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An Intelligent Manufacturing System for Injection Molding

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Abstract

In recent years, the great trends of industry 4.0, internet of things (IoT), big data analytics, and cloud computing, the design and development of plastic injection molding (PIM) products has been more requested to achieve the requirements of light, thin, short, small, multi-function, high-precision, energy-saving, and obliged to fulfill a large number of customized production. To tackle this arduous challenge, effectively developing a novel PIM intelligent manufacturing system will play a crucial role. The aim of the proposed study is to carry on building an intelligent manufacturing system (IMS) for PIM industry, which is composed of three subsystems: a multiple response optimization systems of PIM, a database management system of process parameters, and a PIM real-time monitoring and control system. Firstly, the multiple response optimization systems present an intelligent optimization system to find optimal process parameters of multiple quality characteristics in the PIM process. Secondly, the database management system allows for saving the experimental data, PIM process parameter settings and quality goals. The third is a PIM real-time monitoring and control system, which establishes a graphic monitoring and control interface to real-time monitor the parameters of PIM machine and the optimal process parameter settings. The proposed PIM intelligent manufacturing systems enable the functions of real-time monitoring, process parameter optimization and database management, which can assure better PIM product quality and yield rate, effectively reduce the manufacturing cost, and promote the competition of the PIM industry in the future.

Keywords: PIM, industry 4.0, IoT, big data, cloud computing, IMS, BPNN, modified PSO-GA

1. Introduction

Plastic injection molding (PIM) is a very important process to produce plastic parts. PIM is suitable to use for mass production of products because it is easy to convert raw material to be a plastic product in a single automation process. Other advantages of utilization of PIM are easy to produce light, corrosion resistance, shape, and low processing cost. There are several processes of injection molding to produce plastic parts: plastic, injection, packing, cooling, and ejection. Even though most engineers argue that this is an easy process, but in the practice PIM, process is more complex than it is thought. Inappropriate material selection, process parameters, part and mold designs can affect the quality of plastic products. Several defects that frequently occur in the PIM process, for instance, warpage, shrinkage, sink marks, and weld lines. In view of current market trends of plastic products, injection molding machine can be the most crucial plastic processing machinery, accounting for 60%-85% in developed countries, and it finds application mainly in numerous fields such as electronic communications, automobile, plastic building materials, household appliances, food & beverage packaging, and medical electronic apparatus.

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However, in recent, the PIM production faces copious critical challenges where the customers or ends users continuously require highly customized products in small batches and in a short period [1]. The development of new generation of more flexible and intelligent PIM manufacturing systems was desired to satisfy their requirements in terms of variety, response time and quality [2]. In recent years, with the vigorous and rapid development of the smartphone, panel, biotechnology, sports and medical wearable devices industry under the great trends of industry 4.0, internet of things (IoT), big data analytics, and cloud computing, the design and development of 3C (Communication, Computer, and Consumer electronics), car electronics, and medical electronics products become increasingly diversified and complicated. Besides, these products have been more requested to achieve the requirements of light, thin, short, small, multi-function, high-precision, energy-saving, and obliged to fulfill a large number of customized production. To tackle this arduous situation, effectively creating a novel PIM intelligent manufacturing system of real-time executing ,monitoring and supervision, self-adapting, and reconfiguring rapidly will play a crucial role.

2. Industry 4.0

The first industrial revolution was introducing mechanical production facilities, which commenced in the second half of the 18th century and being consolidated throughout the entire 19th century. In the second industrial revolution the electrification and the Taylorism's division of labor were developed from the 1870s. The third industrial revolution, also called "the digital revolution", occurred in the 1970s, and promoted in the automation of production and advanced electronics, and information technology. The "Industrie 4.0 Working Group" advocates that the "Industry 4.0" integrating the Internet of Things (IoT) and Cyber-Physical Systems (CPS) into the manufacturing process as a crucial enabler will be the fourth industrial revolution [3]. The term and an initiative named "Industry 4.0" became known publicly in 2011 as an association of representatives from business, politics, and academia supported the concept as an approach to strengthening the competitiveness of the German manufacturing industry [4]. The German federal government declares that Industry 4.0 will be an integral part of its "High-Tech Strategy 2020 for Germany" initiative, attempts to reach technological innovation leadership of the German economy [3]. The "Industrie 4.0 Working Group" developed first implementing recommendations published in April 2013, and they named three main components of Industry 4.0: the internet of things (IoT), cyber-physical systems (CPS), and smart factories and consider the merge of IoT into the manufacturing process for the fourth industrial revolution. Moreover, the IoT, CPS can become the fusion of the physical and the virtual world, and realize integrations of computation and physical processes while embedded computers and networks monitoring and control them, normally with feedback loops [5-6].

A recent paradigm is called "the fourth industrial revolution" (Industry 4.0) in which technologies are combined to integrate machines and humans to compose value chains of entities (i.e., manufacturing factories) in different geographical locations distributed manufacturing systems, which will provide services and products in an autonomous manner [7]. Industry 4.0 considers the former paradigms comprising reconfiguration and technological advances associated with cyber-physical systems and cloud computing environment. In fact, there is not a unique technique to overcome all the challenges; an alternative solution is a hybrid of complementary characteristics involving different techniques wherein the comprehensive use of holonic and multi-agent system (HMAS) concepts can facilitate the development and integration of distributed heterogeneous systems combining hierarchical and heterarchical structures [8]. Moreover, the number of scientific topics and the achievements in the HMAS field is boosting and been explored to propose solutions for Industry 4.0 [9].

3. Intelligent Manufacturing System

Intelligent manufacturing systems (IMS) are the novel generation of manufacturing systems. All IMS subsystems include parts of so-called machine intelligence (sensor equipment). For the better understanding to term "intelligent" manufacturing systems, it is the most suitable to compare its behavior with the classical ("non-intelligent") automated flexible manufacturing system. There are three basic types of automated manufacturing systems [10]: (1) Flexible manufacturing cell amounts to maximum three of the machine tools characterized by the highest level of flexibility. (2) The flexible manufacturing line can be characterized by the lowest level of flexibility, and its range of goods is narrow and within large batches of products. (3) Flexible manufacturing system includes minimum three machines and more characterized by a lower level of flexibility. The intelligent manufacturing systems present systems, which owned capable of adaptation to unexpected changes, and they also consisted of software components using such techniques as parameter optimization, fuzzy logic, neural networks, expert systems and machine learning [11]. Intelligent manufacturing, which combines multi-functional machines and mobile robots, can be achieved in three basic ways [2]: 1. Existing manufacturing processes become more intelligent by monitoring and controlling the state of the manufacturing machine. 2. Existing processes can be intelligent by adding sensors to monitoring and control the state of the processed product. 3. New processes designed intelligently to produce parts of desired quality without the need of sensing and control of the process. This example comprises a part agent- running in an industrial personal computer (IPC), three machine agents - representing three computer numerical control (CNC) machines, and a transport agent- representing an automated guided vehicle (AGV) and running in a programmable logic controller (PLC) [12]. The production data are fell into three categories: product (or order), knowledge (NC program, processing time, and transportation time), resource (storage, machine, AGV). The basis of closed-loop control for distributed production control system is the introduction of real-time information of the product as a feedback [13]. Comparing with the client-server paradigm, the mobile agent will strengthen the system adaptability and flexibility [14].

4. Research Methods, Procedures, and Progress

The proposed intelligent manufacturing simulation system will be composed of three main subsystems: a database management system of process parameters, a multiple response optimization system of PIM, and a real-time monitoring and control system. A schematic module for the PIM intelligent manufacturing system can be seen in Fig. 1 and its procedures are described in the following sections.

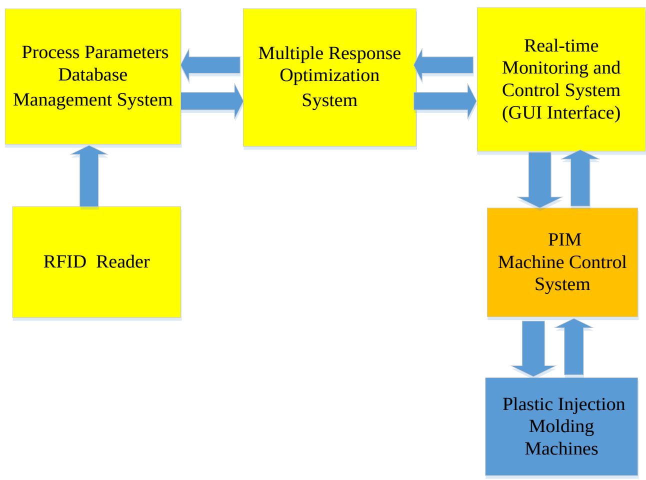

Fig. 1 A schematic module for a PIM intelligent manufacturing system

4.1. Multiple response optimization system

The study proposed a two-stage multiple response optimization system to find optimal process parameters of multiple quality characteristics in the PIM process. The Taguchi method, back-propagation neural network (BPNN), multi-objective analysis of variance (ANOVA), and modified hybrid genetic algorithms and particle swarm optimization genetic algorithms (modified PSO-GA) were used to find optimum parameter settings. Length and width characteristics were employed as the product quality. The experimental work was conducted using the Taguchi orthogonal array table. According to the result from the Taguchi experiment, S/N ratios were calculated. The S/N ratio response factor chart of integrating into a single quality (i.e., total bias) and the main effects plot for S/N ratios of total bias were demonstrated. In addition, the S/N ratio predictor and the quality predictor were constructed using BPNN. A modified PSO-GA algorithm is proposed to improve numerical performance for a hybrid PSO-GA algorithm, which was used to find initial weights of BPNN in conjunction with multilayer perceptron (MLP) and to reduce the training time of BPNN. In the first stage optimization, the S/N ratio predictor and GA were used to reduce variance of the quality characteristic. Then, in the second stage optimization, the S/N ratio predictor and the quality predictor with a modified PSO-GA algorithm were employed to find optimal parameter settings for product quality and stability of the process. Finally, confirmation experiments were conducted to assess the effectiveness of the proposed system.

4.2. Database management system of process parameters

The study utilizes MySQL 5.7 to construct the process parameters database, and uses the Microsoft Visual Studio 2015-Visual Basic to develop an information platform (i.e., GUI control interface) of the Intelligent Manufacturing System, which encompasses three subsystems: a database management system of process parameters, a multiple response optimization system, and a real-time monitoring and control system. The database management system by functions can be separated into two portions: the first part is the intelligent process parameter optimization database, which can access the implemented experimental data; the second part is optimal parameter settings generated by a multiple response optimization system, which can access the results created by multiple response optimization system. The above databases have different functions, and their column name and data types of database design and structure are quite distinct. The data type of data configuration of process details database can be seen in Table 1, which represents the data type of the remain columns are set "Single" with respect to requiring higher precision figures and setting the Product ID as "Varchar". On the other hand, Data type of database for results of the process parameters optimization system is in Table 2. It suggests that the database is associated with a Product ID, which is beneficial to the follow-up relation query. The target of length and width will be read by the RFID Reader and save them into a quality database.

Table 1 Data type of database for the experimental data

Column Name	Product ID.	IT	IV	PP	PT	PT	Ave. Length	Ave. Width	Std. Length	Std. Width	S/N Length	S/N Width
Data Type	Varchar	Single										

Table 2 Data type of database for results of the process parameters optimization system

Column Name	Product ID.	Length Goal	Width Goal	IT	IV	PP	PT	CT
Data Type	Varchar	Single						

4.3. Real-time monitoring and control system

The proposed monitoring and control system will provide the PIM process demonstration, process parameter settings, records, and so on. It is also a communication channel and response interface with the multiple response optimization system and the database system. The flow chart of a real-time monitoring and control system can be represented in Fig. 2, and its software utility and hardware appliance can be denoted below:

<u>Software utility</u>

(1) Process parameter database records all the PIM process parameters and their quality characteristics.

(2) Monitoring and control system will provide the PIM process demonstration, process parameter settings, records, and etc. The system is a communication channel and response interface with the multiple response optimization system.

(3) The multiple response optimization system offers the injection molding machines real-time adjusted control parameters and quality control details for determining the optimal process parameter settings, which can achieve the quality requirements.

Hardware appliance

(1) The hardware communication interface is an interface which connects the workstation and plastic injection molding machines. The control interface of PIM machines need to abide the communication paradigms such as RS-232C, 422, 485, Ethernet, EtherCAT, … etc., owing to the professional use of the proposed PIM machine control system.

(2) The signal transformation module proceeds to supervise and control the alternative parameters, like temperature of Ice water machine, which are not encompassed in the PIM machines, or caters the required signals transformation for on-line quality inspection system.

(3) The workstation of real-time monitoring and control system plays an essential core of the whole intelligent manufacturing system, which operates the multiple response optimization system, accesses process parameter database, and supervises and controls PIM machines via hardware communication interface, signal transformation module, on-line quality inspection module, network control module,…etc.

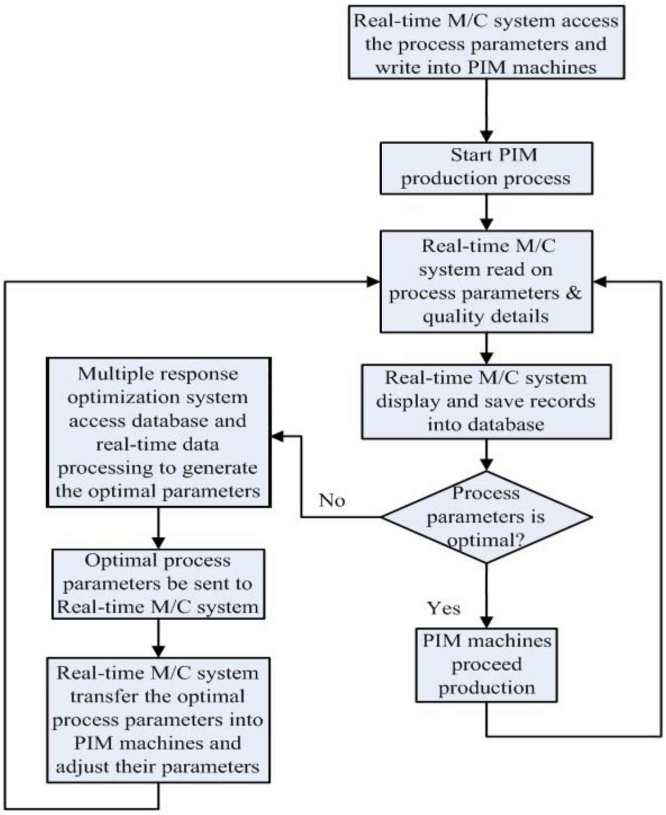

Fig. 2 Flowchart of a real-time monitoring and control system

5. Conclusions

This study proposed an intelligent manufacturing system (IMS) composed of three subsystems: intelligent parameter optimization system of PIM process, database management system, and real-time monitoring and control system. Firstly the intelligent parameter optimization system uses Taguchi Method, ANOVA, Bnd mPNN aodified PSO-GA methodologies to search for the optimal parameter setting. Then the database management system is dedicated to accessing the experimental data and PIM process parameter settings of FMM, which encompasses etching product ID with quality targets. As to the PIM real-time monitoring and control system, it will establish a graphic monitoring and control interface, whose monitoring scopes includes real-time monitoring the parameters of PIM machine and the optimal process parameter settings created by the multiple response optimization system, and transferring the optimal process parameter settings into PIM machines and simultaneously changing their parameters. The proposed intelligent manufacturing system of a PIM process will help the PIM firms search for better parameter settings for new plastic products, and facilitate the PIM firms easier to avoid product defects and build the sustainable competitive advantage over their competitors in the world.

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