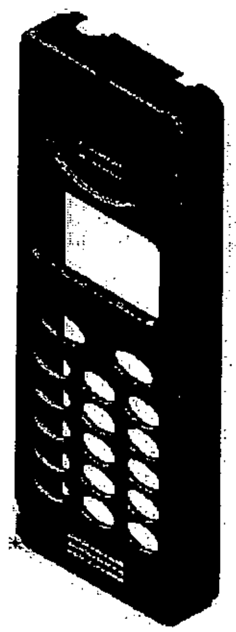
4.2.2 Validation test one

The data and information of a mobile phone casing as shown in Figure 4.16 are input to the system for the determination of initial process parameters for injection moulding. Table 4.1 shows the operating results of the CBR module and the hybrid NN-GA module respectively.

CBR Module	Hybrid NN-GA Module
Overall similarity index : 0.90	Highest fitness value : 0.68
Reference case no: 3	Number of iterations : 124

Table 4.1 Operating results of CBR module and hybrid NN-GA module (Test 1)

Part Number : ER_233



Production Volume:	100,000 Parts
Allowable Working Days:	27 Days
No. of Shifts per Day:	2 Shifts
Reject Rate:	1 %
Machine Utilisation:	85%
Required no. of cavities:	1 cavity
Wall Thickness:	1.8 mm
Part Envelope Length:	132 mm
Part Envelope Width:	48 mm
Part Envelope Height:	13 mm
Projected Area:	35.12 cm^2
Part Volume:	15.19 cm^3
Moulding Material:	ASAHI CHEM/ ABS STYLAC-ABS 100
Machine :	Kawaguchi/K25-B
Coolant Material:	Water (pure)
Mould Material:	Tool Steel P-20

Figure 4.16 Input problem of validation test one

Table 4.2 shows two sets of initial process parameters for injection moulding of the mobile phone casing, which were obtained from the CBR module and the hybrid NN-GA module respectively.

Injection Moulding Process Parameters	Unit	Solution from CBR module	Solution from hybrid NN-GA module
Nozzle temperature	°C	265	260
Barrel temperature	°C	265, 245, 230, 220	260, 240, 225, 215
Injection pressure	bar	365	273
Holding pressure	bar	295	219
Back pressure	bar	5	6
Clamping force	ton	10	10.5
Fill time	sec.	0.8	0.84
Holding time	sec.	6.0	5.0
Cooling time	sec.	8.5	8.9

Table 4.2 Two sets of initial process parameters for injection moulding (Test 1)

The two sets of initial process parameters for injection moulding were then input to the C-MOLD analysis package for mould flow simulation. Results of the C-MOLD analyses are summarised in Table 4.3.

Quality Measures	Unit	Quality criteria	Result A	Result B
Maximum wall shear stress	MPa	< 0.28	0.264	0.263
Maximum representative shear rate	1/s	$< 1.2\times10^4$	7.78×10^3	7.23×10^3
Average cavity temperature	°C	< 120	94	93
Average volumetric shrinkage	%	< 1.8	1.5	1.5

Result A - C-MOLD results based on the initial process parameters recommended by CBR module

Result B - C-MOLD results based on the initial process parameters recommended by hybrid NN-GA module

Table 4.3 Results of flow simulation (Test 1)

Apart from the above quantitative data, plots of the melt-front advancement, air trap locations and the weld line locations obtained from the C-MOLD analysis are shown as follows:

a. Melt front advancement

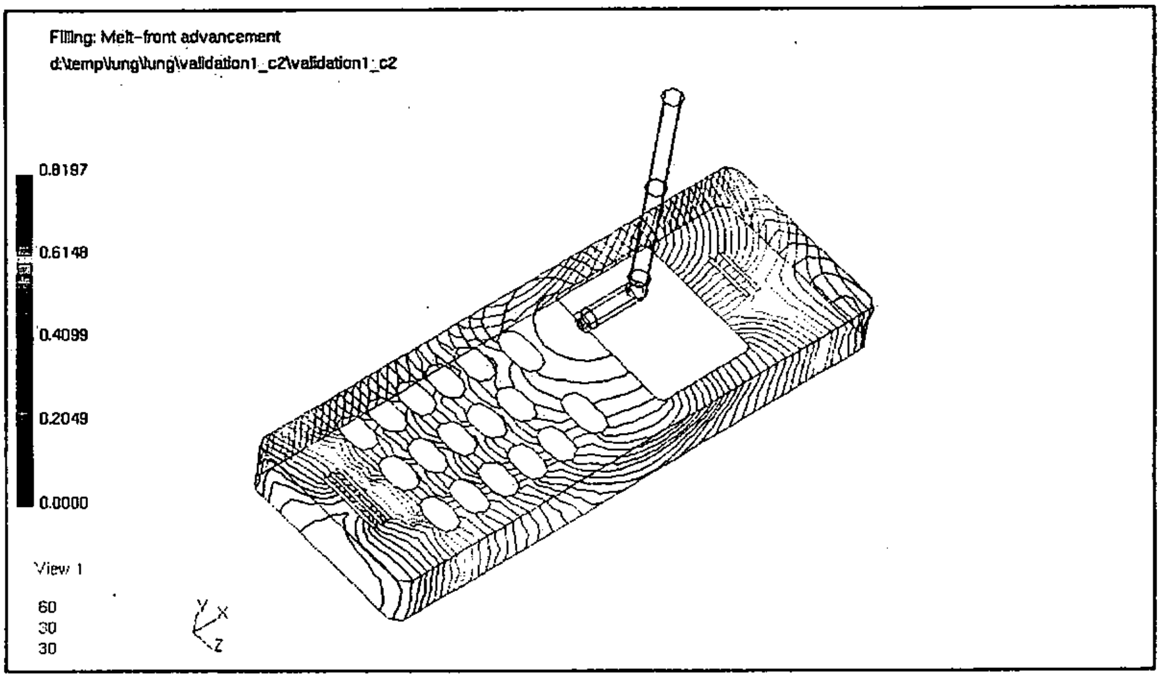


Figure 4.17. Melt front advancement (validation test 1: CBR module)

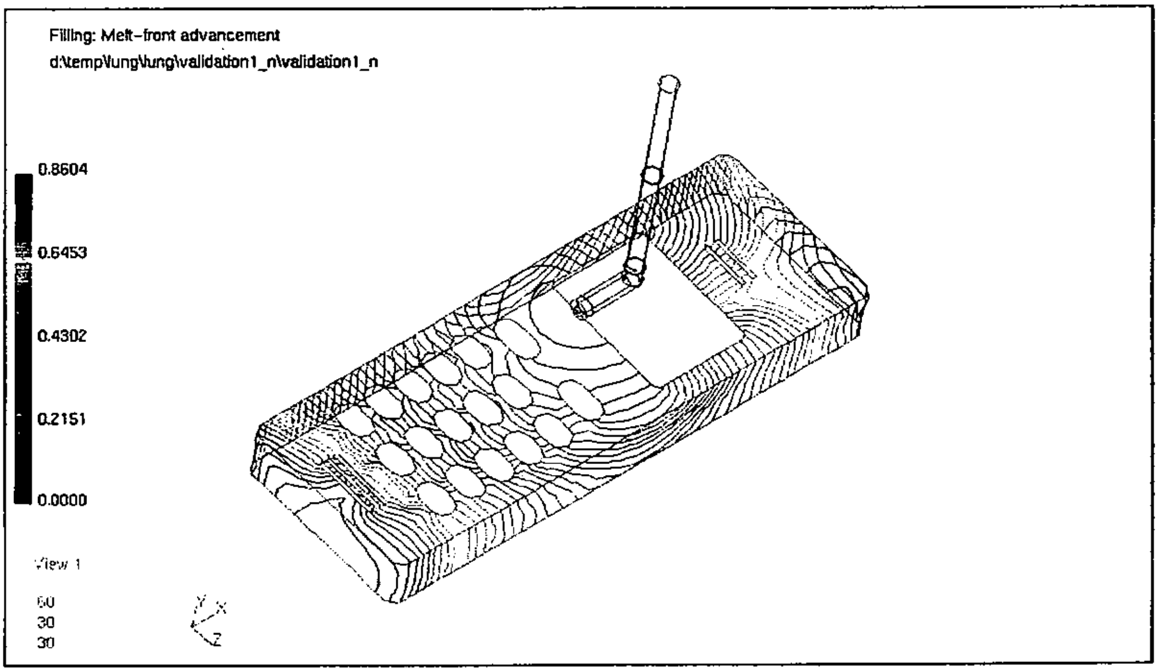


Figure 4.18. Melt front advancement (validation test 1: hybrid NN-GA module)

b. Air trap locations

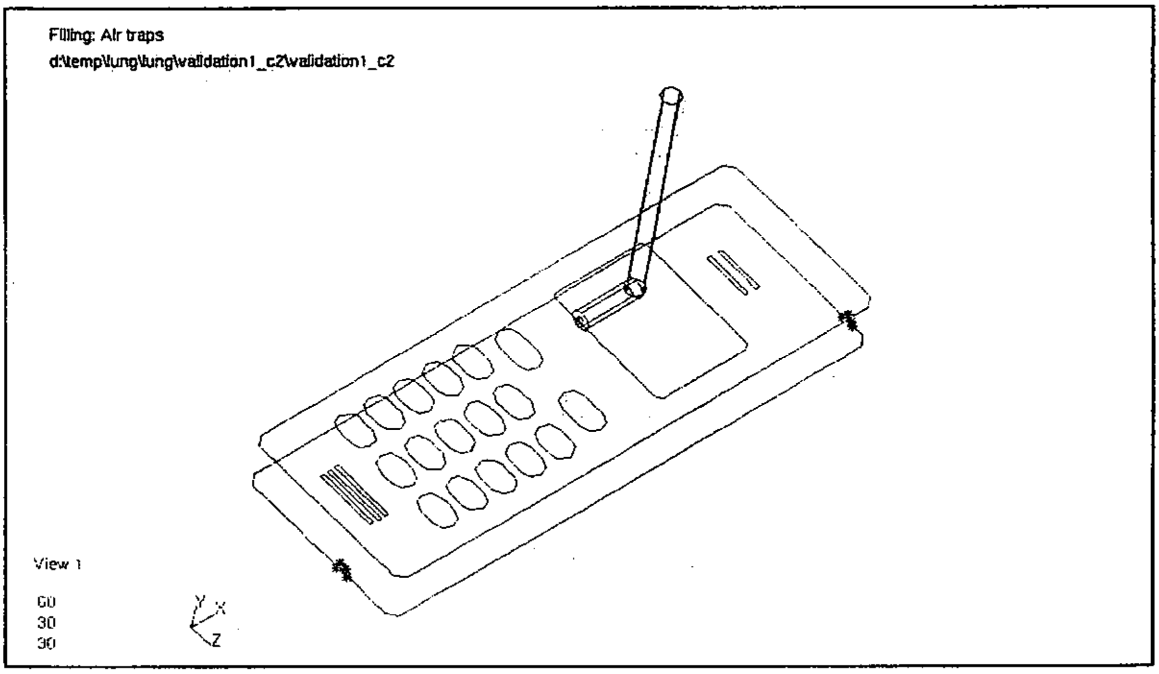


Figure 4.19. Air trap locations (validation test 1: CBR module)

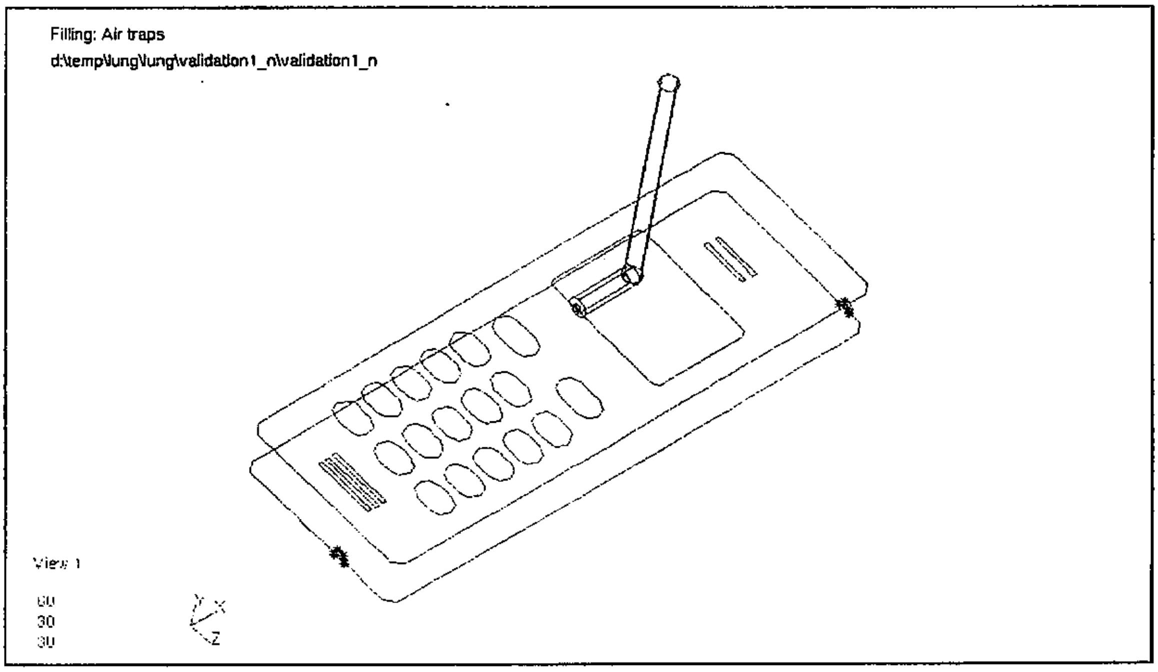


Figure 4.20. Air trap locations (validation test 1: hybrid NN-GA module)

c. Weld line locations

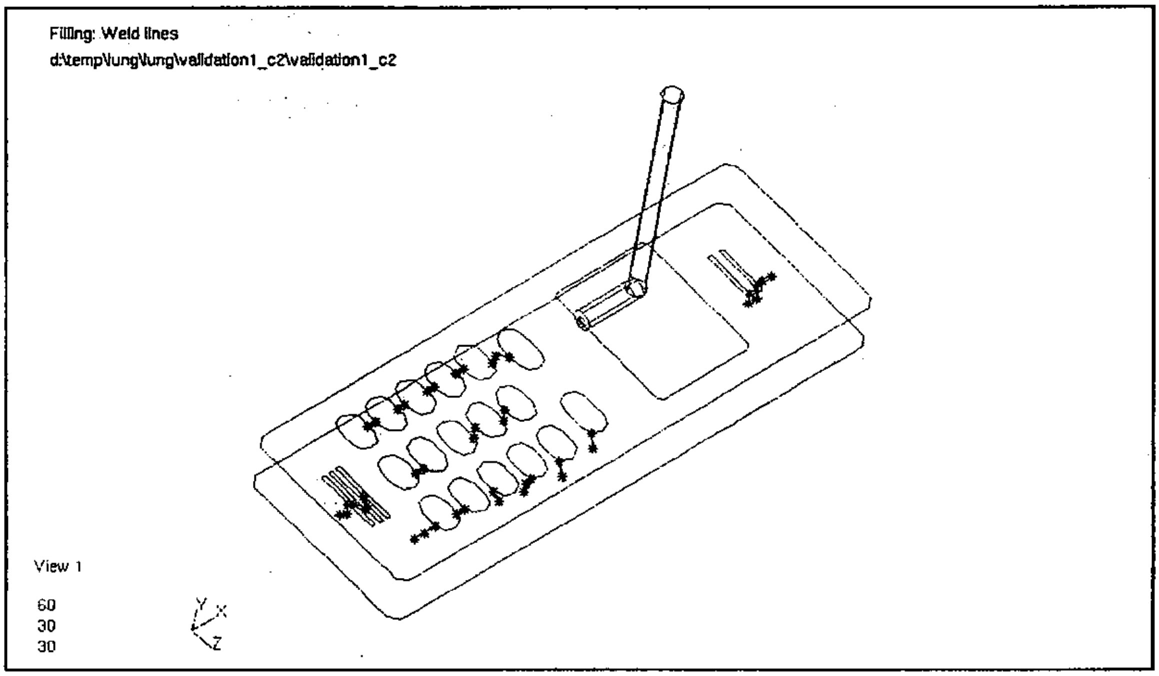


Figure 4.21. Weld line locations (validation test 1: CBR module)

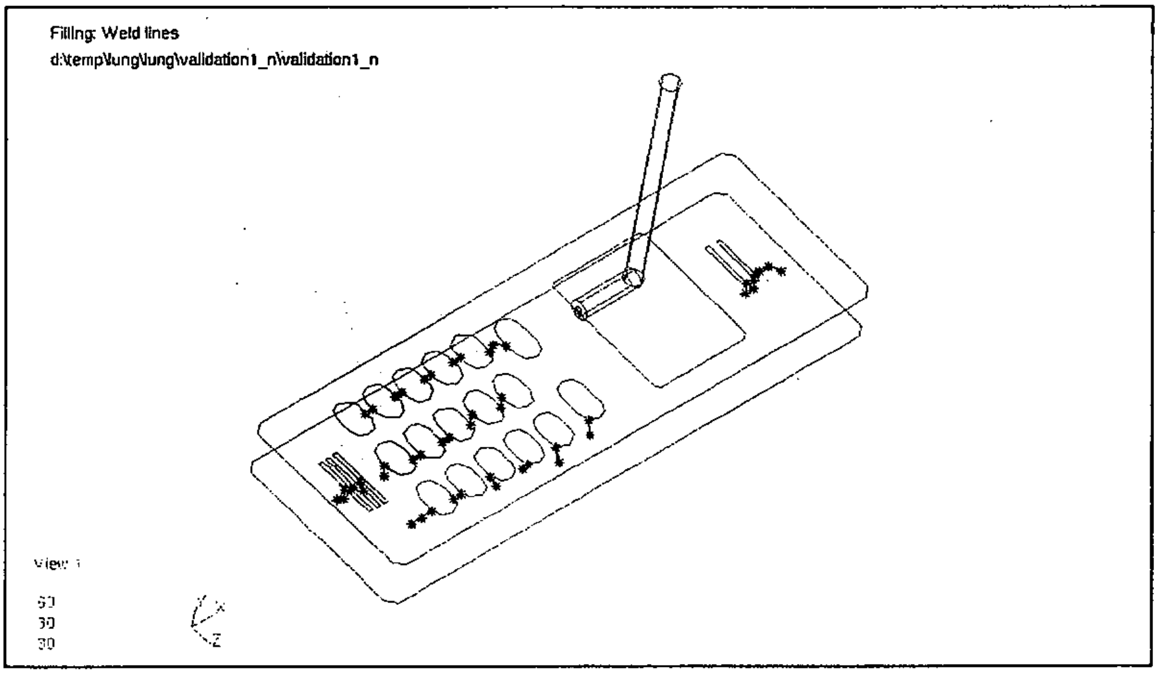


Figure 4.22. Weld line locations (validation test 1: hybrid NN-GA module)

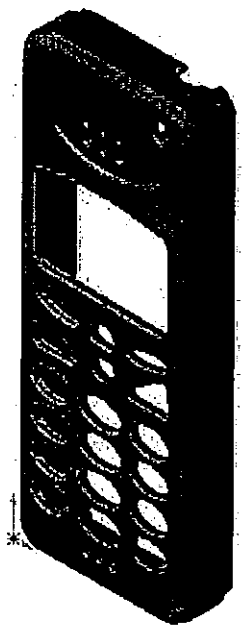
4.2.3 Validation test two

The data and information of another mobile phone casing as shown in Figure 4.23 are input to the system for the determination of initial process parameters for injection moulding. Table 4.4 shows the operating results of the CBR module and the hybrid NN-GA module respectively.

CBR Module	Hybrid NN-GA Module
Overall similarity index : 0.52	Highest fitness value : 0.64
Reference case no: 7	Number of iterations : 232

Table 4.4 Operating results of CBR module and hybrid NN-GA module (Test2)

Part Number : PE_933



Production Volume:	110,000 Parts
Allowable Working Days:	28 Days
No. of Shifts per Day:	2 Shifts
Reject Rate:	1 %
Machine Utilisation:	85%
Required no. of cavities:	1 cavity
Wall Thickness:	1.6 mm
Part Envelope Length:	110 mm
Part Envelope Width:	42 mm
Part Envelope Height:	13 mm
Projected Area:	28.92 cm^2
Part Volume:	10.14 cm^3
Moulding Material:	ASAHI CHEM/ABS 100
Machine :	Battenfeld/BA230/50E
Coolant Material:	Water (pure)
Mould Material:	Tool Steel P-20

Figure 4.23 Input problem of validation test two

Table 4.5 shows two sets of initial process parameters of injection moulding for the mobile phone casing, which were obtained from the CBR module and the hybrid NN-GA module respectively.

Injection Moulding Process Parameters	Unit	Solution from CBR module	Solution from hybrid NN-GA module
Nozzle temperature	°C	245	259
Barrel temperature	°C	245, 225, 210, 200	259, 239, 224, 214
Injection pressure	bar	417	370
Holding pressure	bar	250	296
Back pressure	bar	5	7
Clamping force	ton	10	10
Fill time	sec.	0.8	0.58
Holding time	sec.	6.0	8.6
Cooling time	sec.	10.5	11.2

Table 4.5 Two sets of initial process parameters for injection moulding (Test 2)

The two sets of initial process parameters for injection moulding were then input to C-MOLD analysis package for mould flow simulation. Results of the C-MOLD analyses are summarised in Table 4.6.

Quality Measures	Unit	Quality criteria	Result A	Result B
Maximum wall shear stress	MPa	< 0.28	0.28	0.27
Maximum representative shear rate	1/s	$< 1.2\times10^4$	9.4×10^3	1.08×10^4
Average cavity temperature	°C	< 120	76	82
Average volumetric shrinkage	%	< 1.8	3.9	1.75

Result A - C-MOLD results based on the initial process parameters recommended by CBR module

Result B - C-MOLD results based on the initial process parameters recommended by hybrid NN-GA module

Table 4.6 Results of flow simulation (Test 2)

Plots of the melt front advancement, air trap locations and the weld line locations obtained from the C-MOLD analysis are shown as follows:

a. Melt front advancement

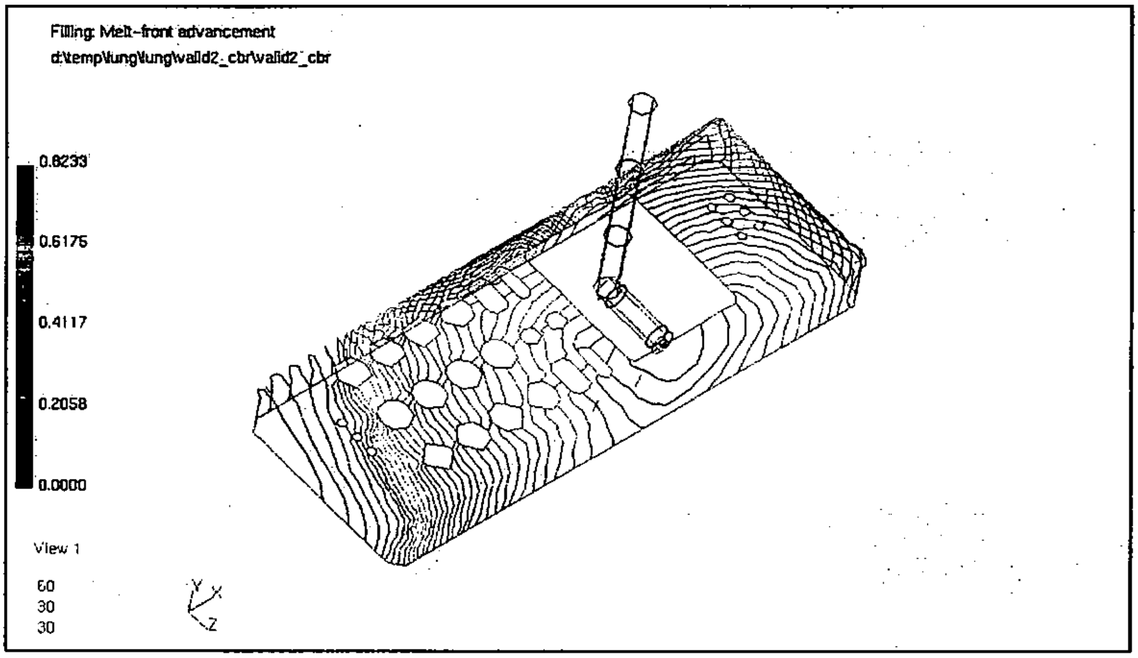


Figure 4.24. Melt front advancement (validation test 2: CBR module)

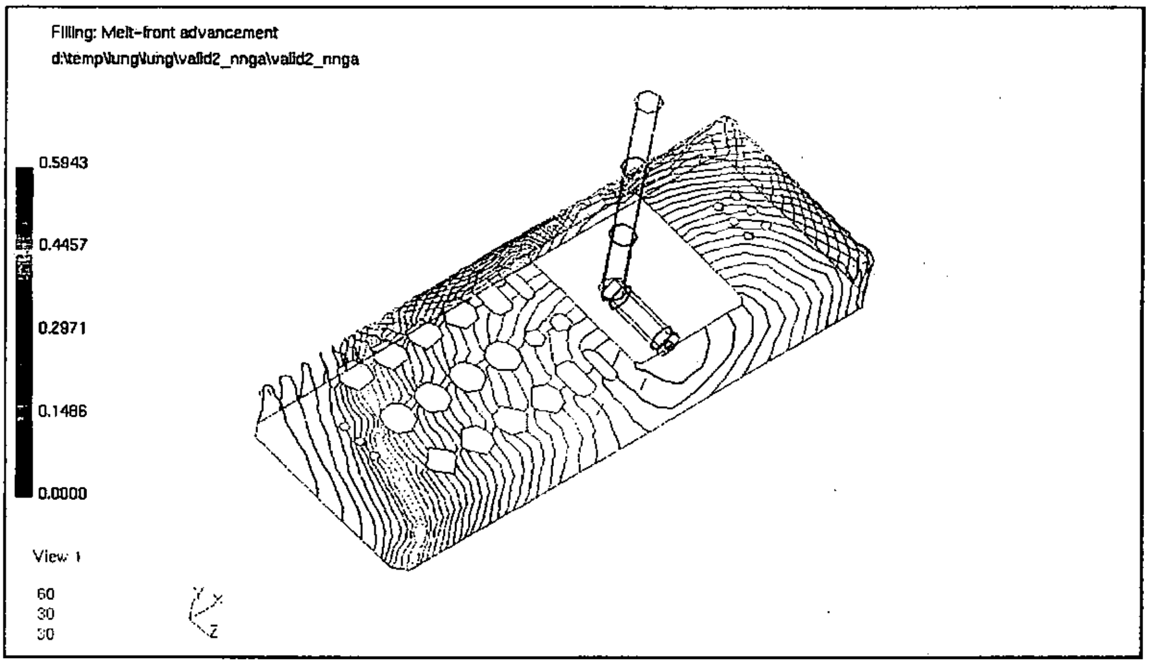


Figure 4.25. Melt front advancement (validation test 2: hybrid NN-GA module)

b. Air trap locations

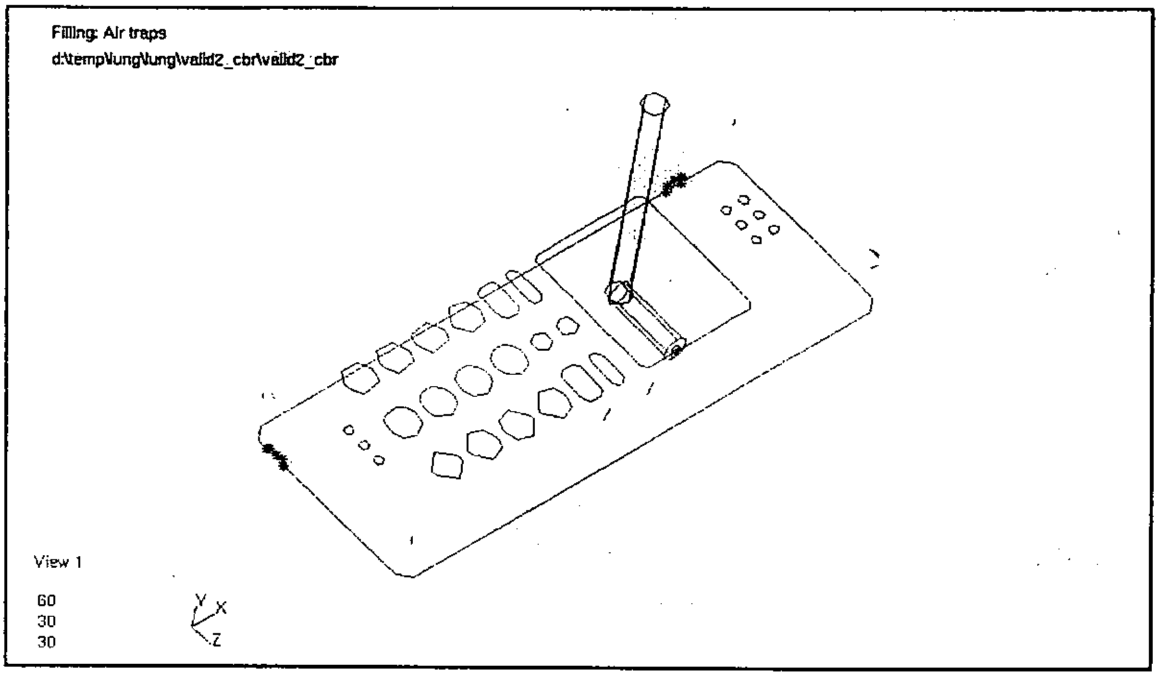


Figure 4.26. Air trap locations (validation test 2: CBR module)

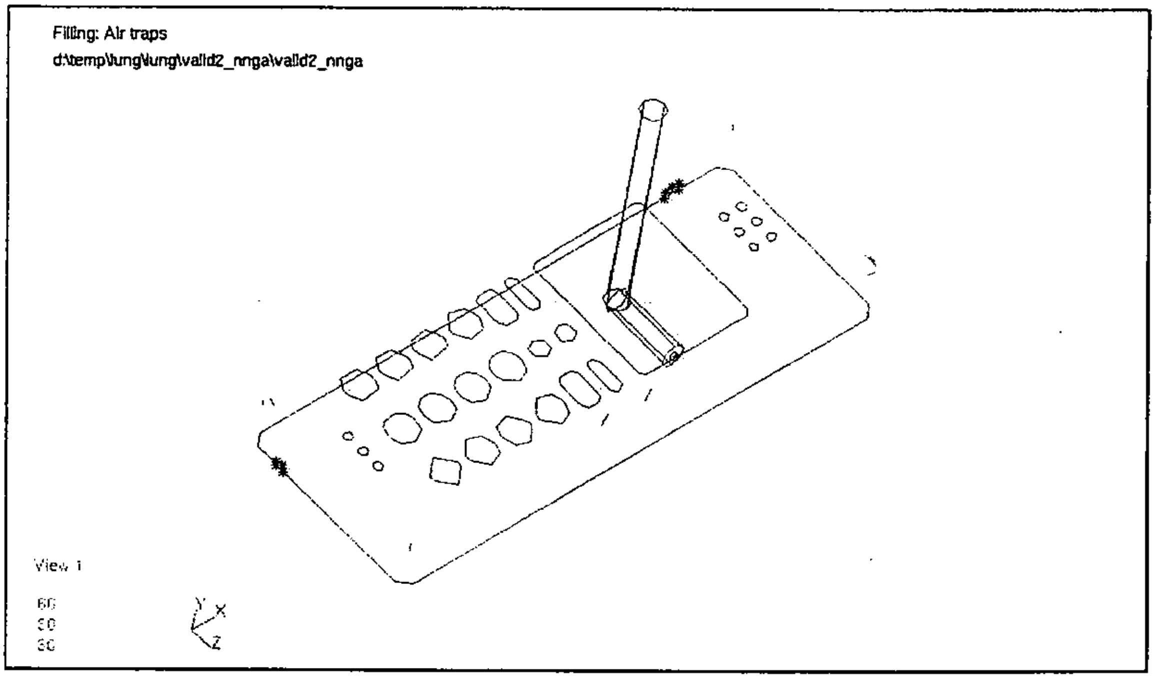


Figure 4.27. Air trap locations (validation test 2: hybrid NN-GA module)

c. Weld line locations

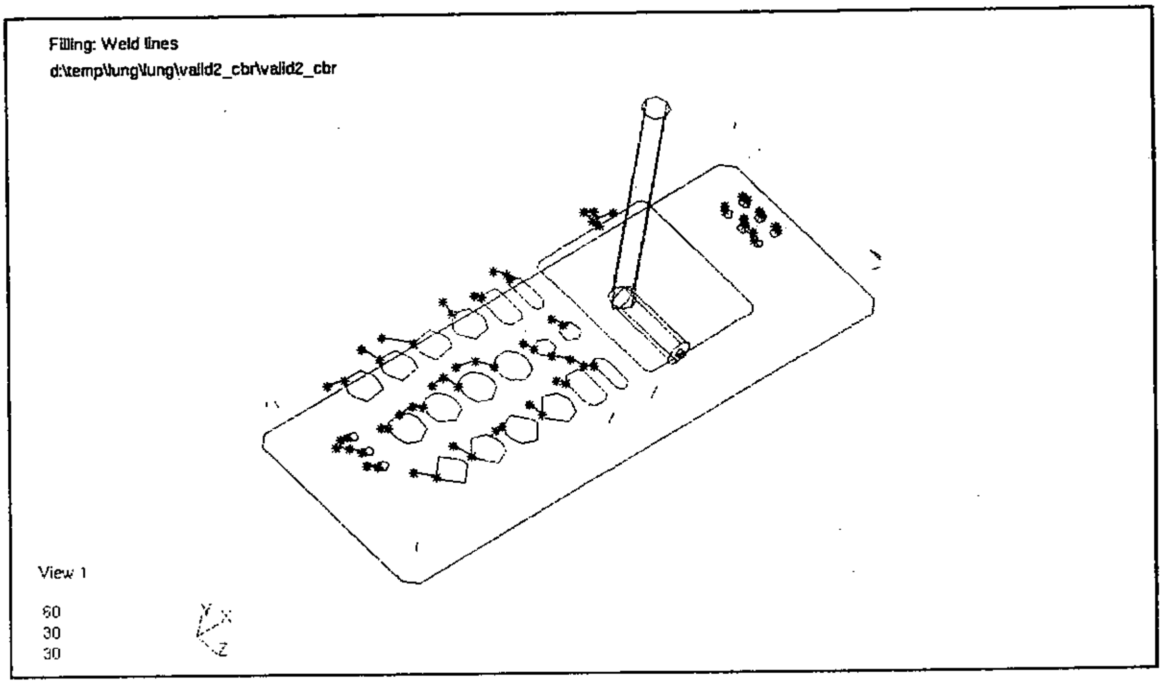


Figure 4.28. Weld line locations (validation test 2: CBR module)

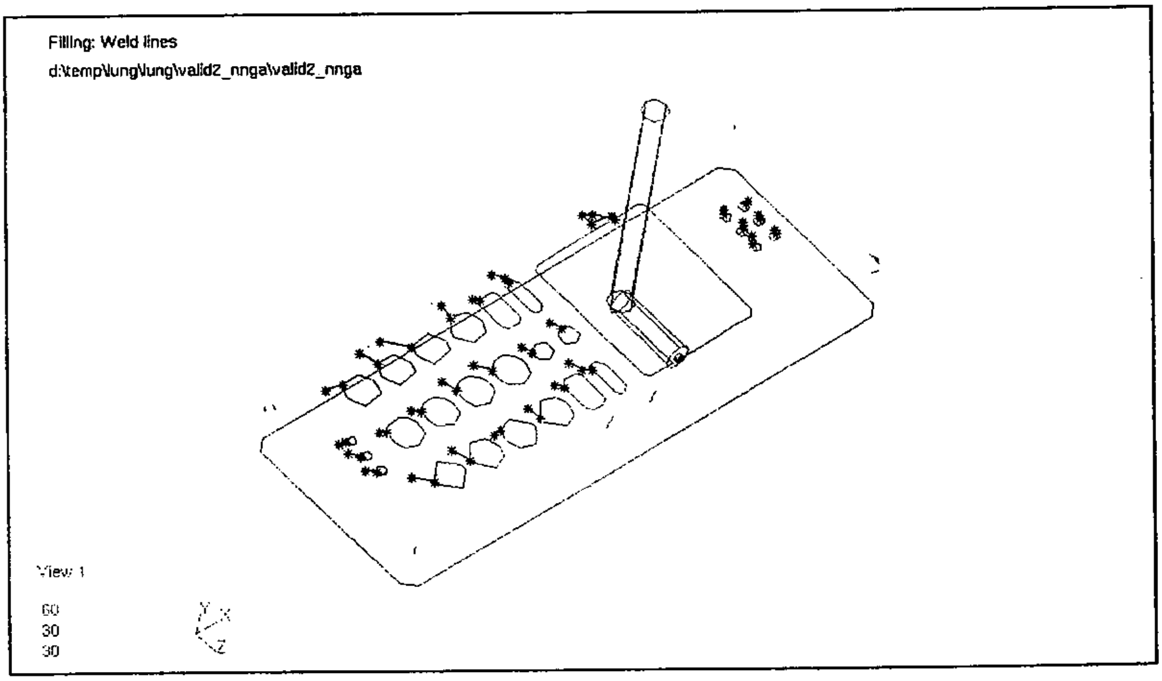


Figure 4.29. Weld line locations (validation test 2: hybrid NN-GA module)

CHAPTER FIVE – RESULTS AND DISCUSSIONS

5.1 Discussions on Validation Results

In this research, two validation tests have been performed to validate the effectiveness of HSIM. In the validation tests, four quality criteria are used to assess the quality of moulded parts. It should be noted that the quality criteria do not reflect all types of defects. For example, diesel effect (burns), which is strongly related to the venting condition, is not considered in the quality criteria. In spite of the limitations, the experimental results show that these quality criteria are adequate for practical usage [Tan 1997].

Two validation tests were performed on a desktop computer with a PII-300 processor and 128 Mbytes of memory. In the validation test one, the results of C-MOLD analyses, based on the two sets of initial process parameters obtained from the CBR module and the hybrid NN-GA module respectively, show that no quality criterion was violated. Plots of melt front advancement as shown in Figure 4.17 and Figure 4.18 indicated that the casing of mobile phone was filled successfully. Plots of air trap locations as shown in Figure 4.19 and Figure 4.20 indicate that only few air traps would appear in the moulded part. The air traps can be eliminated easily by placing proper venting in the cavity. On the other hand, plots of weld line locations as shown in Figure 4.21 and Figure 4.22 show that some weld lines would appear in the moulded parts. In practice, weld lines are difficult to be eliminated from moulded parts. However, use of surface texture combined with dark colour of plastic material or painting on plastic parts can easily make the weld lines invisible. In overall, results of the C-MOLD analyses indicate that the initial process parameters of injection moulding generated from the

CBR module can lead to the moulding of good quality parts when good matching cases can be retrieved from the CBR module.

In the validation test two, no good matching case was retrieved from the CBR module and the hybrid NN-GA module was invoked to determine the initial process parameters of injection moulding. The results of C-MOLD analyses, based on the initial process parameters obtained from the hybrid NN-GA module, indicate that no quality criterion was violated. However, when the initial process parameters obtained from the CBR module was used in the C-MOLD analyses, the quality criterion, volumetric shrinkage, was found to be violated. The average volumetric shrinkage obtained from the simulation exceeds the acceptable average volumetric shrinkage. It could lead to various defects in moulded parts such as incorrect dimensions. Plots of melt front advancement as shown in Figure 4.24 and Figure 4.25 indicated that the casing of mobile phone was filled completely at the end of filling. In other words, no short shot was resulted. Plots of air trap locations as shown in Figure 4.26 and Figure 4.27 and plots of weld line locations as shown in Figure 4.28 and Figure 4.29 show that few air traps and weld lines would appear in the casing of mobile phones. In overall, results of the C-MOLD analyses indicate that even no good matching case is retrieved from the CBR module, HSIM can still generate initial process parameters of injection moulding based on the hybrid NN-GA approach which can also lead to the moulding of good quality parts.

From the two validation tests, it can be observed that the performance of the CBR module greatly depends on the relevance of retrieved cases and the deficiency can be made up by the hybrid NN-GA module.

In each validation test, HSIM totally takes about 3 minutes including the time for user input to obtain a set of initial process parameters corresponding to an input problem. In view of the CAE analyses performed in the validation tests, the time to run a CAE analysis for individual validation tests takes about 55 minutes which excludes the time for the creation of the FEM model and the interpretation of the analysis results. It can be seen that HSIM can greatly reduce the time to generate initial process parameters of injection moulding in comparison with the CAE analyses for injection moulding.

5.2 General Discussions

Based on the combined CBR and hybrid NN-GA approach, a prototype system for the determination of initial process parameters for injection moulding, HSIM, was developed in this research. The prototype system not only generates initial process parameters for injection moulding, but also provides some parameters of injection mould design such as runner and gate size. The solutions generated by HSIM can be used in the following areas.

Firstly, the initial process parameters of injection moulding obtained from HSIM can be used as a starting condition to perform CAE analyses for injection moulding or actual trial-runs of moulding. It is believed that proper initial process parameter setting can reduce the time and efforts required to obtain an optimal/near optimal solution in CAE analyses and also reduce the time of trial-runs of moulding. Secondly, the parameters of injection mould design obtained from HSIM could be used to design the runner and gating system of the injection mould for the input problem. Since the mould design parameters are derived based on the previous successful mould design, the risk of producing poor design can be reduced. Finally, the cycle time estimated by HSIM could be used in the estimation of processing cost of moulded parts. This could help to reduce the demand of experienced moulding personnel in the cost estimation.

HSIM is not intended to replace the existing CAE analysis packages for injection moulding. In fact, HSIM can complement them in several ways. HSIM can handle some special cases where the existing CAE analysis packages for injection moulding may hardly deal with. It is no doubt that the CAE analysis packages can provide satisfactory results under a wide range of situations. However, the CAE analyses could generate less accurate results in some cases such as the use of regrind materials and moulding of thin-wall moulded parts. In fact, considerations of these special issues can be easily embedded into the HSIM. In the CAE analysis for injection moulding, a knowledgeable moulding personnel is generally required to interpret the results of the analysis in order to obtain a set of initial process parameters for injection moulding. In view of the time required to interpret the analysis results and the demand of knowledgeable moulding personnel, the CAE analysis seems not to be appropriate in moulding shop floor application. However, HSIM can generate initial process parameters for injection moulding without the interpretation of results and demand of knowledgeable moulding personnel which makes it as a potential tool to be used in moulding shop floor environment. Existing CAE analysis packages for injection moulding cannot learn from their previous analyses. In HSIM, setting of process parameters for injection moulding after successful trial-run of moulding can be stored in the case library which could be referenced in future for solving the similar problems.

Although the problem domain of this research to be studied is injection moulding, the approaches and techniques proposed in this research could be applied in other moulding processes such as gas-assisted injection moulding, compression moulding and transfer moulding. Nevertheless, HSIM is by no means a panacea for solving all the moulding problems and some limitations should be noted. In this prototypical stage, HSIM can only support the injection mould design in the aspects of runner system design and gating design. In addition, only two-plate type injection mould is considered in the development of HSIM. Although the mould design parameters recommended by HSIM are very likely to be applied in the input problem, the parameters may not yield optimal design. To enhance the capability of mould design of HSIM, more sophisticated adaptation models have to be developed. Nevertheless, HSIM has high potential to be further developed for detailed injection mould design. In fact, the research work of Hu W.G. et. al. [Hu 1998] have shown that CBR has high potential to be used in injection mould design.

Implementation of HSIM in real world environment involves two considerations. Firstly, HSIM was developed and used in stand-alone environment. For the system implementation in real world environment, a local area network (LAN) should be constructed to allow system users sharing the data and information stored in the case library. An application server has to be dedicated to access vast amounts of moulding data and information while maintaining performance and security to system users. Since server-based sharing of data is centrally administered and controlled, security can be easily managed by authorised persons and the data can be backed up on a regular schedule. Secondly, in actual moulding practice, quality of moulded parts is assessed by moulding personnel qualitatively such as little weld line, serious flash and obvious sink mark. In order to capture those kinds of quality information in HSIM and facilitate case retrieval based on the quality information, quantitative measures of moulded part quality should be developed. One possible way is to introduce rating method in the part quality assessment.

5.3 Discussions on the Design and Development of the CBR Module and Hybrid NN-GA Module

In the case retrieval, image comparison was introduced to improve the similarity analysis of part complexity. In the image comparison, degree of similarity can be assigned easily between the part design of two cases. However, it should be noted that the image comparison involves subjective judgements in the assignment of the degree of similarity. If the difference between two part designs is fuzzy, the subjective judgements may result in the unreliable assignment. Therefore, a method that can deal with the fuzziness in the assignment of the degree of similarity should be investigated.

In the case adaptation, NN approach was introduced to formulate a neuro-adaptation model for the determination of initial process parameters of injection moulding. Since the model can handle the complex and non-linear relationships among the mould design parameters, part design parameters and the process parameters, a more accurate solution could be obtained in comparison with the conventional structured adaptation models. However, since the neuro-adaptation model is formulated by generalising the cases that are similar to a particular input problem, it should not be employed as a generic model for the determination of initial process parameters for injection moulding.

In the hybrid NN-GA module, the NN prediction unit was trained by using back-propagation training scheme. In the prototypical stage, only thirty-five input-output pairs were obtained from the CAE analyses for training the NN prediction unit. Consequently, there may have a risk that new cases may fall into the regions that could be beyond the range of the training set. This may affect the accuracy of the results obtained from the hybrid module. To enhance the capability of the NN prediction unit, more training patterns should be obtained in the system validation under the real world environment.

In the GA optimisation unit, the setting of GA control parameters such as mutation rate, crossover rate and population size are the key factors in the determination of the exploitation/exploration balance and the performance of the genetic search. In this research, the standard GA control parameters suggested by DeJong K.A. [DeJong 1975] are used in the development of the GA optimisation unit. The suggested setting of control parameters works well in a wide range of problems and is good enough for the development of this prototype system. However, it should be noted that a fixed parameter setting may not be good enough over the whole run. Since the population is diverse initially, a high crossover is the best way to put good information together. When the population converges on a small section of search space where crossover is of much less use, a high mutation operator should be used to search for better solutions. On the other hand, the population size should also be varied throughout the evolutionary process to balance the speed of evolution with gene diversity. Performance of the GA optimisation unit could be further improved if an adaptive technique can be introduced to dynamically change and optimise the setting of control parameters throughout the optimisation cycle.

CHAPTER SIX – CONCLUSIONS AND FUTURE RESEARCH

6.1 Conclusions

Determination of initial process parameters is one of the crucial activities in the process design of injection moulding. Proper setting of initial process parameters can shorten the development time and improve the quality of moulded parts. Determination of initial process parameters for injection moulding is a highly skilled job and based on skilled operator's "know-how" and intuitive sense acquired through long-term experience rather than a theoretical and analytical approach. Facing with the global competition with emphasis on the high quality plastic products and short time-to-market, the current practices in the determination of initial process parameters for injection moulding seem to be inadequate.

This research aims to explore the mechanism of process parameter selection and to develop techniques for determining the process parameters for injection moulding. Various approaches to the determination of process parameters for injection moulding including mathematical models, numerical simulation, process window, design of experiments (DOE), knowledge-based systems, neural networks (NNs), case based reasoning (CBR) and genetic algorithms (GAs) were reviewed in this research. The potentials and limitations of individual approaches were also discussed. In view of the nature of the determination of initial process parameters for injection moulding, CBR is deemed to be a promising approach to deal with the problem of initial process parameter setting for injection moulding due to its capability of capturing experience from moulding personnel. However, the performance of CBR is limited by the size of case library, effectiveness of indexing, relevance of old cases stored in the case library as well as the design of adaptation models.

To make up the deficiencies of CBR in the determination of initial process parameters for injection moulding, a hybrid neural network and genetic algorithm (NN-GA) approach to the determination of initial process parameters was proposed. Based on the combined CBR and hybrid NN-GA approach, a computer-aided system for the determination of initial process parameters for injection moulding, called HSIM, was developed and implemented in Visual Basic programming language.

HSIM mainly consists of two modules: a case based reasoning (CBR) module and a hybrid neural network and genetic algorithm (NN-GA) module. The CBR module is firstly invoked to retrieve a number of similar cases from the case library. If there are similar cases found in the case library, a neuro-adaptation model is formulated based on the similar cases which can derive a set of initial process parameters for injection moulding corresponding to the input problem. If no good matching case is retrieved from the case library, a pre-defined number of partially matched cases are retrieved and set as a part of the initial population for performing GA based optimisation in the hybrid NN-GA module. The hybrid NN-GA module is then activated to generate a set of initial process parameters for injection moulding. The initial process parameters recommended from HSIM can be used in actual trial-runs of moulding. Eventually, the validated parameters and the corresponding moulding results could be stored in the case library through the user interface for future reference.

In the design of the CBR module, some techniques have been introduced to enhance the capability of the CBR module in dealing with the problem of the determination of initial process parameters for injection moulding. They include fuzzy set theory in case indexing and case retrieval, similarity assessment of part complexity based on image comparison, Saaty's matrix and TOPSIS algorithm, and neural network in case adaptation. In the design of the hybrid NN-GA module, partially matched cases retrieved from the CBR module are used as a part of the initial population in order to improve the searching process of the module.

HSIM was preliminarily validated by using the CAE analysis package for injection moulding, C-MOLD. Two validation tests were performed to investigate the effectiveness of HSIM. Results of the two validation tests indicate that HSIM can determine a set of initial process parameters for injection moulding quickly without relying on experienced moulding personnel, from which good quality moulded parts can be produced.

Implementation of HSIM has demonstrated that the time required to the determination of initial process parameters for injection moulding can be greatly reduced. The solutions recommended by HSIM can contribute to the production of good quality moulded parts. Daily experience of moulding personnel can be captured and self-learning capability can be facilitated. In the following, major contributions of this research are summarised.

1. In view of the nature of the determination of initial process parameters for injection moulding, CBR is found to be a promising approach to deal with the problem of initial process parameter setting because of its inherent characteristic of capturing of human's experience and self-learning. However, the performance of CBR system is limited by the size of its case library, effectiveness of indexing, relevance of old cases stored in the case library as well as the design of adaptation models. In this research, the hybrid NN-GA approach was introduced to make up the deficiencies. In some cases, CBR may not generate the solution. The initial process parameters of injection moulding can still be determined based on the hybrid NN-GA approach. This research is believed to

be the first work in the determination of initial process parameter setting for injection moulding based on the combined CBR and hybrid NN-GA approach.

2. In the calculation of part complexity, as Poli's method cannot derive accurate part complexity of a plastic part design in some circumstances as mentioned in Chapter Three, the qualitative assessment based on image comparison was firstly introduced in this research to improve the accuracy of part complexity calculation. In addition, a multiple attribute decision making algorithm called TOPSIS algorithm was employed to combine the quantitative and qualitative similarity indexes into an index which can be used to assess the similarity of part complexity between a retrieved case and an input problem more accurate.

3. This study can be seen as the first attempt to employ neural network approach in the formulation of an adaptation model for initial process parameters of injection moulding. With the use of the NN approach, the non-linear and complex relationships among the part design parameters, mould design parameters and the initial process parameters of injection moulding can be properly modelled. This can help to generate more accurate initial process parameters of injection moulding from the CBR module in comparison with using the conventional structured adaptation models.

4. The implementation of HSIM based on the combined CBR and hybrid NN-GA approach demonstrates that initial process parameters for injection moulding can be derived in short time and without the involvement of experienced moulding personnel. This enables HSIM as a potential tool to be applied in moulding shop floor environment for the provision of initial process parameter setting.

6.2 Future Research

Introduction of the combined CBR and hybrid NN-GA approach to the determination of initial process parameters for injection moulding has raised several further research issues.

1. Setting of the control parameters in HSIM, such as α-cut, number of partially matched cases injected to the hybrid NN-GA module, initial population size, crossover rate, mutation rate etc., could be further studied to improve the performance of the system. For example, in the GA optimisation unit, it is possible to introduce fuzzy logic techniques in the control and optimisation of GA control parameter setting throughout the GA based optimisation process.
2. Some sophisticated techniques and approaches for case representation and organisation, such as object-oriented representation, could be further investigated in order to deal with the problem of explosive growth in the number of cases stored in the case library. Besides, apart from the similarity value (distances between two cases), more indexes for assessing the usefulness of a retrieved case to an input problem could be considered in the further development of the system. For example, user requirements of injection mould design, such as the aesthetic requirements of moulded parts and mould costs, could be considered in the determination of the usefulness of an old injection mould design to an input problem.
3. In this research, a hybrid NN-GA approach was introduced to complement CBR when there is no relevant case found in the case library. Neural network approach was also explored to improve the case adaptation. Further research of adoption of NN and GA in CBR paradigm could be explored in order to improve

the performance of HSIM. For example, the use of neural networks in similarity analysis could be explored. Genetic algorithms could be considered to determine weighting of indexes for the CBR module.

4. Fuzzy set theory was introduced to handle the fuzziness involved in the case retrieval process. In fact, it could also support fuzzy induction of rules when a certain number of cases are stored in the case library. After converting all numerical attributes into fuzzy terms, regular induction procedure can be applied to induce rules or decision trees from the cases stored in the case library. Through the application of these rules, new problem can be solved in more direct and effective way. Moreover, it could also help to uncover the interrelations among the parameters involved in injection moulding.

5. Determination of process parameters for injection moulding contains two subtasks, initial process parameter setting and process parameter resetting. In this research, an intelligent system was developed to deal with the problem in the determination of initial process parameters. Further research could explore the CBR techniques in conjunction with other techniques in the resetting of process parameters for injection moulding.

6. HSIM could be further expanded to support concurrent process design activities. Apart from the determination of process parameters, some other activities including the selection of injection moulding machines, injection mould design and cost estimation are involved in the process design of injection moulding. Therefore, various modules are required to be developed to capture the multi-disciplinary knowledge. The modules are then organised into a unified system by using an information system architecture such as blackboard architecture and

co-operative distributed problem solving in order to facilitate a concurrent process design system for injection moulding.

7. The second stage of system validation is planned to be carried out in order to assess the effectiveness of the system in real world environment. In this stage, HSIM will be validated incorporating with a local injection moulding company. The initial process parameters of injection moulding recommended by HSIM will be used in actual moulding. Results of the moulding and the system effectiveness will be evaluated with the assistance from experienced moulding personnel of the company.

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APPENDIX A

Mathematical Models of Number of Cavities

According to the work of Busch, J.V. et. al. [Liang 1992], cycle time can be calculated by using the following equation. This equation was derived based on a combination of theoretical and statistical methods.

$$T_{cyc} = 1.35 \times \frac{S^2}{2\alpha\pi} \times \ln\left[\frac{8}{\pi^2} \times \left(\frac{\theta_i - \theta_w}{\theta_e - \theta_w}\right)\right] + 0.0151 \times W_p \times N_{cav} + 8.87 \quad \text{(A1)}$$

where T_{cyc} is the estimated cycle time in sec., S is the maximum wall thickness in mm, α is the thermal diffusivity of the material in cm^2/sec, W_p is the part weight in gm, N_{cav} is the number of cavities in the mould, θ_i is the melt temperature in °C, θ_w is the mould temperature in °C and θ_e is the ejection temperature in °C.

Let $$A = 1.35 \times \frac{S^2}{2\alpha\pi} \times \ln\left[\frac{8}{\pi^2} \times \left(\frac{\theta_i - \theta_w}{\theta_e - \theta_w}\right)\right] + 8.87$$

$$B = 0.0151 \times W_p$$

Thus, $$T_{cyc} = A + B\,N_{cav} \quad \text{(A2)}$$

Since $$N_{cav} = \frac{PV \times K \times T_{cyc}}{PD \times T} \quad \text{(A3)}$$

$$K = 1 / (1 - RR)$$

$$T = NS \times MU \times 8 \times 3600$$

where PV is the production volume, K is the reject factor, PD is the number of production days, T is the total operation time per day in sec., RR is the rejection rate, NS is the number of shifts per day and MU is the machine utilisation.

Combining the equation (A2) and (A3), the required number of cavities can be determined by using the following equation:

$$N_{cav} = \frac{PV \times A \times K}{(PD \times T) - (B \times PV \times K)} \quad \text{(A4)}$$

APPENDIX B

Poli's Coding Method

<table>
<tr><td colspan="2" rowspan="4"></td><td colspan="3" rowspan="4">Basic Complexity</td><td colspan="4">L ≤ 250 mm</td></tr>
<tr><td colspan="4">Number of external undercuts</td></tr>
<tr><td>zero</td><td>one</td><td>two</td><td>more than two</td></tr>
<tr><td>0</td><td>1</td><td>2</td><td>3</td></tr>
<tr><td colspan="2" rowspan="3">Parts without internal undercuts</td><td rowspan="2">Parts whose peripheral Height from a planar dividing surface is constant</td><td>Part in one half</td><td>0</td><td>1.64</td><td>1.87</td><td>2.02</td><td>2.16</td></tr>
<tr><td>Part not in one half</td><td>1</td><td>1.69</td><td>2.09</td><td>2.24</td><td>2.38</td></tr>
<tr><td colspan="2">Parts whose peripheral height from a planar dividing surface is not constant, or parts with a non-planar dividing surface</td><td>2</td><td>1.92</td><td>2.15</td><td>2.29</td><td>2.44</td></tr>
<tr><td rowspan="4">Parts with internal undercut</td><td rowspan="2">On only one face of the part</td><td colspan="2">Parts whose ONLY dividing surface is planar, or parts whose peripheral height from a planar dividing surface is constant</td><td>3</td><td>3.19</td><td>3.43</td><td>3.57</td><td>3.72</td></tr>
<tr><td colspan="2">Parts whose peripheral height from a planar dividing surface is not constant, or parts with a non-planar dividing surface</td><td>4</td><td>3.73</td><td>3.97</td><td>4.11</td><td>4.26</td></tr>
<tr><td rowspan="2">On more than one face of the part</td><td colspan="2">Parts whose ONLY dividing surface is planar, or parts whose peripheral height from a planar dividing surface is constant</td><td>5</td><td>5.37</td><td>5.61</td><td>5.75</td><td>5.89</td></tr>
<tr><td colspan="2">Parts whose peripheral height from a planar dividing surface is not constant, or parts with a non-planar dividing surface</td><td>6</td><td>6.28</td><td>6.52</td><td>6.66</td><td>6.81</td></tr>
</table>

Table B.1. Basic complexity rating table for box-sharp component

<table>
<tr><td colspan="3" rowspan="3">Subsidiary Complexity</td><td colspan="2">External Undercut Complexity</td></tr>
<tr><td>Without extensive external undercuts</td><td>With extensive external undercuts</td></tr>
<tr><td>0</td><td>1</td></tr>
<tr><td rowspan="3">1.45</td><td>Low</td><td>0</td><td>1.00</td><td>1.25</td></tr>
<tr><td>Moderate</td><td>1</td><td>1.25</td><td>1.45</td></tr>
<tr><td>High</td><td>2</td><td>1.60</td><td>1.75</td></tr>
</table>

Table B.2. Subsidiary complexity rating table

Localised Features	No / Type of Features	Penalty
Peripheral ribs	0	0
	All around	1
Longitudinal ribs	0	0
	3	2
	3	3
Lateral ribs	0	0
	3	2
	3	3
Radial ribs	0	0
	3	2
	3	3
Concentric ribs	0	0
	3	2
	3	3
Bosses	0	0
	3	1
	3	2
Holes	0	0
	3	1
	3	2
Side shut-offs	None	0
	In one side	1
	Two or more	2
Lettering	None	0
	Localised	1
	Extensive	2
Regularity	Regular	0
	Irregular	1

Table B.3. Penalty table for the determination of cavity detail

Rules for the Determination of Cavity Detail	
IF	THEN
Total Penalty ≤ 4	Low Cavity Detail
4 < Total Penalty ≤ 8	Moderate Cavity Detail
Total Penalty > 8	High Cavity Detail

Table B.4. Rules for the determination of cavity detail

<table>
<tr><td colspan="3" rowspan="2">Tolerance &
Surface Finish</td><td colspan="2">Tolerance</td></tr>
<tr><td>Commercial</td><td>Tight</td></tr>
<tr><td colspan="3"></td><td>0</td><td>1</td></tr>
<tr><td rowspan="4">Surface
Finish</td><td>SPI 5-6</td><td>0</td><td>---</td><td>---</td></tr>
<tr><td>SPI 5-6</td><td>1</td><td>1.00</td><td>1.05</td></tr>
<tr><td>Texture</td><td>2</td><td>1.05</td><td>1.10</td></tr>
<tr><td>SPI 5-6</td><td>3</td><td>1.10</td><td>1.15</td></tr>
</table>

Table B.5. Tolerance and surface finish rating table

APPENDIX C

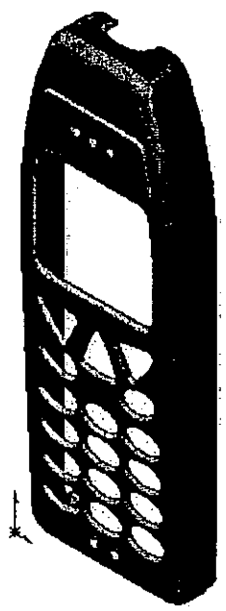
Verification Tests of the CBR Module

In this research, two validation tests were conducted to investigate the retrieval accuracy and consistency of the CBR module. Results of the verification tests are shown as follows.

C.1 Verification test one

Verification test one involves the study of retrieval accuracy of the CBR module. Figure C.1 shows some data and information of a case (case number: 26), which in fact is one of the cases stored in the case library. The data and information were input to the CBR module and a set of initial process parameters for injection moulding was generated. Table C.1 shows the contents of the solution stored in the input case and the contents of the solution recommended by HSIM.

Part Number : CR_26



Production Volume:	120,000 Parts
Allowable Working Days:	28 Days
No. of Shifts per Day:	2 Shifts
Reject Rate:	1 %
Machine Utilisation:	85%
Required no. of Cavities:	1 cavity
Wall Thickness:	1.3 mm
Part Envelope Length:	130 mm
Part Envelope Width:	46 mm
Part Envelope Height:	13 mm
Projected Area:	39.0 cm^2
Part Volume:	9.1 cm^3
Moulding Material:	ABS

Figure C.1 Input problem of verification test one

Injection Moulding Process Parameters	Unit	Solution of input problem	Solution from HSIM
Nozzle temperature	°C	230	230
Barrel temperature	°C	230, 210, 195, 185	230, 210, 195, 185
Injection pressure	bar	561	561
Holding pressure	bar	285	285
Back pressure	bar	5	5
Clamping force	ton	18	18
Fill time	sec.	0.30	0.30
Holding time	sec.	3.10	3.10
Cooling time	sec.	3.30	3.30
Cycle time	sec.	6.6	6.6

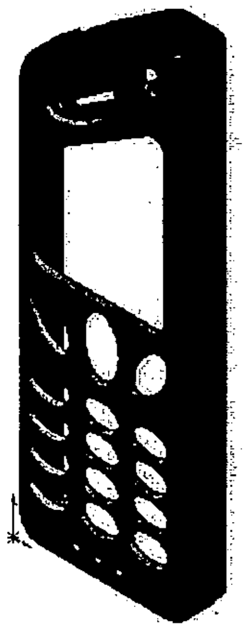
Table C.1 Results of verification test one

From the Table C.1, it can be observed that the solution recommended by HSIM is exactly same with the solution stored in the case (case number: 26). This indicates that HSIM can perform high accuracy of case retrieval.

C.2. Verification test two

Verification test two involves the study of retrieval consistency of the CBR module. The data and information of an input case are shown in Figure C.2. The data and information were input into HSIM two times and hence two sets of initial process parameters for injection moulding were obtained. Table C.2 shows the contents of the two sets of initial process parameters for injection moulding.

Part Number : CR_21



Production Volume:	115,000 Parts
Allowable Working Days:	28 Days
No. of Shifts per Day:	2 Shifts
Reject Rate:	1 %
Machine Utilisation:	85%
Required no. of Cavities:	1 cavity
Wall Thickness:	1.5 mm
Part Envelope Length:	140 mm
Part Envelope Width:	48 mm
Part Envelope Height:	13 mm
Projected Area:	41.06 cm^2
Part Volume:	11.27 cm^3
Moulding Material:	ABS

Figure C.2 Input problem of verification test two

Injection Moulding Process Parameters	Unit	Solution of first trial	Solution of second trial
Nozzle temperature	°C	230	230
Barrel temperature	°C	230, 210, 195, 185	230, 210, 195, 185
Injection pressure	bar	561	561
Holding pressure	bar	285	285
Back pressure	bar	5	5
Clamping force	ton	475	475
Fill time	sec.	0.40	0.40
Holding time	sec.	2.60	2.60
Cooling time	sec.	4.30	4.30
Cycle time	sec.	7.7	7.7

Table C.2 Results of verification test two

From the Table C.2, it can be observed that the two sets of initial process parameters are identical. It indicates that HSIM has high consistency in case retrieval.

APPENDIX D

Structured Adaptation Models of HSIM

D.1. Adaptation models of runner dimensions

As shown in Figure D.1, three types of runner cross-sectional design are considered in the HSIM, namely full round runner, trapezoidal runner and modified trapezoidal runner. The adaptation models for these three types of runner design are given below:

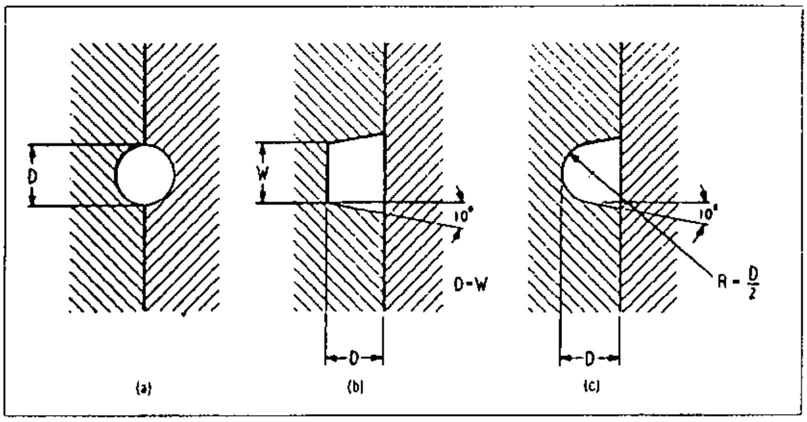


Figure D.1. Full round runner, trapezoidal runner and modified trapezoidal runner

➢ *Full-Round Runner*

$D = (Wt^{0.25} * L^{0.5}) / 3.7$

where D is the runner diameter of the input problem in mm, Wt is the part weight of the input problem in gm and L is the runner length of the reference case in mm.

➢ Trapezoidal Runner

$$D = W = (Wt^{0.25} * L^{0.5}) / 3.7$$

where D and W are the depth and width of the runner of the input problem in mm, Wt is the part weight of the input problem in gm and L is the runner length of the reference case in mm.

➢ *Modified Trapezoidal Runner*

$$D = (Wt^{0.25} * L^{0.5}) / 3.7,$$

$$R = D/2, \qquad \text{Taper angle} = 10°$$

where D is the depth of the runner of the input problem in mm, R is the radius of the runner of the input problem in mm, Wt is the part weight of the input problem in gm and L is the runner length of the reference case in mm.

D.2. Adaptation models of gate dimensions

Two types of gate design are considered in the HSIM, which are edge gate as shown in Figure D.2 and submarine gate as shown in Figure D.3. The adaptation models for these two types of gate design are given below:

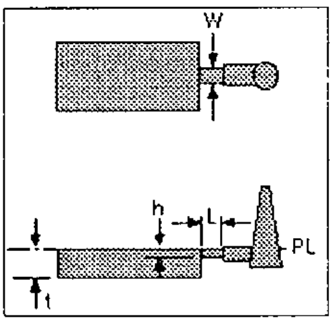


Figure D.2. Edge (rectangular) gate

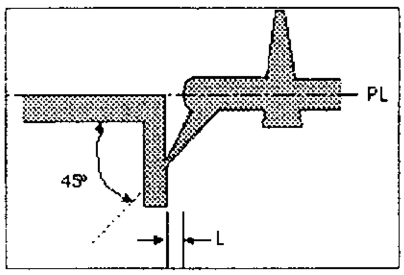


Figure D.3. Submarine gate

- *Edge (rectangular) gate*

  $W = (n\, A^{1/2}) / 30$

  $h = nt$

  $L = 0.5$ mm (minimum)

where W, h and L are the gate width, depth and land length of the input problem in mm, t is the wall section thickness of the input problem in mm, A is the surface area of cavity of the input problem in mm^2 and n is the material constant (ABS = 0.7, PC = 0.7, PS = 0.6).

- *Submarine gate*

  $d = n\, C\, A^{1/4}$

  $L = 1.9$ mm (minimum)

where d and L are the gate diameter and land length respectively of the input problem in mm, A is the surface area of cavity of the input problem in mm^2, C is the function of the wall section thickness based on the input problem and n is the material constant (ABS = 0.7, PC = 0.7, PS = 0.6).

APPENDIX E

Generalised Delta-Rule (GDR) Training Algorithm

In this research, the generalised delta-rule (GDR) algorithm was adopted to perform the training of the back-propagation network of HSIM. A typical three-layer back-propagation network is shown in Figure E.1. The GDR algorithm is described below:

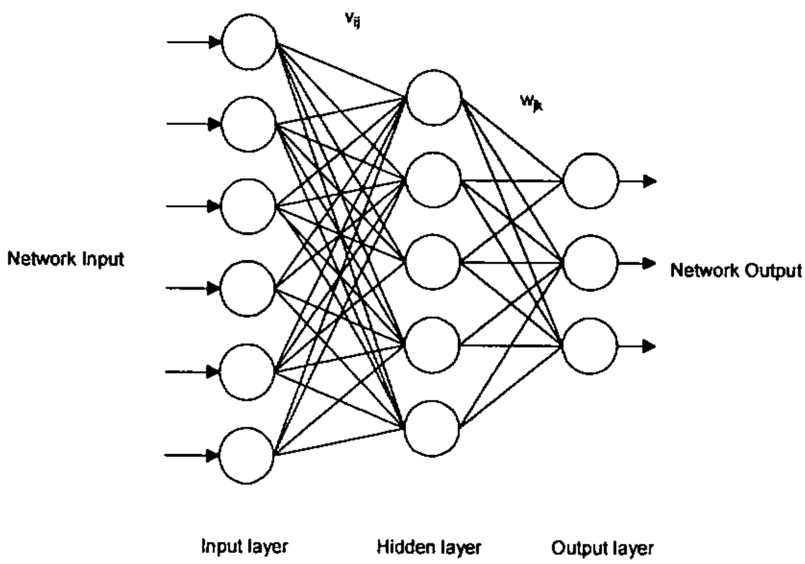


Figure E.1. Typical three-layer back-propagation network

Step1. The weights of v_{ij} and w_{jk} are randomly assigned with values between 0 and 1. The internal threshold values are assigned as follows: all input-layer thresholds (T_{1i}) are set to be 0, and all hidden- (T_{2j}) and output-layer (T_{3k}) are set to be 1.

Step2. The input vectors (I_i) are introduced into the network and the output from the first layer (a_i) can be calculated by using the following equations:

$$x_i = I_i - T_{1i} = I_i - 0 = I_i$$

$$a_i = \frac{1}{1+e^{-x_i}}$$

This calculation is a function of the difference, or error between the input function and the internal threshold.

Step 3. Once the output from the first layer has been determined, output from the second layer can be calculated by using the following equation.

$$b_j = f\left(\sum_{i=1}^{L}(v_{ij}a_i) + T_{2j}\right)$$

where f( ) is the sigmoid function, L is the number of input nodes, and T_{2j} are 1.

Step 4. Once the output from the second layer has been determined, the result from the output layer can be calculated by using the following equation.

$$c_k = f\left(\sum_{i=1}^{m}(w_{jk}b_j) + T_{3k}\right)$$

where f( ) is the sigmoid function, m is the number of hidden nodes and T_{3k} are 1.

Step 5. Step 1 - 4 are repeated for M number of training patterns presented to the input layer. Then the total-squared error, E, can be calculated by using the following equation.

$$E = \sum_{m=1}^{M}\sum_{k=1}^{n}(d_k^m - c_k^m)^2$$

where n is the number of output nodes, d is the desired output and c is the actual value calculated from the network.

Step 6: Once the m-th pattern is determined, the gradient-descent term for the k-th node in the output layer (layer 3) for training pattern m, δc_{3k}^{m}, can be calculated by using the following equation.

$$\delta c_{3k}^{m} = \left(d_k^m - c_k^m\right)\frac{\partial f}{\partial x_k}$$

where f is the sigmoid function of x_k:

$$\frac{\partial f}{\partial x_k} = \frac{e^{-x_k}}{(1+e^{-x_k})^2} \text{ and } x_k^m = \sum_j w_{jk}^m b_j^m + T_{3k}^m$$

Step 7: Once the m-th pattern is determined, the gradient-descent term for the j-th node in the hidden layer (layer 2) for training pattern m, δc_{2j}^{m}, can be calculated by using the following equation.

$$\delta c_{2j}^{m} = \left(\sum_K \delta c_{3k}^{m} w_{jk}^{m}\right)\frac{\partial f}{\partial x_j}$$

where f is the sigmoid function of x_j:

$$\frac{\partial f}{\partial x_j} = \frac{e^{-x_j}}{(1+e^{-x_j})^2} \text{ and } x_j^m = \sum_i v_{ij}^m a_i^m + T_{2j}^m$$

Step 8. Once δc_{2j}^{m} for the hidden layer and δc_{3k}^{m} for the output layer have been determined, the weight changes can be calculated by using the equations:

$$\Delta v_{ij}^m = \eta \delta_{2j}^m a_i^m + \alpha \Delta v_{ij}^{m-1}$$

$$\Delta w_{jk}^m = \eta \delta_{3k}^m b_j^m + \alpha \Delta w_{jk}^{m-1}$$

where η is the learning rate, and α is the momentum factor.

$\alpha\Delta w_{jk}^{m-1}$ and $\alpha\Delta v_{ij}^{m-1}$ are fractional values of the weight change from the previous iteration.

Step 9. Once the weight changes have been determined, the weights can be updated by using the following equations.

$$w_{jk}^{m} = w_{jk}^{m-1} + \Delta w_{jk}^{m}$$

$$v_{ij}^{m} = v_{ij}^{m-1} + \Delta v_{ij}^{m}$$

Step 2 - 9 are repeated for all training patterns until the squared error is less than a threshold value called learning threshold. In this research, the learning threshold is defaulted as 0.001.

APPENDIX F

Operating Range of Process Parameters of Injection Moulding

The operating range of initial process parameters of injection moulding defined by Whelan T. and Goff J. [Whelan 1991] is employed in the genetic algorithm (GA) optimisation unit of the NN-GA module and is shown in Table F.1.

Outputs	Unit	ABS		PC		PS	
		Min.	Max.	Min.	Max.	Min.	Max.
Barrel rear	°C	180	230	275	300	150	180
Barrel middle	°C	180	240	285	315	180	230
Barrel front	°C	210	260	285	315	210	250
Nozzle temperature	°C	210	260	280	310	210	280
Mould temperature	°C	60	90	80	120	10	80
Melt temperature	°C	210	260	280	320	200	250
Clamping force	ton/in^2	2.5	4.0	3.0	5.0	1.0	2.0
Injection pressure	bar	420	1400	700	2100	700	2100
Holding pressure	bar	210	840	280	1260	280	1260
Back pressure	bar	5	150	10	150	5	150
Screw surface speed	mm/s	550	650	400	500	800	950
Injection time	sec.	IT_{min}	IT_{max}	IT_{min}	IT_{max}	IT_{min}	IT_{max}
Holding time	sec.	HT_{min}	HT_{max}	HT_{min}	HT_{max}	HT_{min}	HT_{max}
Cooling time	sec.	CT_{min}	CT_{max}	CT_{min}	CT_{max}	CT_{min}	CT_{max}

Table F.1. Operating range of process parameters of injection moulding [Whelan 1991]

➢ *Minimum and maximum injection time, holding time and cooling time*

Based on the cycle time estimated by the equation (A.1.) given in Appendix A, the minimum and maximum value of injection time, holding time and cooling time can be determined by using the following typical estimation [Whelan 1991]:

Injection Time = 5 - 25 % of cycle time

Holding Time = 5 -50 % of cycle time

Cooling Time = 50 - 85 % of cycle time

Thus,

$IT_{min} = 0.05 \times T_{cyc}$ $IT_{max} = 0.25 \times T_{cyc}$

$HT_{min} = 0.05 \times T_{cyc}$ $HT_{max} = 0.50 \times T_{cyc}$

$CT_{min} = 0.50 \times T_{cyc}$ $CT_{max} = 0.85 \times T_{cyc}$

where IT_{min} and IT_{max} are the minimum and maximum injection time respectively, HT_{min} and HT_{max} are the minimum and maximum holding time respectively, CT_{min} and CT_{max} are the minimum and maximum cooling time respectively and T_{cyc} is the estimated cycle time.

Once the optimal set of process parameters has been found by genetic search, the corresponding machine setting can be calculated by the following equations [Tan 1996]:

➢ *Injection stroke, metering stroke and cushion length*

The injection stroke is set at the position at which the mould is volumetrically filled and it is given below.

$$IST = \frac{W}{A_{screw} \times \rho}$$

where IST is the injection stroke in mm, W is the shot weight in kg, A_{screw} is the cross-sectional area of the screw in cm^2 and ρ is the polymer melt density in g/cm^3

The metering stroke depends on the shot volume required. In order to account for possible back flow or leakage during injection, the volume yield of the screw, C, is included in the equation:

$$MS = \frac{W}{C \times A_{screw} \times \rho} \quad \text{where } C = 0.85$$

The cushion length is set to 10% of the metering stroke and has a range with an upper limit of 9mm for large machines and a lower limit of 3 mm for small machines.

- *Screw rotational speed*

The screw rotational speed, RS, can be calculated by using the following equation:

$$RS = \frac{SS}{D_{screw} \times 0.0524}$$

where RS is the rotational speed in rpm, D_{screw} is the screw diameter of the selected moulding machine in mm and SS is the screw surface speed obtained from the hybrid NN-GA module in mm/s.

- *Coolant temperature*

The coolant temperature is set as 15°C lower than the required mould temperature.

APPENDIX G

Training and Testing Results of the Hybrid NN-GA Module

In this research, 35 input-output pairs were obtained from C-MOLD analyses. The 35 input-output pairs are then divided into a training set which contains 30 input-output pairs and a test set which contains 5 input-output pairs.

The neural network prediction unit was trained for 671,450 learning cycles with the training set and the performance of the network was tested periodically with the test set by using a commercial neural network software package, NeuroShell™ Rel.3.2 [NeuroShell 1989]. A summary of network factors is shown in Table G.1. Results of training and testing the neural network prediction unit are summarised in Table G.2 and Table G.3 respectively.

Network Factors

0.80000	Output threshold (0.0 - 1.0)
0.00001	Learning threshold (0.0 - 3.0)
0.00000	Hidden nodes - 0 means default (0 - 32767)
0.60000	Learning rate (0.01 - 1.0)
0.90000	Momentum (0.0 - 0.9)
100.00000	Maximum cases in memory (1 - 32767)
80.00000	Maximum characteristic definitions (3 - 32767)
0.00000	Presentation: 0=rotate, 1=random (0 - 1)
4.00000	Characteristics: digits left of decimal (1 - 6)
2.00000	Characteristics: digits right of decimal (0 - 6)

Table G.1. Summary of network factors

Summary of Learning Error Factors

Error range		Count	Percent	Histogram
1.0001	99999.0000	0	0.00	
0.5001	1.0000	0	0.00	
0.1001	0.5000	0	0.00	
0.0501	0.1000	0	0.00	
0.0201	0.0500	0	0.00	
0.0101	0.0200	0	0.00	
0.0051	0.0100	0	0.00	
0.0001	0.0050	0	0.00	
0.0000	0.0001	30	100.00	

Input nodes: 21 Hidden nodes: 10 Output nodes: 4

Table G.2. Summary of learning error factors

Trial set #1

Quality Measures	Unit	Desired value	Predicted value	Error (%)
Wall shear stress	MPa	0.13	0.13	0.0
Representative shear rate	$\times 10^4$ 1/s	0.96	0.98	2.1
Mould temperature difference	°C	3.00	3.08	2.7
Cycle time	sec.	8.20	8.25	0.6

Trial set #2

Wall shear stress	MPa	0.09	0.09	0.0
Representative shear rate	$\times 10^4$ 1/s	0.73	0.72	1.4
Mould temperature difference	°C	2.00	1.93	3.5
Cycle time	sec.	11.20	11.15	0.4

Trial set #3

Wall shear stress	MPa	0.10	0.10	0.0
Representative shear rate	$\times 10^4$ 1/s	0.77	0.77	0.0
Mould temperature difference	°C	3.00	3.08	2.7
Cycle time	sec.	8.60	8.67	0.8

Trial set #4

Wall shear stress	MPa	0.22	0.22	0.0
Representative shear rate	$\times 10^4$ 1/s	1.61	1.56	3.1
Mould temperature difference	°C	5.00	4.91	1.8
Cycle time	sec.	6.60	6.53	1.1

Trial set #5

Wall shear stress	MPa	0.13	0.13	0.0
Representative shear rate	$\times 10^4$ 1/s	1.39	1.40	0.7
Mould temperature difference	°C	4.00	3.90	2.5
Cycle time	sec.	7.10	7.05	0.7

Table G.3. Summary of testing results