Intelligent e-monitoring of Plastic Injection Molding Machines

LAU Hau Yu

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Abstract

As one of the major manufacturing centers in the world, Hong Kong (including the nearby Pearl River Delta Area) has over 50,000 manufacturing companies. However, it makes only one kind of manufacturing machinery: plastic machinery. Therefore, create able technologies for the plastic machinery industry is of strategically important. In this research, many works have been done to verify the excellent performances of some monitoring methods: the Design of Experiment which help in finding the optimal settings for the injection molding machine; the Radial Basis Function Neural Network which has been used to predict the nozzle pressure and part weight; Similarity-based monitoring for the short shot; parameters resetting of the injection molding machine using the Support Vector Machine and Virtual Search Method.

With those able technologies, a Remote Monitoring and Diagnosis System (RMDS) has been developed in the research. The system can automatically collect data, conduct data mining an intelligent diagnosis which can help to maintain the health condition of the machines and to assure the part quality. The system consists of an on-line data collection module and an off-line data mining and diagnosis module. The on-line data collection module can collect data from the controllers of the machine and various other sensors, and send the data to the machine manufacturer through the Internet. The off-line data mining and diagnosis module will detect possible malfunction and accordingly, schedule prevent maintenance. Upon detecting possible malfunctions, it will send the data to the manufacturer through the Internet. Accordingly, prevent maintenance can be initiated to minimize the production lost and maintenance cost. Lots of experiments were accomplished to verify the outstanding performance of the monitoring methods and the RMDS.

摘要

作為世界上主要的製造業中心, 香港(包括珠江三角區)擁有超過 50,000 間製造業的公司。然而, 它們主要使用一種機器: 塑膠加工機械。因此, 開發先進的技術對塑膠機械工業有非常重要的意義。在本研究中, 我們完成了很多實驗以驗證一些監控方法的傑出表現: 正交試驗設計(Design of Experiment)幫助找出注塑機的最佳設定; 以 RBF 神經網絡估算射咀壓力和產品的重量; 產品不充滿的類似度監控; 以支持向量機(Support Vector Machine)和虛擬找尋方法(Virtual Search Method)作參數重設。

基於以上的技術, 本研究創建了一個遠程監控診斷系統。這系統能自動收集數據, 進行數據挖掘和智能診斷, 從而幫助機器維持良好狀態及保證產品質量。這系統包括一個在線數據收集組件及一個離線數據挖掘診斷組件。在線數據收集組件能從機器的控制器及不同的傳感器中收集數據, 並將數據經由互聯網傳送至機器製造商。離線數據挖掘診斷組件會偵測可能的錯誤, 從而編制預防維護。一旦偵測到可能的錯誤, 系統便會將訊息經由互聯網傳送至製造商。由此, 預防維護可以減低生產的廢品和維護費用。大量的實驗已完成以驗證系統在監測方面的傑出表現。

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After the past two years working on the research, I have to say, "Succeed is not purity your own efforts". The succeed of the research is actually a combination of the efforts of a community of people. I am indebted to many people and organizations for their help as I pursued this research.

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Chapter 1: Introduction

1.1 Background

According to statistics, the annual production of plastic has surpassed that of the steel in volume and weight [1]. In 1950, about 1 million tones of plastics were produced while expended to more than 150 million tones at the end of the century [2]. Counting varnish, glues, dispersions, and likes products, more than 180 million tones were produced in 2000. It is expected that in the year 2020, the production of polymeric materials will be about 380 million tons [3]. In other words, plastic is now the most widely used material in the world. Among various plastic production technologies, injection molding takes up approximately 32% [4]. Plastic injection molding is one of the most important and efficient manufacturing techniques for polymeric materials, with the capability to manufacture high value added products. It is capable of producing complex parts with low cost and high productivity. However, manufacturing has become a much tougher, more global field since the 1980s. Due to the fact that the product life cycles are reduced and the part quality requirement is continuous increased, companies have to develop new and advance technologies in order to survive. Same as the plastic injection molding industry, it has faced dramatically changes and challenges in the past decades. The only way to make profit and keep survive is to keep quality up, expenses down with no doubt.

Injection molding is a complicated process during which various problems may occur. The most notable one is the product quality, especially for high-end products such as air-tight containers and automobile instrument panels. In recent years, the demand for consistent and enhanced product quality continues to rise. Therefore the assurance of the product quality becomes the key to the further advancement of the injection molding process. On the other hand, the higher demands on quality of parts results a development towards high precision injection molding machine. It is believed that one of the toughest components to being competitive in the injection molding business is maximizing the usage of the manufacturing facility, i.e. the injection molding machine. Injection molding machine plays a crucial role in the injection molding industry, therefore, an injection molding machine having outstanding features and performances will benefit both the manufacturing side and production side. In fact, an excellent injection molding machine can help company to increase its productivity, improve the part quality and lower the production cost. On the other hand, an excellent injection molding machine will also help the machine making company to expand its sale market. To conclude, the two major criteria to survive in injection molding industry is to optimize the injection molding process and injection molding machine.

Optimize the injection molding process aims to improve the product quality, to achieve this propose, there are basically two techniques: the manual technique and the automatic method. For manual technique, an expert has to carry out the optimization procedures according to his experiences and knowledge, which will be time consuming. There are thousands of researches about optimization of injection molding process [5-9]. Although the relationships between those variables and part quality have been widely studied and a few guidelines exist for determining injection molding parameters, there is no standard optimization procedure [10]. In fact, the optimization procedures can be divided into five main categories: the shot size, injection velocity, injection pressure, injection time and pack and holding pressure. As there are too many parameters determines the part quality, optimize the injection molding process manually may not be a good choice. For automated method, usually a software-based system is required. Those software employ the physical laws to simulate the machine and plastics behavior which requires an accurate quantitative, understanding of the material properties and behavior [11]. One shortcoming of this method is that, the system is usually very expensive, it will increase the production cost.

Presently, much work is focused on tooling (i.e., the molds) and the use of advanced materials. However, as the demand for productivity grows, it is difficult to achieve the desired quality level without monitoring and control [12]. The most commonly use monitoring method is Statistical Process Control (SPC). In this technique, quality control personnel routinely take samples and check them against statistical control charts. Should a problem be detected, it is possible to run additional tests to find out the causing factors; and accordingly, make adjustment. Unfortunately, this method has a number of limitations: (a) it cannot be done on-line, (b) it is rather laborious, and (c) it is not precise. Moreover, making statements about the whole production on a basis of samples may not be accurate enough, as the declarations can be wrong. The more advanced technology will be the neural network. The increasing development of artificial intelligence offers the wide field of neural networks for quality prediction, monitoring and closed-loop quality control for the injection molding process. Lots of researches have been done to prove its outstanding performance [1, 13-19]. However, they are usually dependent on learning and optimization. As a result, they may not have clear physical meanings and often fail when encountering unseen cases.

With the rapid advancement in personal computer networking and Internet, people focus on remote monitoring and diagnosis system. Many companies develop "Computer Integrated System" which can collect quality information, manage production information and monitor remote machines. The system combines advanced information technology and traditional condition monitoring system to provide remote monitoring and diagnosis of machines [11,20-24]. All the above shown the importance and necessity of developing the intelligent monitoring and diagnosis system for machines.

1.2 Objective

In this research, we aim to develop a totally new and advance system for monitoring and diagnosing of the injection molding machine. The system will be a PC computer installed next to the plastic injection molding machine on the shop floor. It can automatically collect data, conduct data mining and intelligent diagnosis. Upon detecting possible malfunctions, it will send the data to the manufacturer through the Internet. Accordingly, prevent maintenance can be initiated to minimize the production lost and maintenance cost. In addition, the data will help to improve the design and manufacture of the plastic injection molding machines. In the research, we decide to work out the most effective and outstanding method for optimizing the plastic injection molding process, therefore improve the quality of injected part. Moreover, the system we design will be aimed to optimize the performance of the injection molding machine. The ultimate objective of the research is to bring positive impact to the plastic injection molding industry.

The structure of the thesis is as follows. In the next session, some literature surveys about the plastic injection molding process, monitoring and diagnosis method and remote monitoring system will be given, showing the background and recent researches in these fields. Then, the monitoring methods used in this research will be shown in detail, which includes the Radial Basis Function Neural Network, Similarity method, Support Vector Machine and Virtual Search Method. The procedures and results of some conducted experiments will also be given as well. After that, the developed monitoring system will be described further, with both the hardware and software parts. Last but not the least, there will be a conclusion and future working direction of the research.

Chapter 2: Literature Survey

2.1 Plastic Injection Molding Process [22]

The injection molding machine (Figure 2-1) has the function of *injecting molten plastic material into a tightly closed mold* where the shape of a product is formed. The mold is kept closed for a specified time, the cure time, during which the fluid material becomes solid and rigid. A coolant circulates through passages in the mold, so that heat from the fluid plastic is transferred to the mold and from there to the circulating fluid, a process that accelerates the curing (solidification of the part). At the end of cure time, the mold is opened, and the parts are ejected, ready for packaging or other operations if required. At this point, a new cycle begins.

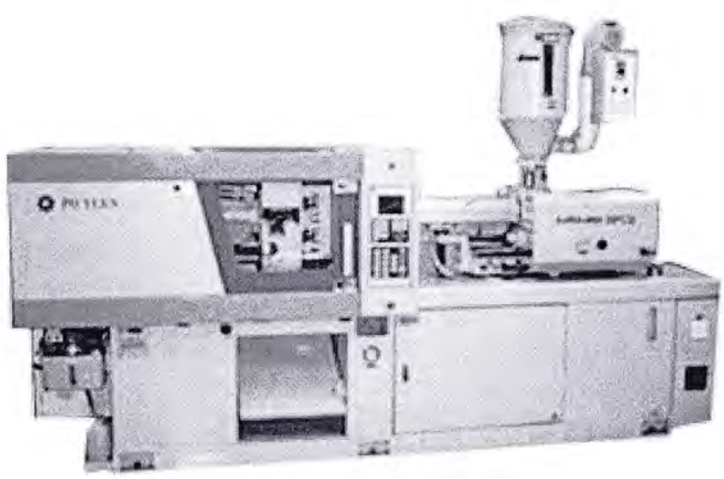

Fig.2-1: An injection molding machine.

The cavity half of the mold is attached to the stationary platen (stationary mold), where it is centered by means of the locating ring. The core half of the mold is mounted on the moving platen (moving mold). When the press gate in front of the mold is closed, a hydraulic circuit is activated that caused the main ram to move forward at a fast rate.

This movement is brought about by supplying a large volume of oil from pumps directly into the booster ram. This oil exerts a pressure on the body of the main ram, causing it to slide over the booster ram and move forward until at a designated position the moving main ram actuates a limit switch that sends a signal to the hydraulic circuit ordering the high-volume pump to dump its oil at low pressure in to the prefill tank, while at the same time, the low volume pump keeps supplying its oil to the booster ram, thus causing slow main ram movement.

The pressure at which this slow movement takes place is controlled by a mold protection valve. The pressure of this valve is set at a low figure (around 200 psi), so that the pressure exerted on mold halves, if something is caught between them, will be low and not cause damage to the mold. The space vacated in the clamp cylinder housing is filled with oil by gravity from the prefill tank through the opening of the prefill piston in its retracted position. The mold halves make contact at the low speed of the ram movement, and at this point, another limit switch closes the prefill piston and activates a high pressure pump (2,000 to 3,000 psi), which will apply its full pressure over the main ram, holding the mold halves tight and resisting opening when plastic material is injected into the mold at pressures up to 20,000 psi. This second limit switch also initiates the movement of the injection ram, which injects the plastic into the mold. Injection is carried out by the front of the screw, which contains a shutoff valve that *prevents any possible backflow* of the fluid plastic. The screw is firmly attached to the injecting ram, whose movement takes place at a fast rate (usually in about 1 to 2 sec for the full shot capacity).

The injection time is controlled by a timer (the injection high timer), and the ability to respond to the timer setting is determined by the pressure of injection and fluidity of the material. The speed of injection can be varied by means of a flow control valve that can by-pass a desired amount of the pump oil and thereby reduce the speed. This valve usually has 10 bypassing positions, thus providing a considerable degree of injection-speed variation. Once the shot is completed, the high-volume oil injection pump is ordered by a signal from the timer to dump its oil into the prefill tank at low pressure; at the same time, a low-volume pump (hold pump) *maintains pressure* on the material in the cavity until the gate through which the material was fed freezes and prevents back flow to the cylinder. (Back flow can be caused by the pressure within the cavity if the feed gate is open.) The hold-pump duration is set by the injection hold timer. At the expiration of this timer, the screw starts rotating, picks up material from the throat in the cooled chamber, and moves, compresses, and shears it in the extruder chamber, where it absorbs heat and liquefies before entering the measuring portion of the injection chamber.

The extruder barrel is *heated by strip heater bands*. A group of heaters is divided into zones, with each zone having a pyrometer for controlling the temperature. There are usually three or four zones on the extruder chamber. The extruder work—represented by feeding, compressing, and shearing of the material—partly shows up as heat induced in the plastic. The heat needed to fluidize the plastic is derived partly from the work of the screw, the balance coming from the strip heaters of the extruder chamber. As the material comes off the extruder screw, it creates pressure on the front face of the screw, causing it to retract so that a space is created for the incoming material required for the shot. This backward movement of the screw makes it necessary to push oil out from behind the injecting ram.

The displaced oil passes through a controlled valve, which can be adjusted to provide varying degrees of *resistance for the screw's backward travel.* This resistance, known as the back pressure, is utilized to provide good mixing and homogenizing of the material in the injection chamber, when a slight temperature adjustment is needed for the material that is to be injected, a small increase in the back pressure will accomplish this requirement. The duration of *screw rotation* is determined by a limit switch, which is activated by the backward-moving screw at a position where the necessary volume of material required for the shot has been reached. The screw limit switch may also start a melt decompress timer, which will cause continued limited backward movement of the screw. This additional screw movement creates a space in front of the screw that permits the built-up pressure to decrease enough that, when the mold opens, no drooling of plastic takes place.

The final stop of the screw movement usually coincides with the expiration of the cure time as determined by the corresponding cure timer. On a signal from the cure timer, the press starts opening the mold. This is accomplished by feeding oil from a small-volume pump into the space behind the ram bushing. This causes the press to start opening slowly; then another limit switch is actuated by the ram movement, which orders a large volume of oil to be fed into the space so as to shorten the press opening time. Since the area between the clamp cylinder and the main ram is small, and this *area multiplied by the pump pressure gives the* force for mold opening, this force is small in comparison with the clamping tonnage (usually around 5% of the clamping tonnage). Before striping (ejecting) starts, the ram is slowed down by actuating still another limit switch for gentle action of the knockout pins, to prevent the pins from punching through the parts while pushing them off the cores. With hydraulic ejection, the slowdown can be so delayed that no banging takes place when the ram returns to the starting position. After ejection, the parts are removed from the press, and the cycle starts all over again. All limit switches have numbers that tie them to specific actions.

2.2 Monitoring and Diagnosis Methods

Thousands of researches have been done about monitoring and diagnosis method of injection molding machines, follows are some of them. [19] showed that a relative assessment of polymer melt viscosity may be achieved using nozzle melt pressure or hydraulic injection pressure measurements. It found that hydraulic injection pressure measurements have at least equal sensitivity to polymer viscosity variations, compare to nozzle melt pressure measurements. This result confirmed that hydraulic pressure signal may replace the nozzle pressure signal and use to monitor the injection molding process. [13] showed the strategy how to build a reliable process model effectively for quality forecast, how to predict the quality of a manufactured part with the existing model, the necessity and the mechanism of adaption of the process model. The strategy is based on the use of artificial neural networks. Experiments showed that the non-linear transmission characteristic of neural networks and their ability to deal with interactions correspond well to the characteristics of the injection molding process. However, the experimenter narrowed the range of the parameters limits in order to optimize the training results of the neural network. This made the trained neural network can only work on a narrow range of data. Data that outside the ranges result as inaccurate responses.

[16] presented a method to predict the injected part weight using the Widrow-Hoff neural network. Input of the network is the hydraulic pressure during plastication, while the output is the part weight. Among the 36 testing injected parts, there were 16 in total miss the actual part weight as much as 1.8grams (the injected part was about 35 grams), which is a little bit disappointing. The reason may because Widow-Hoff neural network is limited to linearly separable problems, however, the relationships between hydraulic pressure and part weight is not the case. [9] proposed a virtual sensing approach for on-line monitoring process variables of injection molding process. A virtual nozzle pressure sensor is developed. The screw velocity data is used to predict the behavior of the nozzle pressure. Experiments confirmed the feasibility and effectiveness of the virtual sensor. In the experiment, the machine operated without any mold installed, that may affect the results as in real manufacturing, mold should always be installed in the injection molding machine.

[5] described an algorithm for initial determination of injection velocity based on rheological calculations of the melt flow inside the mold cavity. Use of the algorithm for initial setting of process parameters streamlines consecutive computer-assisted defect elimination and optimization of injection molding process. However, the algorithm only consider the injection pressure, melt temperature, shear rate and shear stress as the critical factors for the injection velocity. To get a better result, the melt properties should not be omitted. In [6], an expert system aim to assist the setting of machines with the help of CAE analysis was presented. The proposed algorithm

requires a description of the mold and part features. The performance of the system highly depend on the inputs, i.e. the description of part/mold features, which may be very complicate and make the suggested machine settings inaccurate.

[7] presented a Knowledge-Based Tuning (KBT) Method which takes advantage of the *a priori* knowledge of the process, in the form of a qualitative model, to reduce the demand for experimentation. This on-line tuning method will continuous estimate the process window during tuning, and use the learning to adapt its input-output model after each tuning iteration. [8] presented a monitoring strategy for the injection molding machines using an ultrasonic transducer. It monitors the conditions inside the cavity during processing which suit for use in controlling the transition from injection phase to packing phase, as a short shot detector, as feedback for Statistical Process Control and for melt temperature monitoring. The main advantage of this method is the ultrasonic transducer is inexpensive and sensitive to the conditions inside the mold cavity, however, an ultrasonic crystal have to install inside the mold plate in order to obtain better result. It is not preferable in manufacturing as this will increase the production cost.

2.3 Remote Monitoring

For remote monitoring, usually it will be a computer integrated system providing data mining and network communication. [22] presented the functions and sample applications of the simplified central control system "CAMOT LINK10" which aims to support the production stage of injection molding. The software is actually made up of three major functions:

1. Measurement data collection
    - Collect, display and print measurement data
    - Process data statistics and display trend graphs
    - Save data on and read from HDD (CSV text format)
2. Molding conditions management
    - Upload and download the settings
    - Save the settings on and read from HDD
3. Remote console
    - Display on PC the controller screen of injection molding machine for operation
    - Save the screens in image file (BMP format)

The pros of the software are it can simultaneous collection of measurement data from up to 10 injection molding machine that are connected to the network. It also provides some smart functions such as report generation and operation management. The cons of the software are it is really simple, especially the graphic interface. The software is text-based which is not user-friendly enough. Also the software can only provides local area network (LAN) communication between the injection molding machines and the host computer. Data management is not supported through FTP or Internet which limited its usage. Moreover, the quality control method in the software is based on simple comparison of the detected signal with the sample signals, which is not an advanced method for quality monitoring.

In [21], a low-cost process monitoring and control system using nozzle-based pressure and temperature sensors was presented. Experiments showed that temperature and pressure measurements in the nozzle can provide effective control of melt quality and shot size uniformity. With the help of the LabVIEW, signal can be viewed remotely. Although the results showed in the paper is pleased, the system required an add-on nozzle pressure sensor mounted in the injection molding machine, which is not economic compare with the built-in hydraulic sensor.

MMS/Production Monitoring [23] of the "Moldflow" is a manufacturing execution system that tracks and reports production and machine efficiencies. The system can be attached to virtually any piece of cyclic equipment used for discrete manufacturing and also provides capabilities for work order management, job scheduling, mold and machine maintenance tracking, labeling and SPC/SQC functions. MMS/Production Monitoring allows manufacturing managers to measure constraints, identify production delays and assess machine capacity, providing critical information in real time to maximize the efficiency of shop floor operations.

ERC2 [24] is the Allen-Bradley's patented Expert Response Compensation closed-loop control technology. It provides many functions such as automatic tuning of the pressure and velocity loops associated with clamp, injection and ejector motion; precise temperature control and molding control; network communication for data processing. All this functions can help company to optimize the injection molding process and increase the productivity.

Chapter 3: Monitoring Methods

This chapter describes the monitoring methods that have been used in the research. The first one is the Radial Basis Function Neural Network (RBFNN), which has been used in predicting the nozzle pressure and part weight; another one is the Similarity that I used to monitor the short shot of injected part; last is the Support Vector Machine (SVR) and Virtual Search Method (VSM) which has been used in parameter resetting. The experiments conducted will also be described to verify the performance of the proposed methods.

3.1 Predict nozzle pressure and part weight using the Radial Basis Function Neural Network

3.1.1 Motivation

For monitoring of part quality of injection molding machine, nozzle pressure is perhaps the best among various signals. It is however rather expensive to acquire. On the other hand, most plastic injection molding machines have a build-in hydraulic pressure sensor and a ram position sensor. Therefore we tried to predict the nozzle pressures from the hydraulic pressure and the ram position. The new method was based on the Radial Basis Function Neural Network (RBFNN).

3.1.2 Background

For monitoring of injection molding machine, artificial neural network is suitable as it has the ability of learning from experience, i.e. finding out the relationship between input and output from large amount of experimental data. Another advantage of ANN is it can use in prediction. After training the ANN, one can get the correct predicted value from an untrained input data. Among different types of artificial neural network, Back-Propagated Delta Rule Networks (BP) and Radial Basis Function Networks (RBF) are two famous neural networks to learn arbitrary mappings or classifications. A typical BP network consists of one input layer, one output layer and several hidden layers. It uses the delta rule to adjust the weights in order to minimize the error function. A typical RBF network consists of 3 layers (input, hidden and output) which the error function is minimized by adjusting the distance between the input vector and the centre of the network. B.H.M. Sadeghi developed a BP-neural network predictor that use to predict the quality of the plastic injected parts [15]. In general, a RBF network need a shorter training time than a BP network. W.He *et al.* developed a fuzzy-neuro system to predict the amount to be adjusted for the injection molding parameter in order to reduce the observed defects [1].

In order to conduct on-line monitoring, the first step is to select appropriate sensors. An injection molding machine usually has a number of built-in sensors, which can be categorized into one of four types: temperature, pressure, speed and stroke (position). Souder et al. [26] investigated the correlation between the peak pressure and the product quality. In his study, a number of pressure sensors were used, including the hydraulics system pressure, the injection nozzle sensor, and two mold cavity sensors. The results showed that the mold cavity sensor is the most sensitive (the correlation coefficient $r = 0.8$), follow by the nozzle pressure sensor ($r = 0.7$), and the hydraulic pressure sensor ($r = 0.4$). Since the cavity pressure sensor must be reinstalled every time a mold is changed, the nozzle pressure sensor is a more practical choice. In [27], the nozzle pressure signal is used to control the packing phase to assure the product quality. It also showed that the nozzle pressure signal is even better than the cavity pressure signal. Nevertheless, the use of nozzle pressure sensor involves two problems: first, it requires additional costly investment (while most plastic injection molding machines have built-in hydraulic system sensors). Second, it is not directly correlated to the product quality. The first problem motivates us to use the hydraulic system sensor, which is readily available for many plastic injection molding machines but has much lower signal-and-noise (S/N) ratio. The second problem motivates us to use advanced learning method, which is the Radial Basis Function Neural Network (RBFNN).

3.1.3 Hybrid RBF neural network

Radial basis function (RBF) neural networks offer some advantages over multi-layer perceptions (MLP) in some applications, because RBF neural networks are easier to train than MLP neural networks (Mark Orr 1995). Meanwhile, RBF neural networks can transform the n-dimensional inputs nonlinearly to an m-dimensional space like the MLP neural network, and then estimate a model by using a linear regression. The non-linear transformation is controlled by a set of m basis functions each characterized by a position or center $\boldsymbol{c}_j$ in the input space and a width or radius vector $\boldsymbol{r}_j$, $j \in \{1,2,\cdots,m\}$ [28]. A popular RBF neural network depicts in Figure 3-1. The basis functions are typically Gaussian-like functions, such as:

$$h_j(\mathrm{x}) = \exp\left(-\sum_{k=1}^{n} \frac{(x_k - c_{jk})^2}{r_{jk}^2} \right) \tag{1}$$

Clearly, the output of basis functions respond most strongly to the inputs nearest to the center $\boldsymbol{c}_j$, in the metric determined by the radius $\boldsymbol{r}_j$. The output of the RBF neural network, $f(\mathbf{x})$, which is a model based on linear regression, is expressed as follows:

$$f(\mathrm{x}) = \sum_{j=1}^{m} w_j h_j(\mathrm{x}) \tag{2}$$

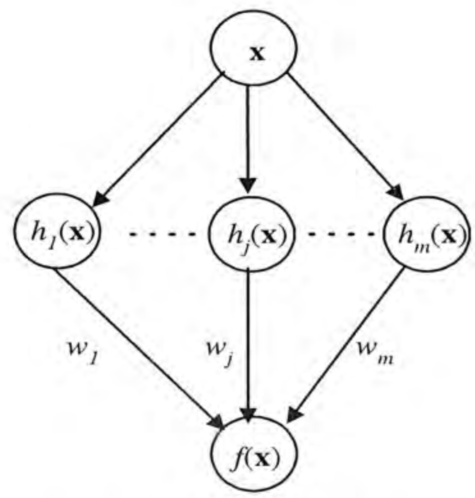

Fig.3-1: An RBF neural network.

In brief, to build a RBF neural network often meet four problems, including (1) the number of nodes for RBF neural network; (2) the identification of Gaussian center $\boldsymbol{c}_j$; (3) the proper setting of the radius $\boldsymbol{r}_j$; (4) the output-layer weights. For the fourth problem, it is relatively simple to determine the output-layer weights w_j by using the delta rule or some traditional statistical approach such as the pseudoinverse matrix. For the first problem, it is involved in the second problem because the identification of Gaussion center $\boldsymbol{c}_j$ includes its size and its number. Therefore, the more difficult problems are the identification of Gaussian center $\boldsymbol{c}_j$ and the proper setting of the radius

r_j. To overcome the aforementioned problems, various methods have been presented [29-33]. However, most of these techniques are computationally expensive. To summarize, the design of a successful RBF neural network involves several nontrivial problems, and so far there does not seem to exist any simple and general algorithms, or heuristic. Reference [34] first suggested combining the decision tree and RBF neural network to overcome the drawbacks of the other algorithms. Each terminal node of the decision tree contributes one unit to RBF neural network, the center and radius of which are determined by the position and size of the corresponding hyper rectangle. The decision tree can sets the number, positions and sizes of all RBF centers in the network. Because the decision tree nodes are converted into RBF unites, the only level of model complexity control is the tree pruning provide by C4.5 software and the choice of RBF scale, α. Unfortunately, Kulbat did not present a method to optimize either the degree of pruning or the value of the parameter α. Orr [35] presented a new method by combining regression tree and RBF networks, and adding an automatic method for the control of model complexity through the selection of RBFs. The Orr method consists of six steps, as shown in Figure 3-2.

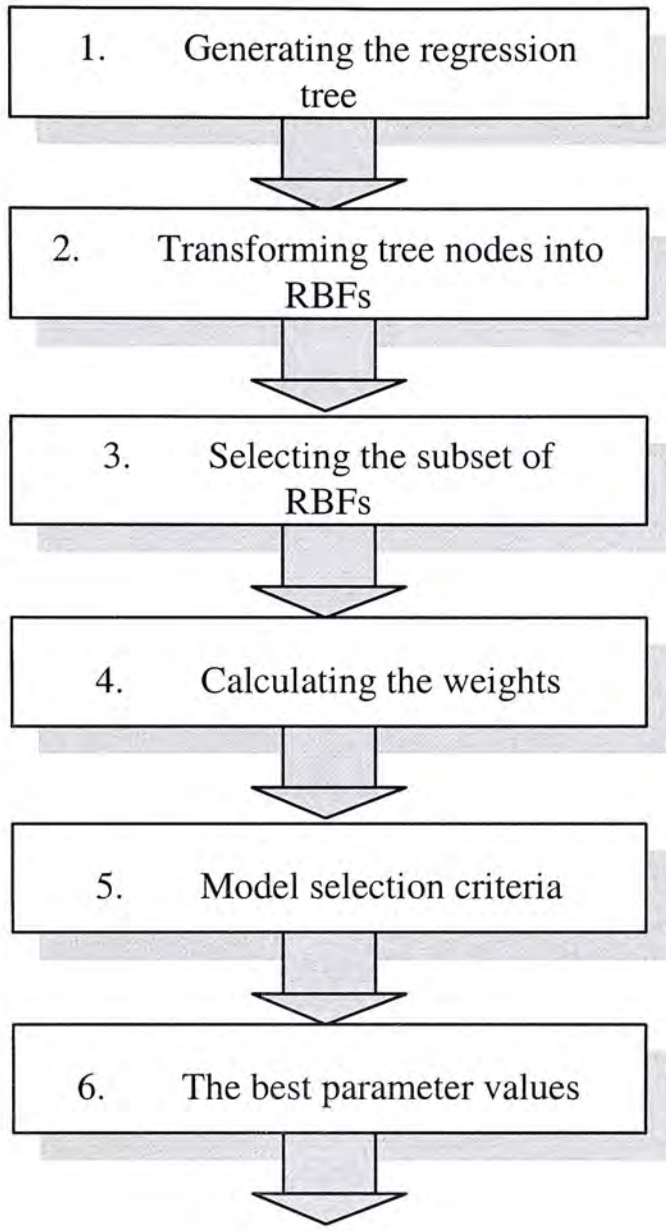

Fig.3-2: Six steps of the Mark Orr method.

(1) *Generating the regression tree.* Given the training data, $\{x_i\}_{i=1}^{p}$, the root node of the tree, which will be the smallest hyper rectangle, can be obtained by the regression tree method. The center values $\boldsymbol{c}$ of these hyper rectangles are calculated.

(2) *Transforming tree nodes into RBFs.* To transform a hyper rectangle into a Gaussian RBF, the center $\boldsymbol{c}$ of the hyper rectangle is taken as the RBF center, and its size (half-width), scaled by a parameter α , as the RBF radius;

(3) *Selecting the subset of RBFs.* If all RBFs from terminal nodes are included in the model, the model complexity is very sensitive to the extent tree pruning. To avoid the problem, Mark Orr combined the backward elimination and forward selection, and used the tree to order the selection process for RBFs.

(4) *Calculating the weights.* Given the training set inputs $\{x_i\}_{i=1}^{p}$, the RBF centers $\boldsymbol{c}_j$ and radius $\boldsymbol{r}_j$, the weights $\mathbf{w}$ are $w = (H^T H)^{-1} H^T y$, where $H = \{h_j(x_i)\}$, and $y = [y_1\ y_2 \cdots y_p]^T$ is the vector of training set output values.

(5) *Model selection criteria.* Generalized cross-validation (GCV) and Bayesian information criterion (BIC) two criteria are used to evaluate and compare different subsets of RBFs.

(6) *The best parameter values.* In the Mark Orr method, there are two main parameters $p_{\min}$, which control the depth of the regression tree and α, which determines the ratio of hyper rectangle and RBF size. Mark Orr has developed a semi-heuristic approach to optimize these parameters.

3.1.4 Estimation of nozzle pressure

Base on the methodology mentioned in 3.1.3 and some final adjustments, the RBFNN can be built. With the RBFNN, we tried to estimate the nozzle pressure using hydraulic pressure and screw position as the inputs of the model. Figure 3-3 shows the idea. After training the RBFNN, it is ready to use for predicting the nozzle pressure during injection process with the new coming inputs. The method can be expressed by following equation:

$$y(t) = f(x_1(t), x_1(t-1), x_2(t)) \tag{3}$$

$f(x_i(t))$ is the modeling function obtained from RBFNN, $x_i(t)$ is the input (i.e. hydraulic pressure and ram position), $y(t)$ is the estimated nozzle pressure. Experiments and results will be shown later.

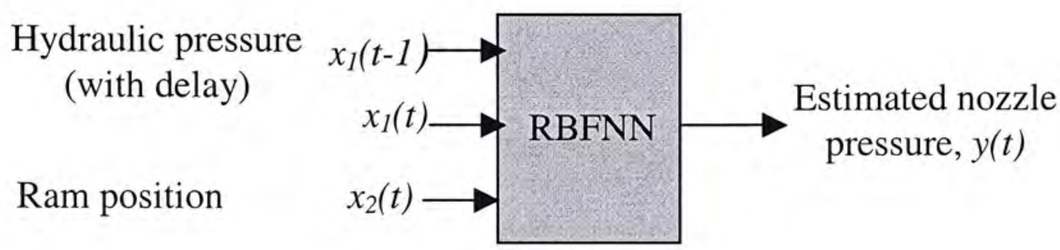

Fig.3-3: Estimate nozzle pressure using RBFNN.

3.1.5 Estimation of part weight: The two steps and one step methods

The idea has been further expanded to predict the part weight using the RBFNN. Part weight has been chosen as an indicator of part quality because it has the physical significance. Figure 3-4 shows the parts used in this research, which contains two rectangular plate joint by the runner.

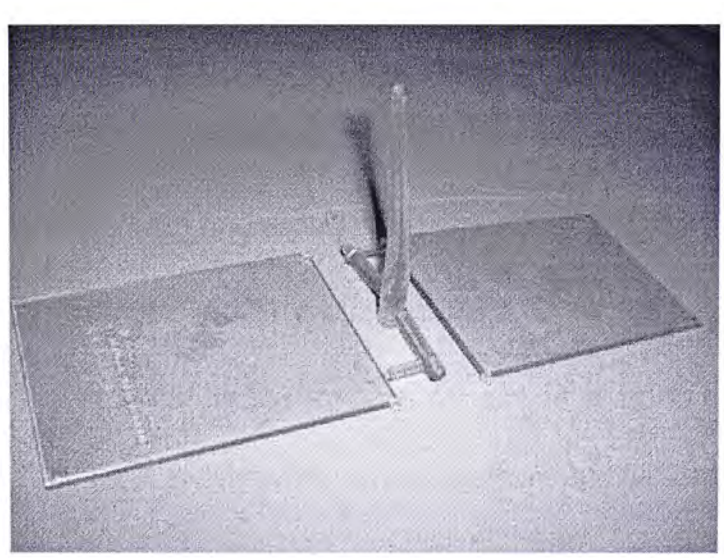

Fig.3-4: The injected part.

The dimensions of the rectangular plate in normal condition are approximate 90x70x2 mm. Let's consider one of the rectangular plates, the volume can be calculated:

$$Volume = Lenght \times Width \times Height$$

$$= 0.09 \times 0.07 \times 0.002 m^3$$

$$= 1.26 \times 10^{-5} m^3$$

The plastic used to produce the part was Acrylonitrile-Butadine-Styrene (ABS), which having a density (ρ) of *1100kg/m³*. Therefore, the mass of the part in normal condition can be calculated using the follow equation:

$$Mass = Volume \times Density$$

$$= \left(1.26 \times 10^{-5}\right) \times (1100)$$

$$= 0.01386 kg \approx 14 g$$

The actual weight for one rectangular plate in normal condition should be between 13g and 15g. The value had small different compared to the one obtained from theoretical calculation because density of the ABS may changed due to the high injection pressure. This showed that the part weight is a good indicator of the part quality, therefore we decided to monitor the injection process by predicting the part weight. The proposed method (we called it two steps method) consists of two steps:

1) Estimate the nozzle pressure by the RBFANN (detail in 3.1.4). Inputs of the system were the hydraulic pressure (with delay, $x_1(t\text{-}1)$ and $x_1(t)$) and ram position ($x_2(t)$), while the output was the estimated nozzle pressure ($y(t)$), as shown in Figure 3-5.

2) Predict the part weight using the estimated nozzle pressure. This was done by making use of the RBFNN again, however, input of the system changed to the estimated nozzle pressure ($y(t)$) and the output was the predicted part weight ($z(t)$), as shown in Figure 3-6. The method can be expressed by the following equations:

$$y(t) = f(x_1(t), x_1(t-1), x_2(t)) \tag{4}$$

$$z(t) = f(y(t)) \tag{5}$$

1st step:

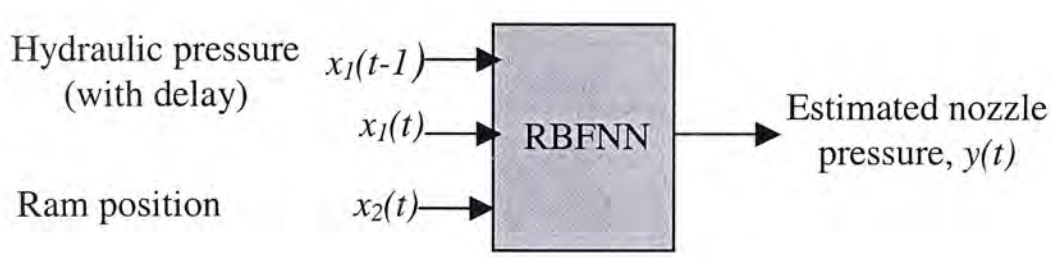

Fig.3-5: Step one of two steps method.

2nd step:

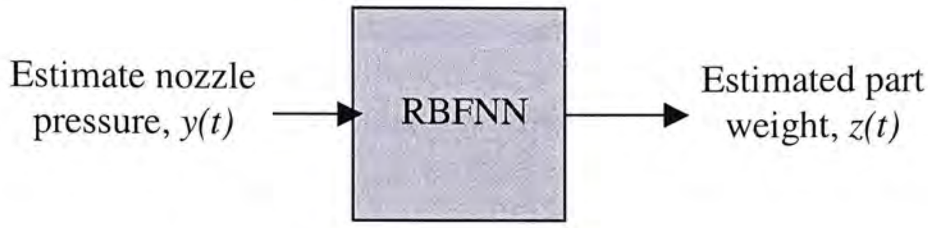

Fig.3-6: Step two of two steps method.

A natural thought is if the two steps can be reduced to just one step. Therefore, the part weight was tried to predict directly from the hydraulic pressure and ram position using the RBFANN (Figure 3-7), which can be expressed as follow:

$$z(t) = f(x_1(t), x_1(t-1), x_2(t)) \tag{6}$$

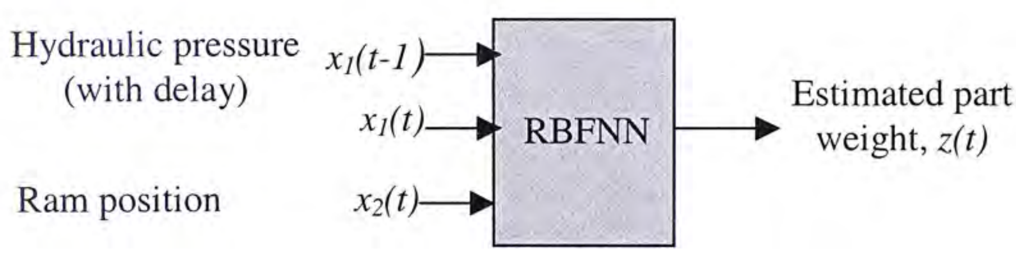

Fig.3-7: The one step method.

Experiments have been conducted to verify the performance of the one step method, which will be described later.

3.2 Short shot Monitoring using Similarity

3.2.1 Background

When there are two sets of data or objects, a common question people wonder is "Are they the same?". Even the data or objects look like the same, it cannot be concluded as equal unless a scientific measurement is applied. On the other hands, if the data or objects look different (or similar), then how "different (similar)" are they? Similarity measurement is a scientific method to find out the different between two sets of data or objects using mathematical calculations and therefore is reliable and accurate. There are lots of methods used to measure the similarity (or dissimilarity) of objects. For examples, Roberto Paredes and Enrique Vidal [36] proposed a class-dependent weighted (CDW) dissimilarity measure in vector spaces to improve the performance of the nearest neighbour (NN) classifier. Dorin Comaniciu, Peter Meer and David Tyler [37] showed that the Bhattacharyya distance is a particular case of Jensen-Shannon divergence for normally distributed features, which can be used for dissimilarity measure.

3.2.2 The Dissimilarity Approach

In the study, the dissimilarity approach used was based on correlation function, for time series x_k^i and x_k^j of length L, dissimilarity γ_{ij} is calculated as:

$$\gamma_{ij} = 1 - \left| C_{ij} \Big/ \sqrt{C_{ii} C_{ij}} \right|, \tag{7}$$

where correlation C_{ij} between x_k^i and x_k^j is :

$$C_{ij} = 1/L \sum_k \left(x_k^i - A_i\right)\left(x_k^j - A_j\right) \tag{8}$$

and A_i is average of x_k^i :

$$A_i = 1/L\sum_k x_k^i \tag{9}$$

The dissimilarity value γ_{ij} will lie between 0 and 1. For uncorrelated pair, $C_{ij} = 0$ and $\gamma_{ij} = 1$, while $\gamma_{ij} = 0$ for identical x_k^i and x_k^j. Stronger correlation between x_k^i and x_k^j results a lower value of γ_{ij}. By comparing the dissimilarity value of the signal with a reference signal, short shot monitoring can be achieved. Experiments and results will be shown later.

3.3 Parameter Resetting using Support Vector Machine (SVM) and Virtual Search Method (VSM)

3.3.1 Background

Support vector machines (SVM) was first introduced by Vapnik [38] and further investigated by many others [39-40]. It is an important new methodology for nonlinear system modeling. While classical Artificial Neural Network (ANN) approaches suffer from problems like trapping in the local minima and being sensitive to the number of hidden units [41], SVM uses convex optimization to determine the parameters of a pre-determined nonlinear model and is sometime more robust. According to literatures, SVMs have been widely adopted for regression analysis [42]. Recently, a new algorithm, called the Least Squares SVM (referred to LS-SVM) is proposed [40]. LS-SVM formulation works with equality instead of inequality constraints and a Sum of Squared Error (SSE) cost function similar to the one used in classical ANN. It greatly simplifies the problem since its solution can be found by linearization. More precisely, it solves the problem by iteration and in each iteration, it solves a Karush–Kuhn–Tucker

(KKT) system, which takes a similar form as a linear system.

3.3.2 Support Vector Regression

In regression modeling, the goal is to find an unknown function based on a finite set of observations: $\{\boldsymbol{x}_i, y_i\}$, $i = 1, 2, \ldots, N$; where, the input is d-dimensional, $\boldsymbol{x}_i \in \mathbf{R}^d$ and the output is one-dimensional $y \in \mathbf{R}$. For SVM regression (referred to as SVR), the input, $\boldsymbol{x}$, is first mapped onto an m-dimensional feature space using a nonlinear mapping ($m > d$), and then a linear model is constructed in the feature space. This procedure is shown in Figure 3-8. Using mathematical notation, the linear model in the feature space is given by:

$$y = \boldsymbol{w}^T \varphi(\boldsymbol{x}) + b \tag{10}$$

where, $\varphi(\boldsymbol{x})$ denotes a set of nonlinear transformations, which maps the input space into the feature space; $\boldsymbol{w}$ is the weighting vector in the primal space; and b is the "bias".

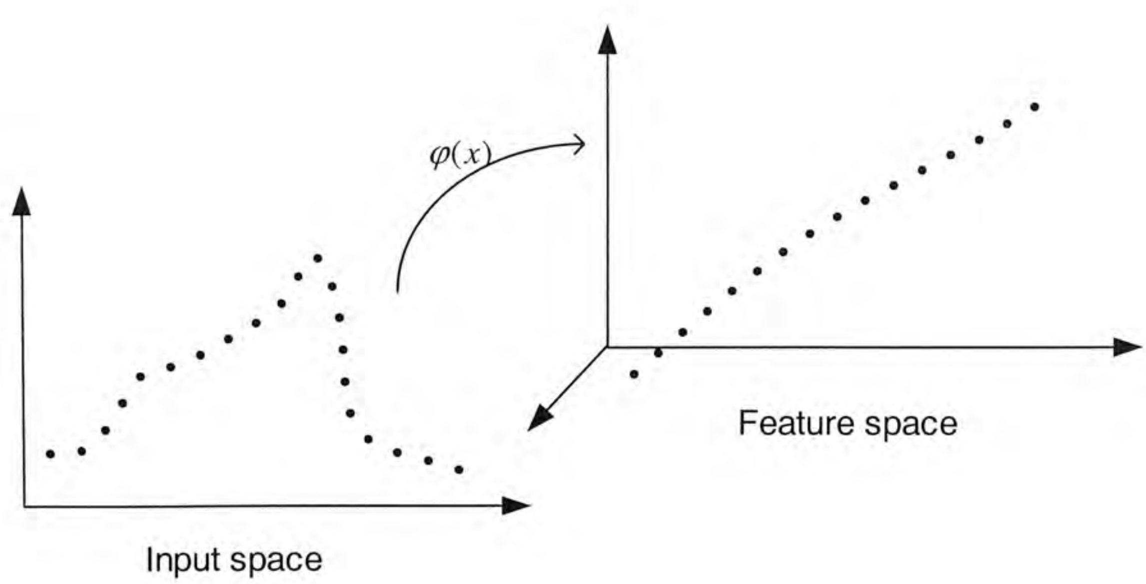

Fig.3-8: Illustration of the transformation from the input space to the feature space by means of a nonlinear transformation ($d = 2$; $m = 3$).

With the Least Square Support Vector Regression (LS-SVR), the transformation can be found by solving the optimization problem below:

$$\min_{w,b,e} J(w,e) = \frac{1}{2} w^T w + \frac{1}{2} C \sum_{k=1}^{N} e_k^2 \tag{11}$$

where, J is the cost function, which consists of a Sum of Square Error (*SSE*) term and a regularization term controlled by a positive real number C; and e_k is error defined below:

$$e_k = y_k - \mathbf{w}^T \varphi(\mathbf{x}_k) + b, \ \ k = 1, 2, \ldots, N$$

It should be pointed out that the weighting vector, $\mathbf{w}$, can be in very high dimension, which makes the calculation of Equation (11) very difficult. To solve this problem, one can compute the model in a dual space instead of the primal space. Define the Lagrangian:

$$L(w,b,e,\alpha) = J(w,e) - \sum_{k=1}^{N} \alpha_k \left\{ w^T \varphi(x_k) + b + e_k - y_k \right\} \tag{12}$$

where, $a_k \in \mathbf{R}$ is the Lagrange multipliers, also called the support vector. Accordingly, the necessary conditions for optimality are:

$$\frac{\partial L}{\partial w}=0;\ \frac{\partial L}{\partial b}=0;\ \frac{\partial L}{\partial e}=0;\ \text{and}\ \frac{\partial L}{\partial \alpha}=0;$$

Or:

$$\begin{cases} w=\sum_{k=1}^{N}\alpha_k\varphi(x_k) \\ \sum_{k=1}^{N}\alpha_k=0 \\ \alpha_k=Ce_k \\ w^T\varphi(x_k)+b+e_k-y_k=0 \end{cases}, k=1, 2, \ldots, N \tag{13}$$

Note that this is a set of *linear* equations. Eliminating $\boldsymbol{w}$ and e, one can then find $\boldsymbol{\alpha}$ = $\{\alpha_k\}$ and b. Furthermore, choose a kernel function, $K(\cdot, \cdot)$, which meets the Mercer's condition:

$$K(x_k, x_l)=\varphi(x_k)^T\varphi(x_l),\ k, l=1, 2, \ldots, N \tag{14}$$

It results in the LS-SVR model:

$$y(x)=\sum_{k=1}^{N}\alpha_k K(x_k, x_l)+b \tag{15}$$

Comparing (10) and (15), it is seen that LS-SVR changes a primal problem to a dual problem by using support vectors as is shown in Figure 3-9: Figure 3-9(a) shows the primal problem, which requires excessive computation and could suffer from problems like local minima. Figure 3-9(b) shows the dual problem, in which one only needs to solve a set of linear equations to find the support vector, and hence, is much easier. This is an important difference to the traditional ANN methods.

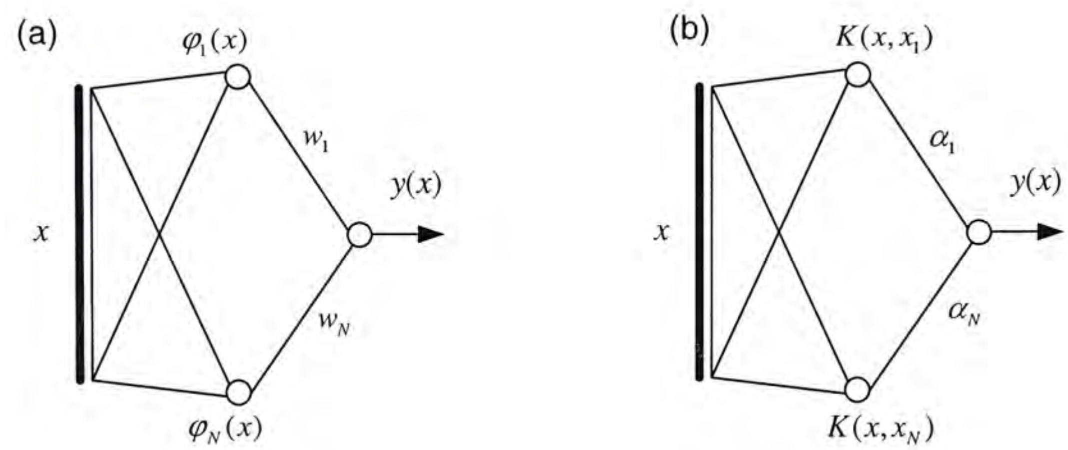

Fig.3-9: From the primal problem to the dual problem.

3.3.3 SVM Parameters Resetting using Virtual Search Method (VSM)

It is no doubt that Support Vector Machine has its own advantages in dueling with the parameters selection problem. However, to further improve the system performance and efficiency, another technology called Virtual Search Method (VSM) was introduced. Virtual Search Method was first introduced by Robert et al. [43], which is an iterative method for automatic tuning of the molding process by on-line developing a 'virtual' model of the process as the basis of search for the appropriate inputs. VSM resorts to the physical process only when it has exhausted the virtual search, in our case, the virtual model was the Support Vector Machine. In fact, relying on direct process feedback can be costly, as many scraps may be produced before the process is tuned. Therefore, it will be an advantage to use VSM as virtual tuning before the best suggested settings are found.

The system worked as follow: First of all, experimenter chose the settings for the injection molding machine based on his/her own judgment. It was not necessary to care about those settings so much as the system would tune them into correct region later. Then, the weight of the first injected part should be measured and input to the system. That's all for the experimenter's part. All the steps after were automatic. Based on the measured weight and the target weight (which should be told to the system), the parameter selection part of the SVR modeling determined the prospective changes to the machine inputs, and suggested a set of new settings. The suggested settings then became the inputs of the SVR weight estimation, and a predicted part weight is given out as the output. If the predicted part weight was within specification, the suggested settings was said to be acceptable and training would be stopped. On the other hand, if the predicted part weight was not within the specification, the SVR model would be updated such that the new settings provided in the next round would be more accurate. This virtual searching was continued until the predicted part weight was within the specification. Finally the suggested settings were found. Figure 3-10 shows the block diagram of the system.

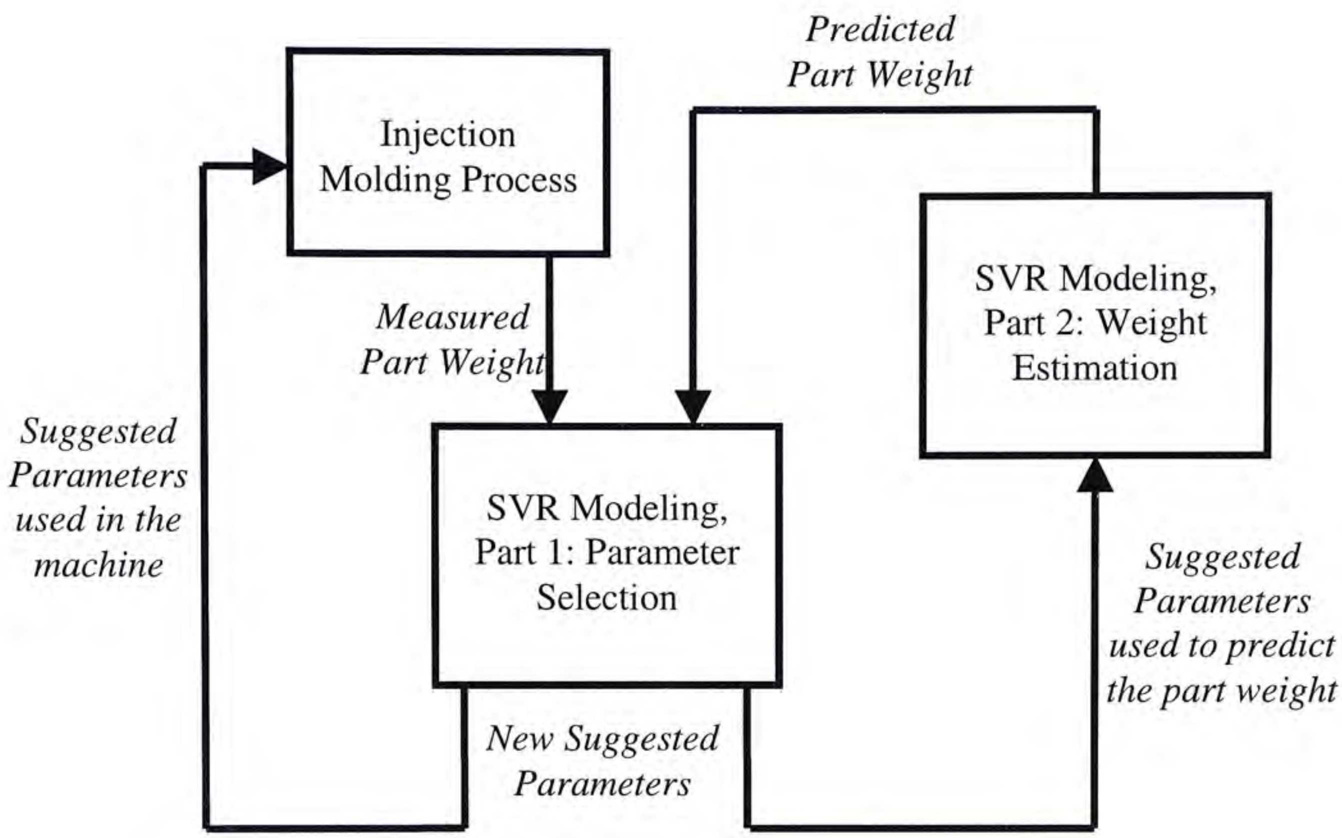

Fig.3-10: Block diagram of the system.

3.4 Experiments and Results

The experiments did in the research were based on the results of Design of Experiment (DOE), which helped to find out the reasonable parameters of the injection molding machine for the experiments conducted. The setups of the experiments were the same and will be describe in the following session.

3.4.1 Introduction to Design of Experiment (DOE)

Design of experiments (DOE) is basically the use of particular patterns of experiments to generate a lot of information about some process while still using an absolute minimum of actual experiments to get the information [44]. Through DOE, people can have detail understanding of the factors in the process and the effects on the output of the process that result from changing those factors, therefore can diagnose the process or provide quality improvement [45-46]. There are many pattern of experiments in DOE, and the mostly basic pattern would be to use ever single possible combination of control parameters and levels. This is called a "full factorial" experiment. For example, if there are 3 factors at two levels each, then there should be 2^3 which is 8 experiments for a full factorial experiment. The advantage of the full factorial experiment is it consider all the possibility of combination of factors, which means all the interactions between factors are analyzed. However, it is sometimes not preferable or even not possible to carry full factorial experiment, try to imagine if there are 8 factors and 3 levels each which will result of 6561 experiments! Experimenter usually tries to avoid using large full-factorial designs, therefore numerous types of "fractional factorials" designs have been development for the DOE. In fractional factorials design, only several sets are selected from all possibilities. The drawback of fractional factorials design is the confounding of interaction effects with main factor effects. Among the fractional factorials designs, the eight-run factorial design is used most.

3.4.2 Set-points selection based on Design of Experiment (DOE)

The injection molding machine used in this study (model no. PYI-50PCIII) was manufactured by PO YUEN (TO'S) MACHINE FTY. LTD. The machine was equipped with PYI-PC(28) control system. This European Design Control System is based on two 16-Bits 80C186 micro-processors. All relevant information can be easily read on the class IP65 oil resistant membrane type Man Machine Interface (MMI). Besides, 30 sets of mould data including 'temperature', 'time', 'speed' and 'pressure' can be stored and retrieved from either RAM memory of from floppy diskette. In the DOE, several signals have been collected from the injection molding machine, they were: Nozzle pressure, Hydraulic pressure, Mold open time, Mold closed time, Injection time and Ram position. For nozzle pressure, it was collected using the Kistler sensor (4083A); hydraulic pressure signal was collected using the Kistler sensor (RAG25A200BV1H); the other signals were collected from the controller of the injection molding machine directly. All the signals collected were passed to the Hioki Memory Hicorder first, then through the LAN to transfer to the computer, sampling frequency was 1 kHz. The plastic material used in this experiment was transparent ABS and the part was two rectangular plates with runners. The experiment set-up is shown in Figure 3-11. In the research, the four factors, nozzle temperature, injection pressure, injection speed and holding pressure were concerned. A standard DOE was accomplished and the results are listed in Table 3-1 and Table 3-2.

Table.3-1: Experiment factors and their ranges.

Variable	A	B	C	D
Name	Nozzle temp.	Injection pressure	Injection speed	Holding pressure
High level (+)	205 °C	98 bar	80%	40
Low level (-)	195 °C	80 bar	55%	5

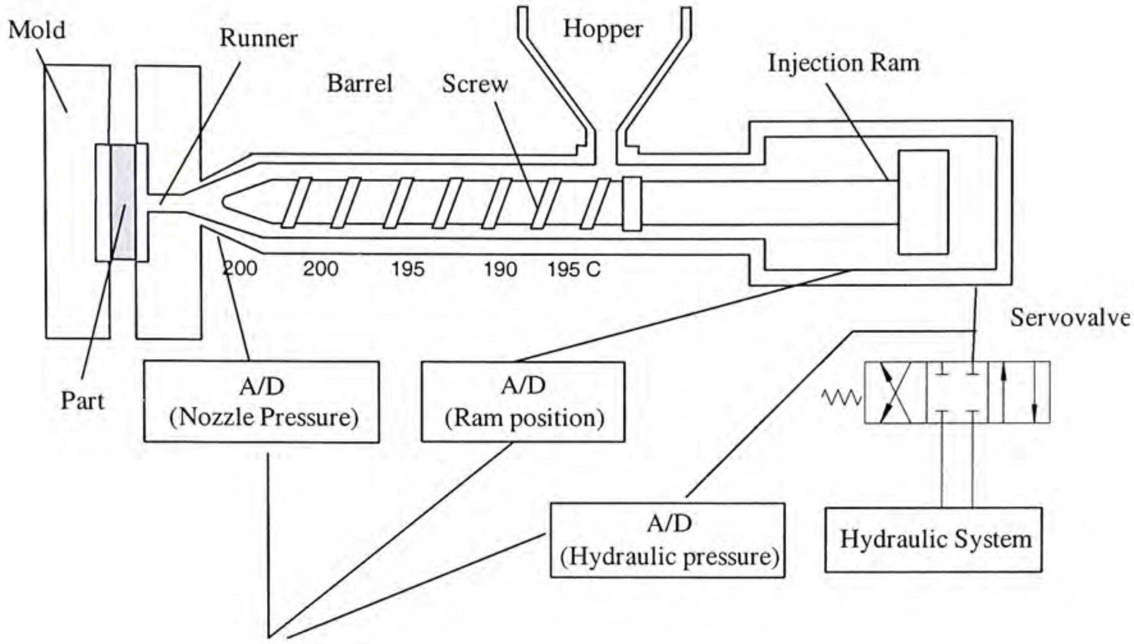

Fig.3-11: The experiment set-up.

Table.3-2: Experimental matrix and the results.

Variables / Run	A	B	A×B	C	A×C	B×C	D	Results (y_i)
1	+	+	+	+	+	+	+	35.5675
2	+	+	+	-	-	-	-	36.1950
3	+	-	-	+	+	-	-	27.4925
4	+	-	-	-	-	+	+	26.5225
5	-	+	-	+	-	+	-	37.0425
6	-	+	-	-	+	-	+	37.8625
7	-	-	+	+	-	-	+	30.8825
8	-	-	+	-	+	+	-	28.1400
I	31.4444	36.6669	32.6963	32.7463	32.2656	31.8181	32.7088	
II	33.4819	28.2594	32.2300	32.1800	32.6606	33.1081	32.2175	
Effect	-2.0375	8.4075	0.4663	0.5662	-0.3950	-1.2900	0.4913	
Effect/2	-1.0188	4.2038	0.2331	0.2831	-0.1975	-0.6450	0.2456	

I: mean of high level ; II: mean of low level

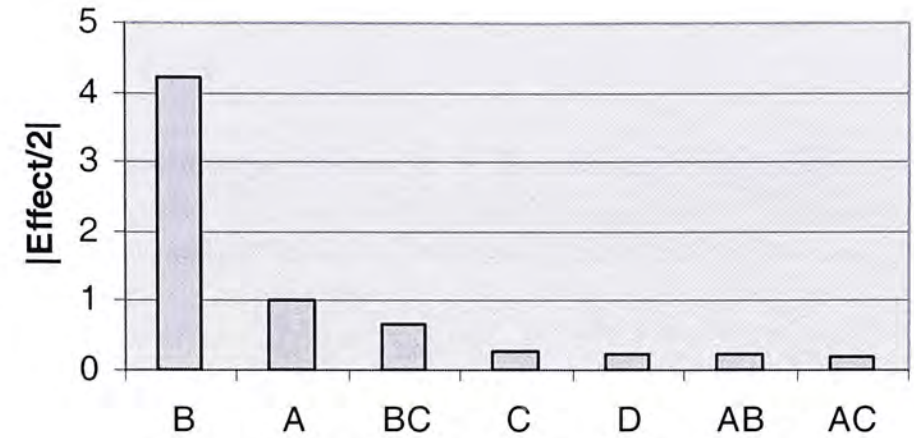

Fig.3-12: Pareto Chart for $|Effect/2|$ values of Half Effects.

From the Figure 3-12, it was found that factors A, B and interaction of BC were more important than the other factors or interactions. Thus, a prediction equation was constructed using A, B and BC as inputs. The prediction equation is given:

$$\hat{y} = \bar{y} + \left(\frac{\Delta_A}{2}\right)A + \left(\frac{\Delta_B}{2}\right)B + \left(\frac{\Delta_{BC}}{2}\right)BC \tag{16}$$

where, $\hat{y}$ = the predicted value; $\bar{y}$ = the average of all results got from the experiment; $\frac{\Delta_A}{2}$ = half effect for factor A; $\frac{\Delta_B}{2}$ = half effect for factor B; $\frac{\Delta_{BC}}{2}$ = half effect for BC interaction. Notes: (a) Only the important effects were included in the prediction equation; (b) The equation can only apply to orthogonally-coded factor settings for 2-level designs.

Based on the experiments, the prediction equation can be written as:

$$\hat{y} = 32.4631 - (1.0188)A + (4.2038)B - (0.6450)BC \tag{17}$$

Compare the estimated values with the actual results from experiments, as shown in Table 3-3, the performance of the prediction equation was acceptable.

Table.3-3: Compare predict value with experiment value.

	Predict value	Experiment value	Percent error (%)
Run.1	35.0031	35.5675	1.5868
Run.2	36.2931	36.195	0.2710
Run.3	27.8855	27.4925	1.4295
Run.4	26.5955	26.5225	0.2752
Run.5	37.0407	37.0425	0.0049
Run.6	38.3307	37.8625	1.2366
Run.7	29.9231	30.8825	3.1066
Run.8	28.6331	28.1400	1.7523

Part weight can be predicted using the above prediction equation with the settings other than those in the experiments; the only restriction is that the settings should be within the range of the settings in the experiment. For example, the nozzle temperature can be used at any value between 195 to 205 ^{o}C in the prediction equation, but not outside this range.

Several experiments have been done using the predicted values from the equation, however, the results was not good. To improve the results, another DOE was done and this time with a smaller ranges for the factors. The DOE settings and results are shown in Table 3-4 and Table 3-5 respectively.

Table.3-4: Experiment factors and their ranges.

Variable	A	B	C	D
Name	Nozzle temp.	Injection pressure	Injection speed	Holding pressure
High level (+)	202 ºC	90 bar	75%	35
Low level (-)	198 ºC	82 bar	60%	15

Table.3-5: Experimental matrix and the results.

Variables / Trail	A	B	A×B	C	A×C	B×C	D	Results (y_i)
1	+	+	+	+	+	+	+	35.4
2	+	+	+	-	-	-	-	35.5975
3	+	-	-	+	+	-	-	33.4125
4	+	-	-	-	-	+	+	33.26
5	-	+	-	+	-	+	-	35.0075
6	-	+	-	-	+	-	+	34.7775
7	-	-	+	+	-	-	+	33.33
8	-	-	+	-	+	+	-	32.64
I	34.4175	35.1956	34.2419	34.2875	34.0575	34.0769	34.1919	
II	33.9387	33.1606	34.1144	34.0688	34.2987	34.2794	34.1644	
Effect	0.4787	2.0350	0.1275	0.2187	-0.2412	-0.2025	0.0275	
Effect/2	0.2394	1.0175	0.0637	0.1094	-0.1206	-0.1013	0.0137	

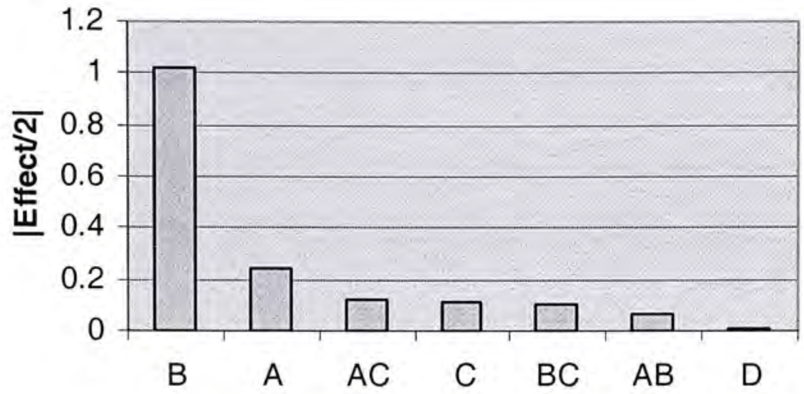

Fig.3-13: Pareto Chart for $|Effect/2|$ values of Half Effects.

The effect factors analysis is plotted in Figure 3-13. From Figure 3-13, factors A, B were found to be more important to the part weight than the other factors or interactions. Thus, the prediction equation can be written as:

$$\hat{y} = 34.1781 + (0.2394)A + (1.0175)B \tag{18}$$

Several experiments have been done to test the performance of the prediction equation and the results have been improved. Therefore, the prediction equation was used to determine the set-points for the production of part.

3.4.3 Nozzle pressure estimation

50 parts were produced using the experiment setups described in the last session. The machine set-points were chosen based on the DOE results (Appendix A). 50 sets of data (included the hydraulic pressure, nozzle pressure, ram position and part weight) were recorded using the sensors in the injection molding machine. The data were used

to train and test the RBFNN. First, only hydraulic pressure was employed to estimate the nozzle pressure, the input of the hybrid RBFNN contained $p(t)$ and its delay $p(t+1)$, the out was $p_n(t)$. One set of data (i.e. hydraulic pressure and nozzle) from the experiment was used as the training data of the network. After training the RBF neural network, the result was shown in Figure 3-14.

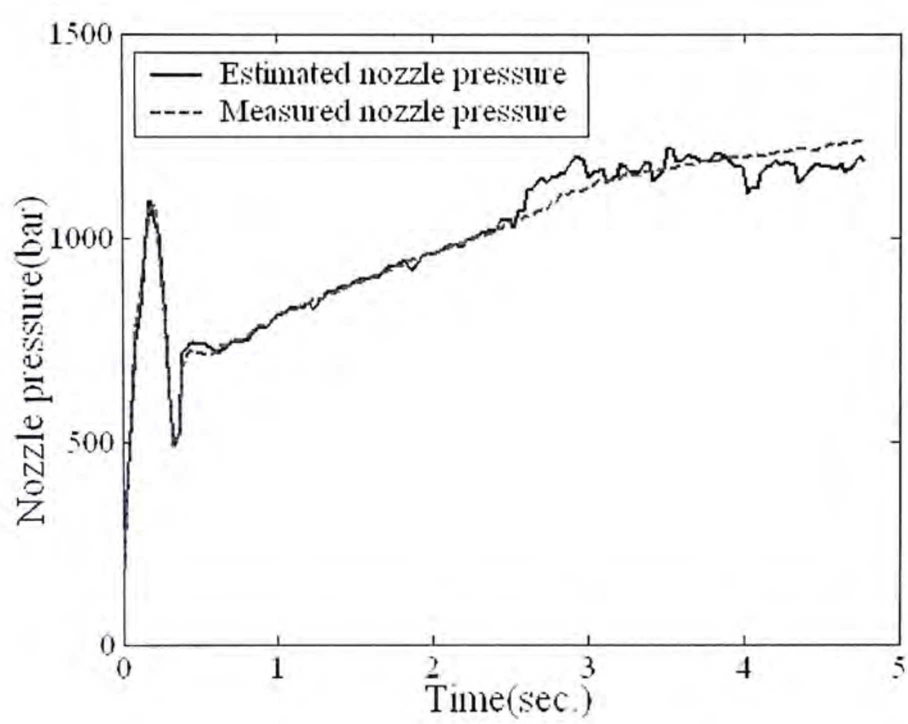

Fig.3-14: Estimated nozzle pressure using RBF (exp.11).

The result was pleased as the estimated nozzle pressure could follow the original nozzle pressure signal well except the part at the later portion. Therefore, the hybrid RBFNN was developed and could be used to estimate the nozzle pressure of the injection molding machine using the hydraulic pressure signal obtained from the experiment. It has been mentioned that the parameters of the injection molding machine were kept the same during the experiments; however, it didn't mean that all the experiment results were conformed or very similar. Actually the results were quite different to each others, thus, the neural network must be checked to verify whether it could work well or not. Some typical results were chosen and shown in the Figures 3-15 and 3-16.

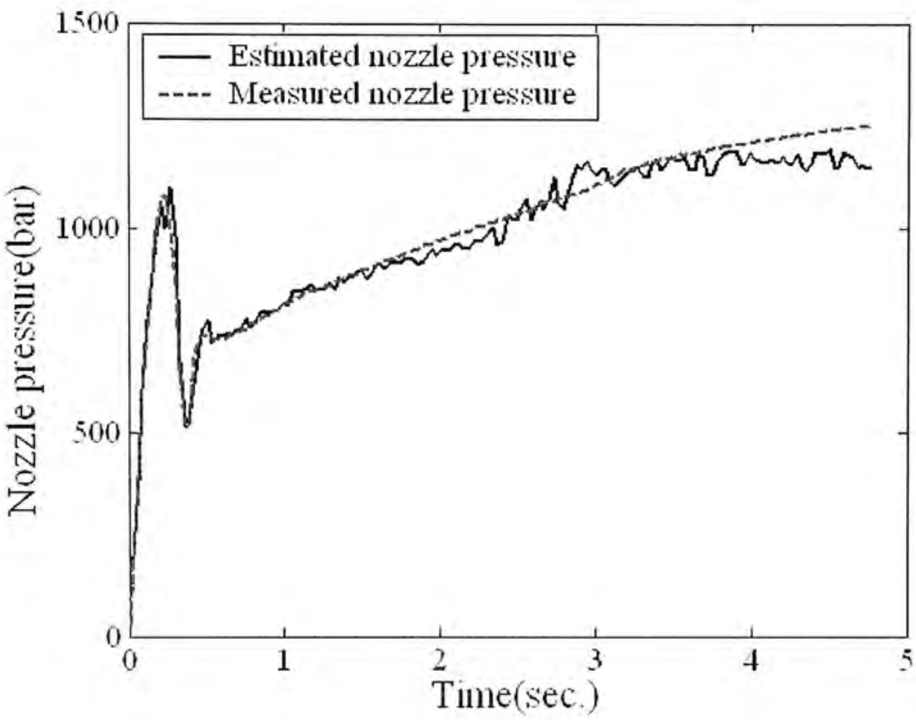

Fig.3-15: Estimated nozzle pressure using RBF (exp.18).

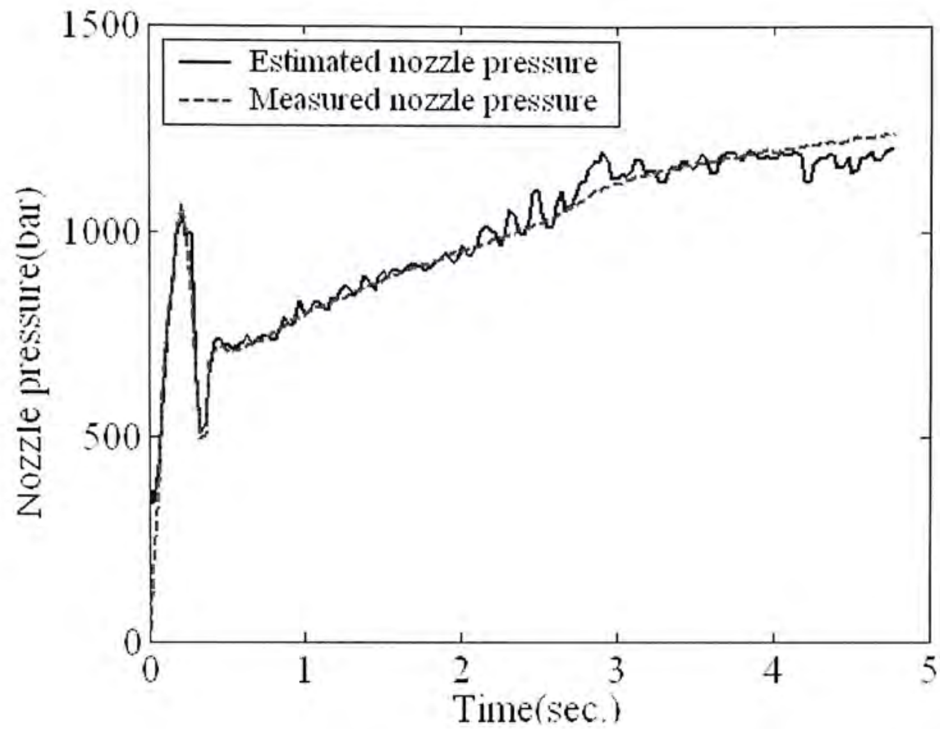

Fig.3-16: Estimated nozzle pressure using RBF (exp.22).

In Figure 3-15, the estimated nozzle pressure could follow the measured nozzle pressure, however, it was not smooth enough. Moreover, the peak value in the measured nozzle pressure curve could not be reflected accurately. Also, the estimated nozzle pressure curve was flat at the later portion, where it should be increased. In Figure 3-16, the peak value of the measured nozzle pressure still could not be reflected accurately, and the starting point of the estimated nozzle pressure was failed to match with the actual value. The later portion was increasing but still could not follow the measured nozzle pressure. From the figures, all the estimated nozzle pressures could follow the original nozzle pressures well except at the later portion. The major features of the original curve were saved and could be reflected from the estimated nozzle pressure. The RBFNN could estimate the nozzle pressure well except the part at the later portion. This might because the hydraulic pressure was not sensitive enough to estimate the later portion of the nozzle pressure. A comparison of the nozzle pressure and hydraulic pressure was shown in Figure 3-17, as the signal of the hydraulic pressure at the later portion was nearly horizontal, it was difficult for the hydraulic pressure to reflect the incline part of the nozzle pressure. To solve this problem, ram position was introduced to train the network together with the hydraulic pressure in order to improve the result. It is easy to imagine that ram position (or ram velocity) is highly related to the nozzle pressure. During the injection period, melt is injected into the mold through the nozzle, the faster the advance of the ram, the faster the melt go into the mold and thus the higher the nozzle pressure. On the other hand, if the ram moves with a slower speed, the melt will go into the mold at a slower speed and results a lower nozzle pressure. Therefore, using ram position and hydraulic pressure as standard to estimate nozzle pressure is better than using hydraulic pressure alone. The new improved network was used to test with the same set of data, the result was shown in Figure 3-18 and 3-19.

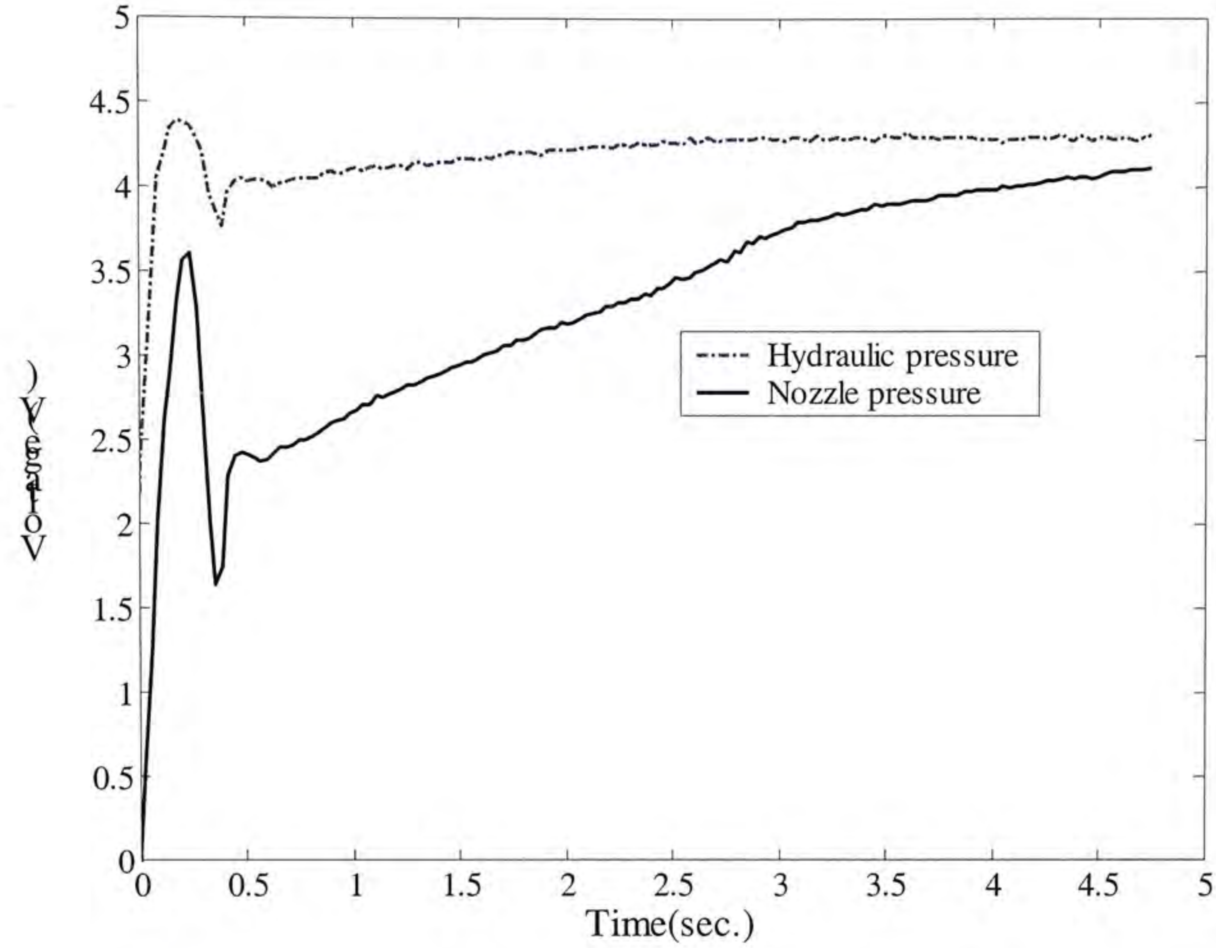

Fig.3-17: Comparison of hydraulic pressure and nozzle pressure.

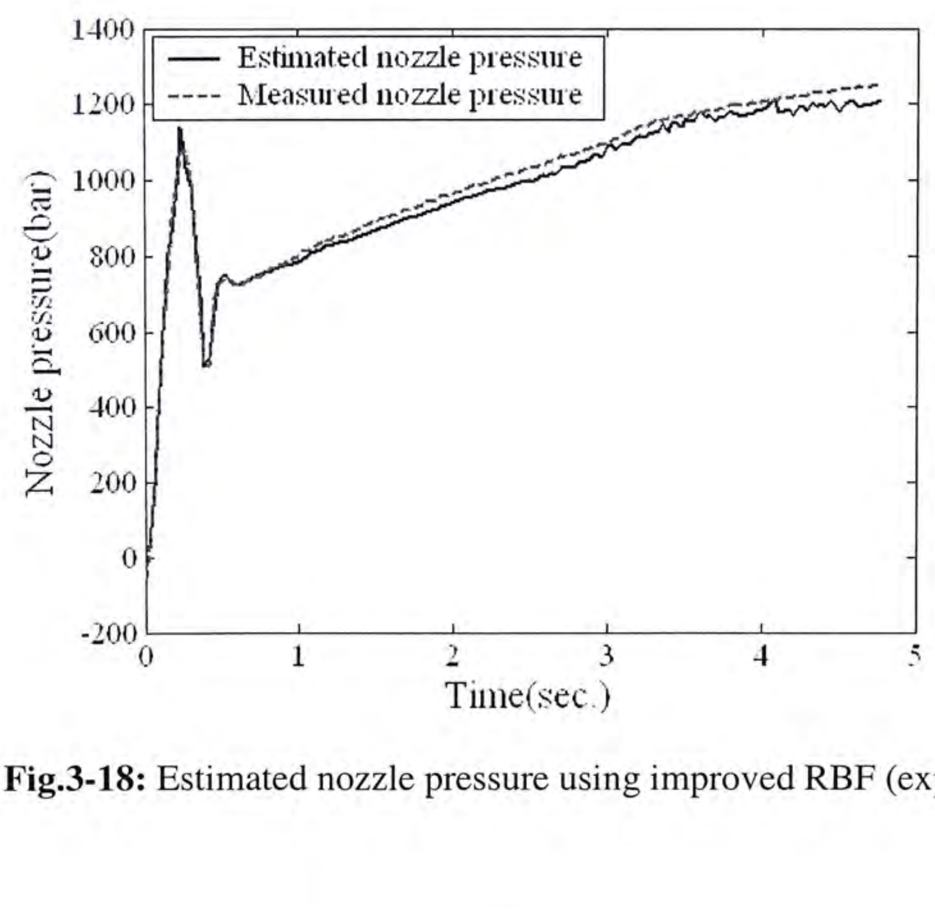

Fig.3-18: Estimated nozzle pressure using improved RBF (exp.18).

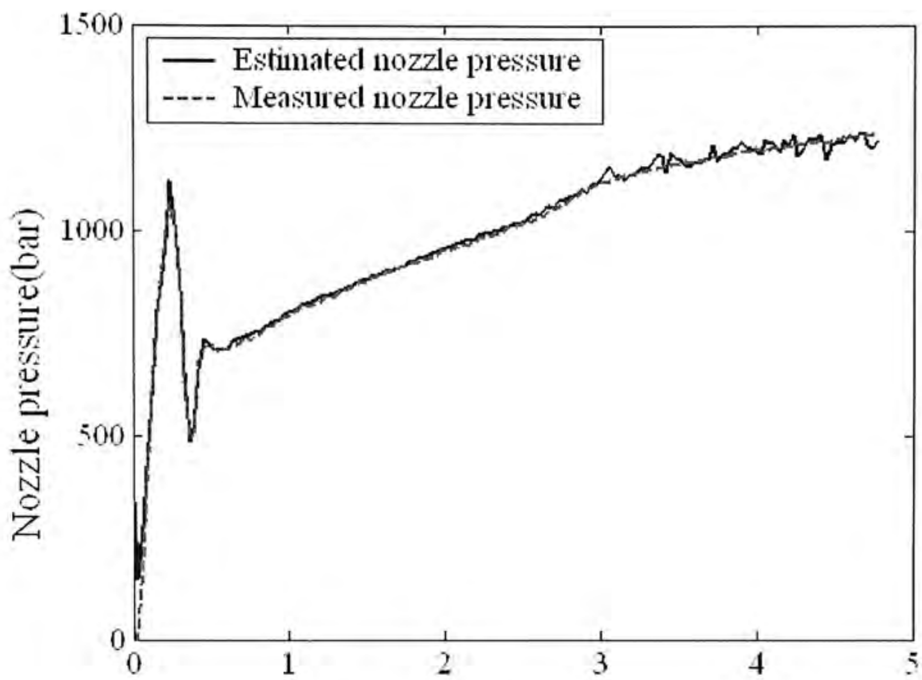

Fig.3-19: Estimated nozzle pressure using improved RBF (exp.22).

In Figure 3-18, the estimated nozzle pressure followed the measured nozzle pressure very well, all the turning points of the measured nozzle pressure curve were correctly reflected in the estimated nozzle pressure curve. In Figure 3-19, although the starting point was still not matched with the measured nozzle pressure, it was closer than in Figure 3-16. Furthermore, the later portion of the estimated nozzle pressure curve was increasing as the measured nozzle pressure. Comparing with the previous result, estimate nozzle pressure using ram position and hydraulic pressure as inputs gave a better result. Especially for the turning points and the later portion of the nozzle pressure curve, the result was greatly improved. Before using the estimated nozzle pressure, it was important to verify the estimated nozzle pressure was reasonable and acceptable to be used. This can be done by finding out the mean squared error between the estimated and actual nozzle pressure. The results were shown in Figure 3-20.

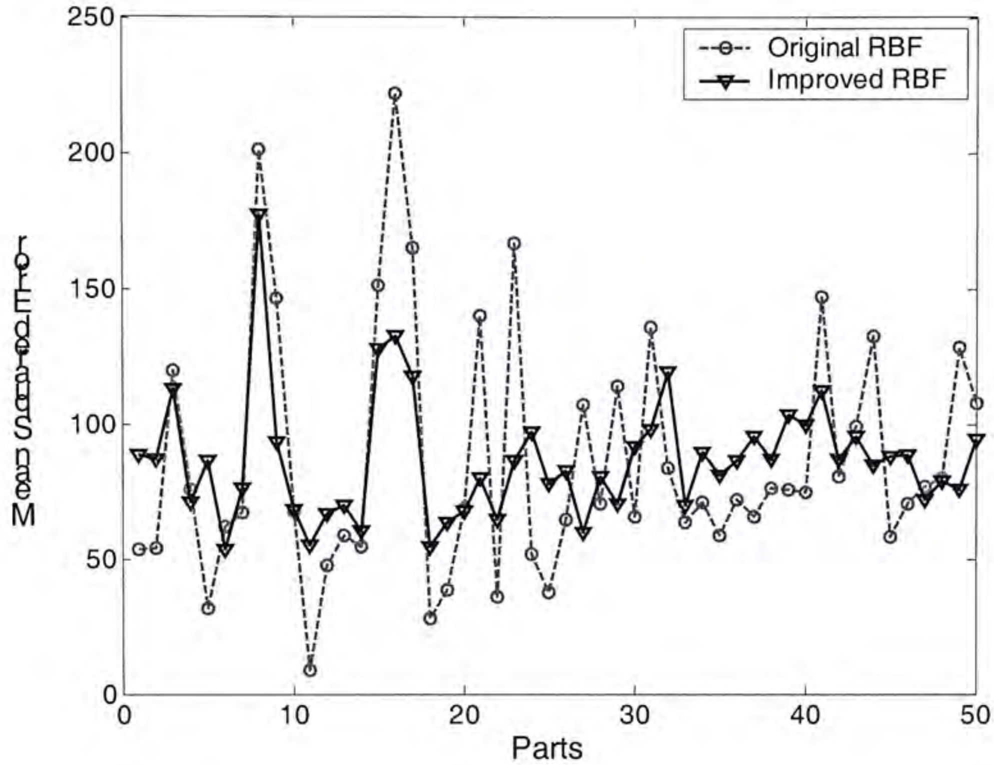

Fig.3-20: Compare MSE of two RBF networks.

The mean squared error for the improved results was smaller than the non-improved results. From Figure 3-20, it can be seen that most of the estimated nozzle pressure had a mean squared error smaller than 100 bar, which was less than 8% of the actual nozzle pressure (about 1300 bar). The errors were small enough for the estimated nozzle pressure of the RBF system to be used without any confuses.

3.4.4 Part weight prediction using the One Step Method

In order to test the performance of the one step methods, an experiment was accomplished. In the experiment, a sample of 60 parts were produced (using the machine settings obtained from DOE, results are shown in Appendix B) and examined in details, among which 30 of them were used as the training inputs for the RBFANN and the other 30 were used to test the performance. Figure 3-21 compares the measured part weight and the predicted part weight by the one step method while Figure 3-22 shows the root mean squared error of the predicted part weight.

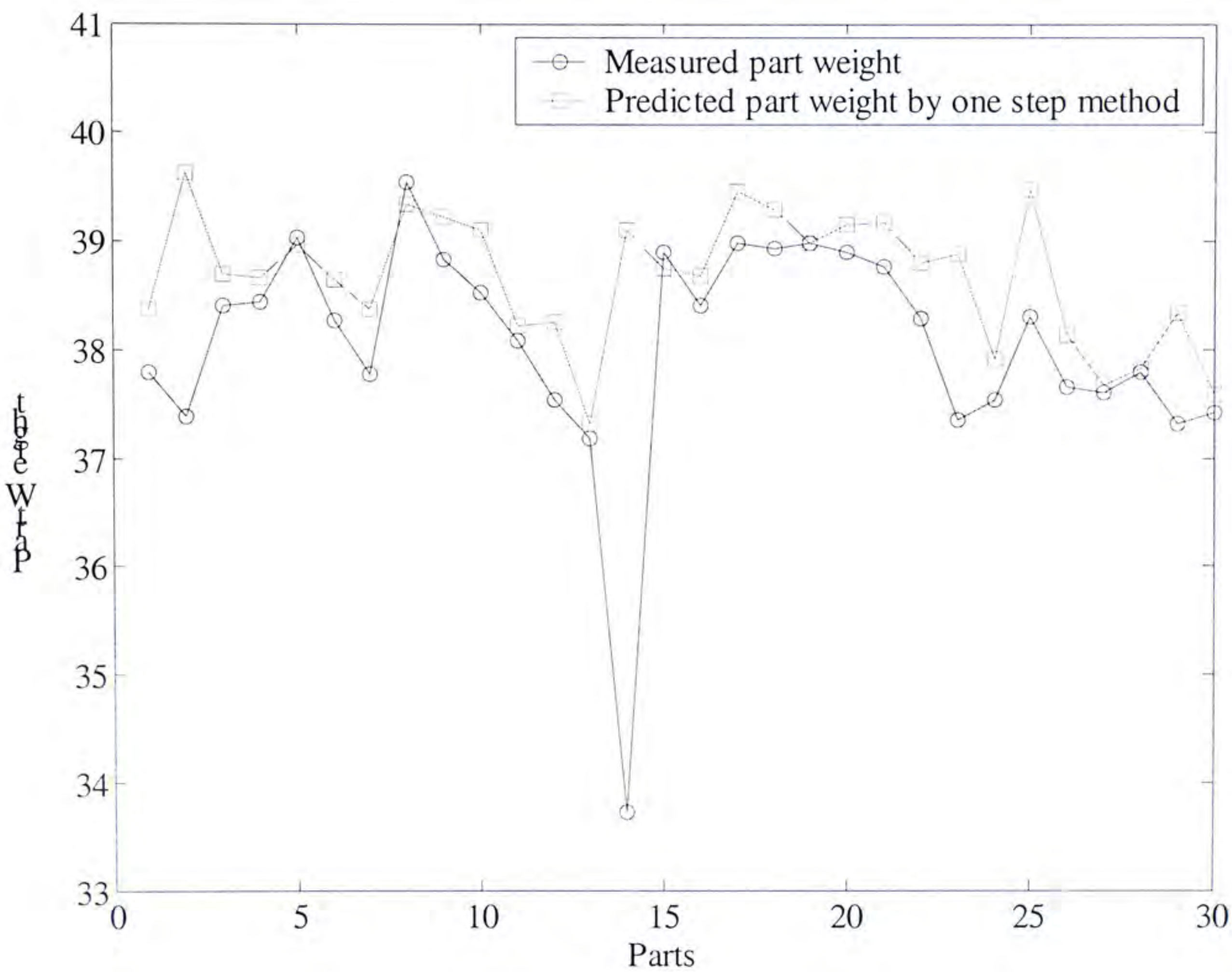

Fig.3-21: Compare measured part weights and predicted part weights by one step method.

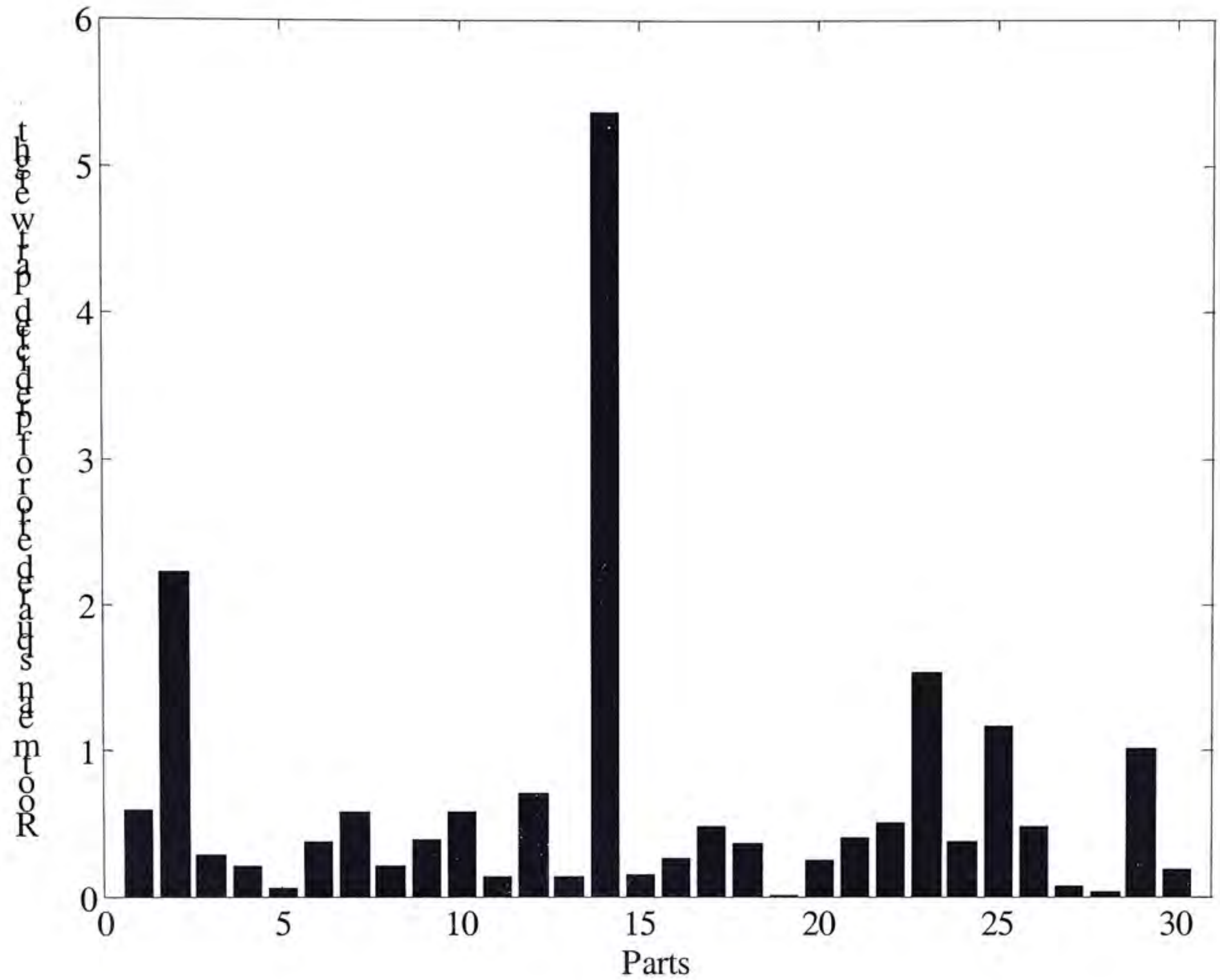

Fig.3-22: Root mean squared errors of predicted part weight by one step method.

From the figures, it can be shown that most of the predicted part weights were closed to the measured part weights and hading an average root mean squared error of 0.64. The greatest error happened in part 14. It was expectable because experiment 14 corresponded to an abnormal part which means it exceeded the nominal value, thus the predicted weight would have a larger root mean squared error.

3.4.5 Similarity Monitoring using estimated nozzle pressure

To test the performance of the similarity monitoring method, an experiment was conducted. In this experiment, the injection molding machine was set based on the DOE results. It is well known that injection pressure and holding pressure is highly related to the quality of part. Nozzle pressure is an excellent reflector for the injection and holding pressure thus can be used to control the quality of part. In the experiment, nozzle pressure during the injection phase was estimated using hydraulic pressure and ram position. With the estimated nozzle pressure, a monitoring system was built for the injection molding machine. 50 parts were produced with the same machine conditions, however, they were not identical (Results are shown in Appendix C). Some were bad in quality and some were good. A simple way to determine the quality of part is the part weight. The lighter the part is, the worse the part quality maybe. Weight can simply find out using an electronic compact balance. As the weights of the 50 parts were different, the nozzle pressures signals were therefore not the same. Once a reference nozzle pressure was found (i.e. typical result that corresponded to good quality), different of nozzle pressure can be found using similarity and as a result, quality of parts can be estimated.

In the similarity method, a reference should be given in order to calculate the dissimilarity and this is the trickiest point of the method. The result is very depended on the reference chosen. If the reference chose is an abnormal result, the dissimilarity results may reflect the normal results and vase verus. Figures 3-23~27 show the different.

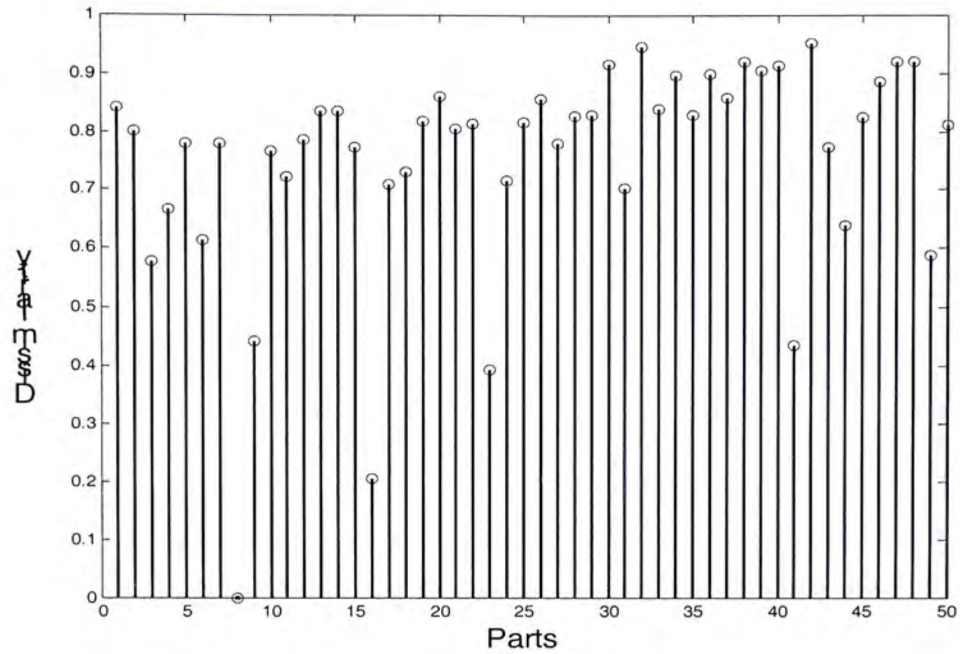

Fig.3-23: Dissimilarity results using exp.8 as reference.

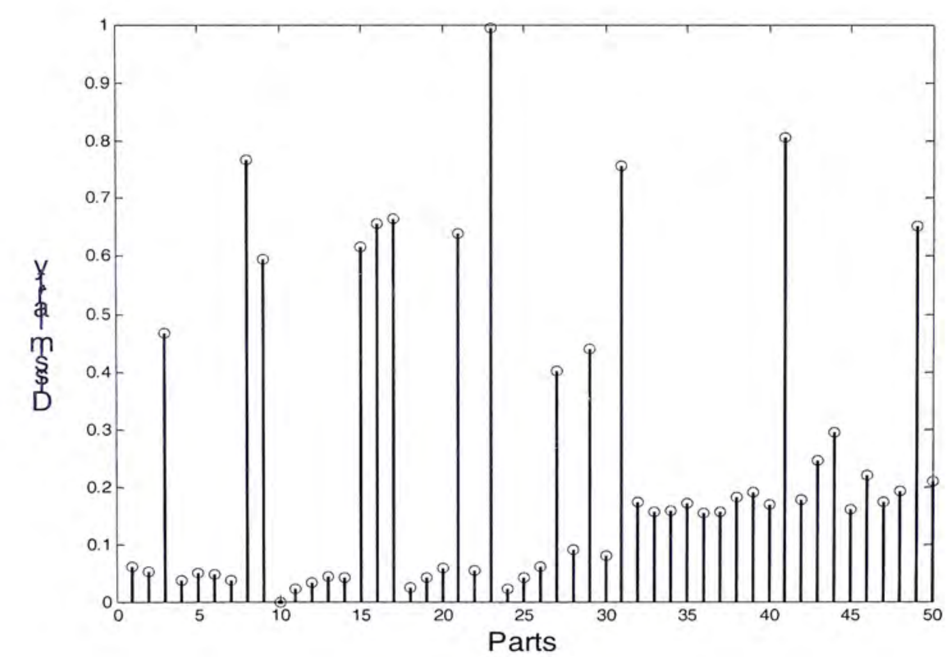

Fig.3-24: Dissimilarity results using exp.10 as reference.

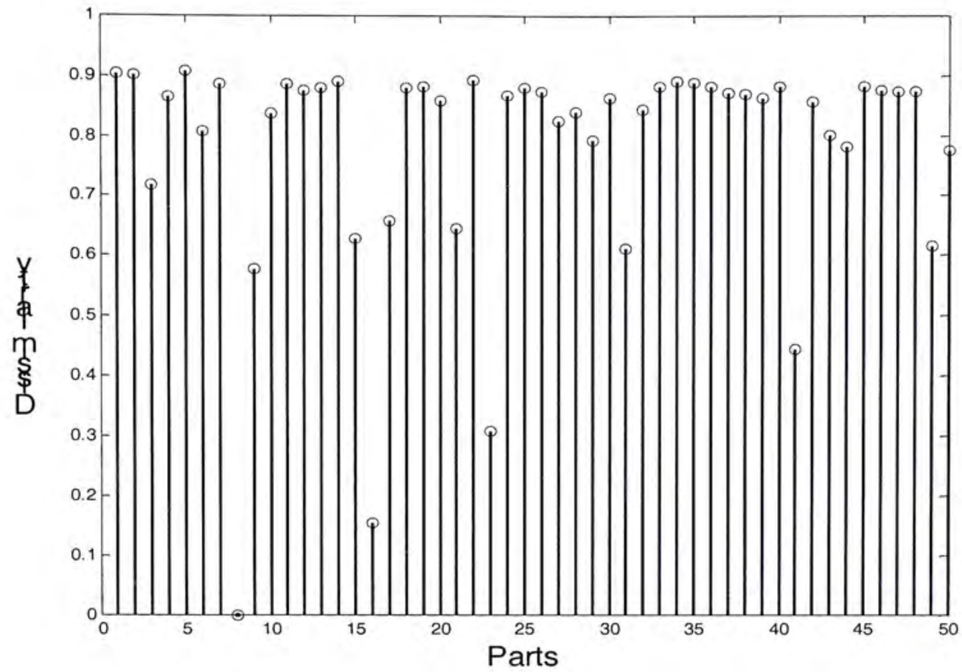

Fig.3-25: Dissimilarity results using exp.29 as reference.

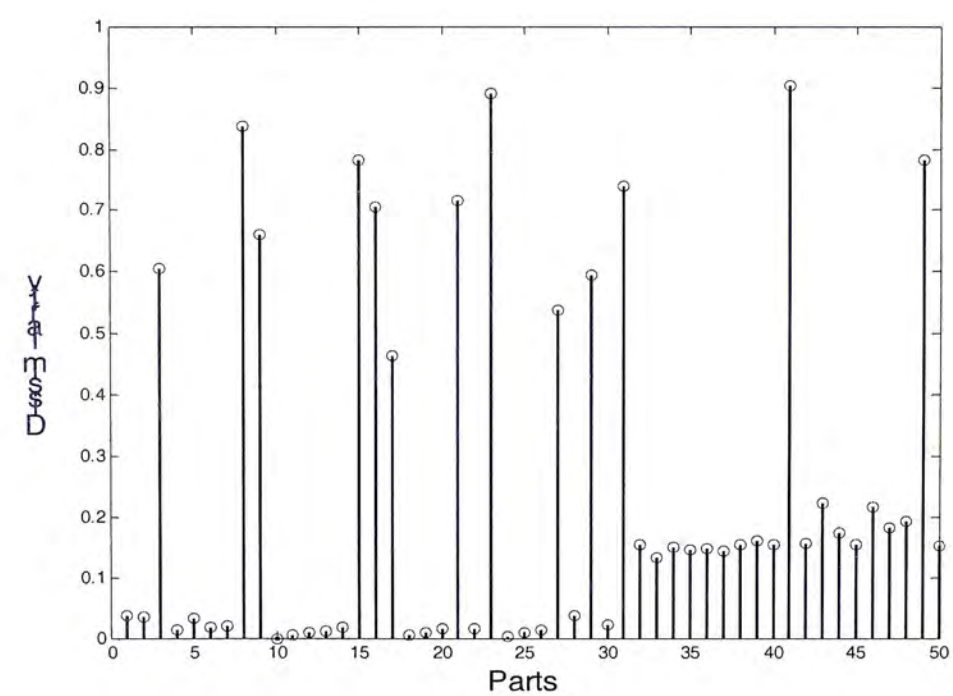

Fig.3-26: Dissimilarity results using exp.32 as reference.

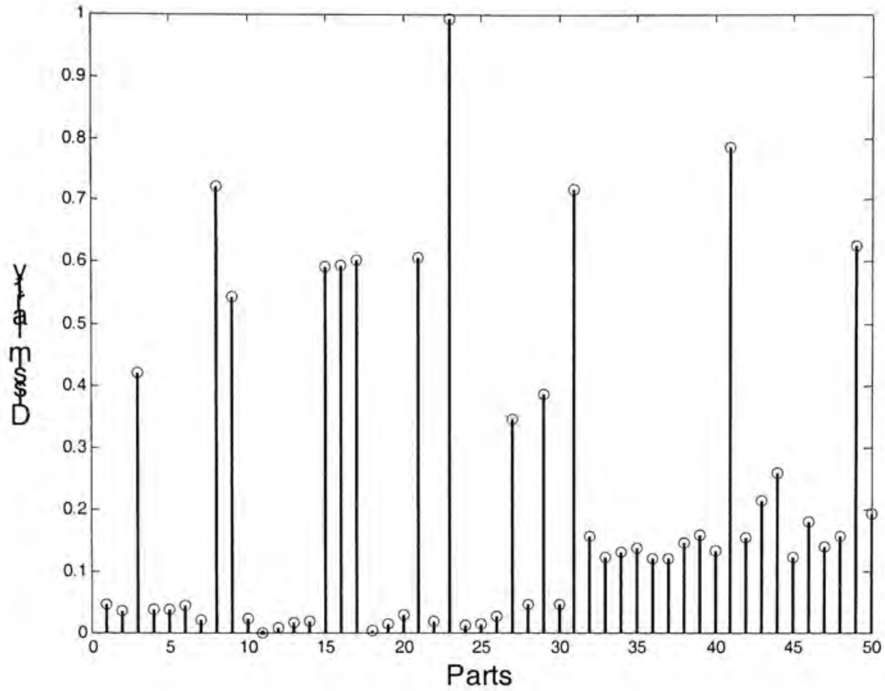

Fig.3-27: Dissimilarity results using exp.11 as reference.

The lines with larger dissimilarity values were considered as bad products. From Figure 3-27, they were part 3, 8, 9, 15, 16, 17, 21, 23, 27, 29, 31, 41 and 49. Compare with the experiment results, part 3, 8, 9, 16, 17, 23, 31, 41 and 49 are diagnosed as bad products correctly. Thus part 15, 21 27 and 29 are diagnosed wrongly. Part 10 was a bad product that hasn't been diagnosed by the system. For experiments 4, 6, 24, 43, 44, 49 and 50, they were all corresponding to the same kind of problem which only half of the part was filled incomplete and the system was failed to diagnose (only experiments 31 and 49 were right). Except for the problem of "half of the part had short shot", the monitoring method functioned correctly for 7 cases out of 8 cases plus 4 false diagnosed. For comparison purpose, dissimilarity was done once using the actual nozzle pressure got from the experiments; the result showed that the different between estimate and actual nozzle pressure was small. Therefore the proposed monitoring method satisfies the requirement. In the above testing, the diagnosis system gave out bad results for the parts that were *Half*. *Half* means that one side of the part is short shot while the other side are normal (Figure 3-28). With this kind of problem, the short shot is usually very small, this small different is very difficult to reflect from the estimated nozzle pressure. That is why the monitoring method failed to diagnose this kind of problem.

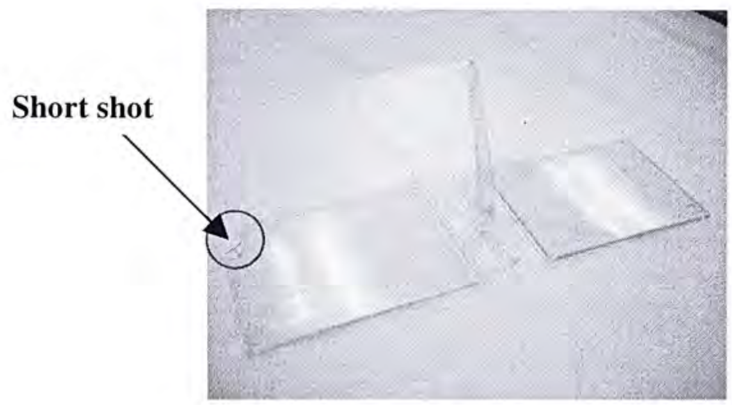

Fig.3-28: Problem of *Half* in part.

3.4.6 Similarity Monitoring using ram position

Similar to nozzle pressure, ram position is sensitive to the quality of part. In Figure 3-29, the ram positions curves with dash-dot lines corresponding to bad parts, where the blue curves corresponding to good parts. The curve of dot line is the "separating curve" that separating the region of bad and good parts. Therefore, if a suitable reference is chosen to act as the "separating curve", ram position can be used to monitoring the quality of parts. As the curve of good part should be under the "separating curve", and vice versa, monitoring can be done by considering the area under the curve of screw position.

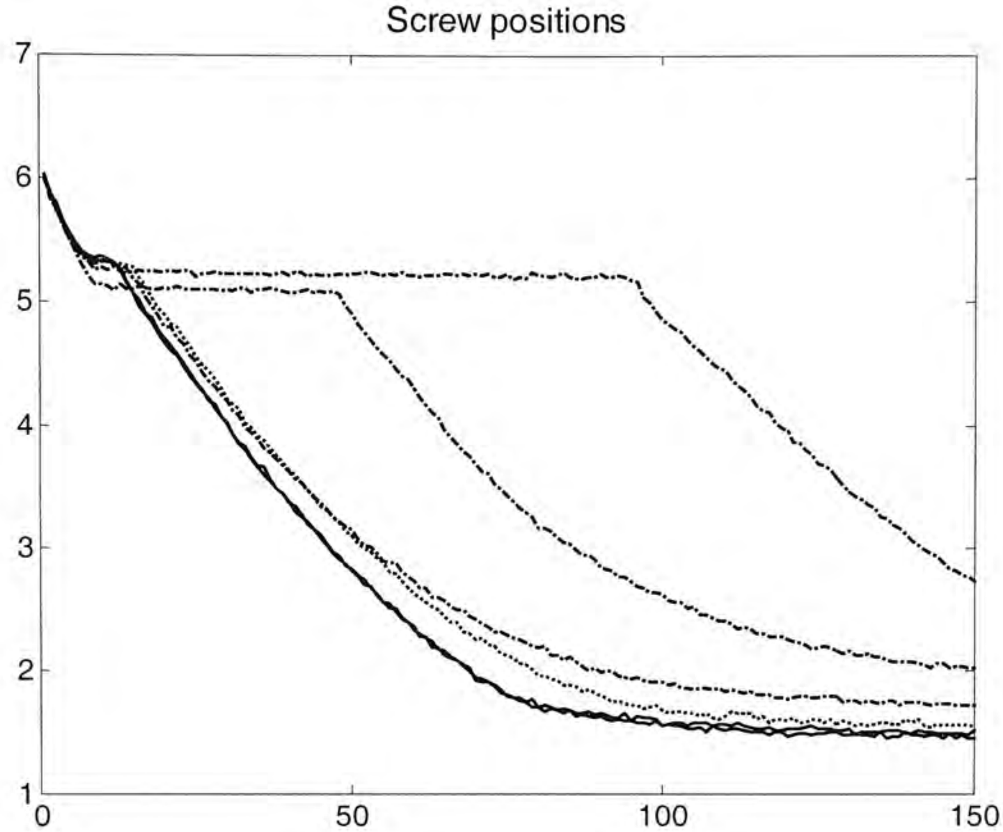

Fig.3-29: Compare ram position curves.

The area under screw position curve, $A(x)$, can be calculated by:

$$A(x) = \int_0^p f(x)dx \tag{19}$$

where $f(x)$ is the function of ram position; p is the number of data points.

The similarity equation is given by (20):

$$S_i(x) = A_i(x) - A_{ref}(x) \tag{20}$$

where $S_i(x)$ is the similarity value of the ***i***th ram position;

$A_i(x)$ is the area of the ***i***th ram position;

$A_{ref}(x)$ is the area of the reference ram position.

If $S_i(x) < 0$, the part is considered as good; if $S_i(x) > 0$, the part is considered as bad.

To compare the result between monitoring using ram position and nozzle pressure, test was done for the ram position system using the same sets of data as the nozzle pressure system. As the conditions of the injection molding machine changed continuously, the 50 experiment data were separated into two groups and two different references were chosen to obtain better results. Figure 3-30 and 3-31 show the similarity values got from the ram position monitoring method.

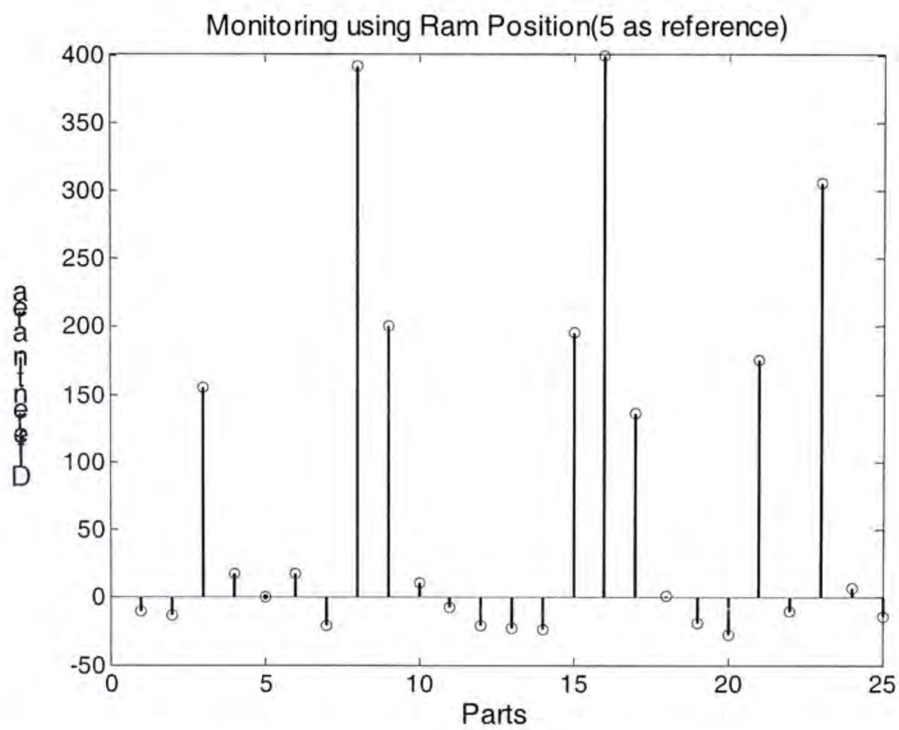

Fig.3-30: Similarity results for first 25 data.

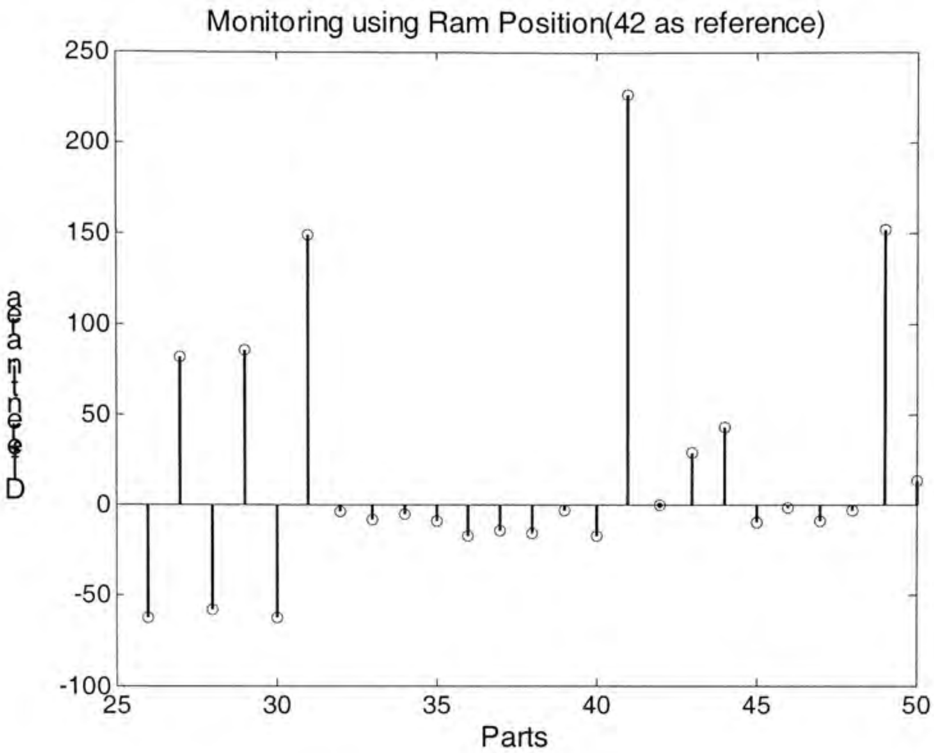

Fig.3-31: Similarity results for next 25 data.

For the value of area different greater than zero, the part considered as bad product. From Figure 3-30 and 3-31, they were part 3, 4, 6, 8, 9, 10, 15, 16, 17, 21, 23, 24, 27, 29, 31, 41, 43, 44, 49, 50. From table 3-6, both monitoring methods had 4 wrong results, however, nearly all (6 out of 8) of the parts with the problem "Half" was missed by monitoring using nozzle pressure.

Table.3-6: Compare monitoring results using nozzle pressure and screw position

Exp.	Problem of part	Mon by nozzle pressure	Mon by screw position
3	Small short shot	OK	OK
4	Half	Miss	OK
6	Half	Miss	OK
8	Very large short shot	OK	OK
9	Large short shot	OK	OK
10	Small short shot	Miss	OK
15	Normal	Wrong	Wrong
16	Very large short shot	OK	OK

17	Large short shot	OK	OK
21	Normal	Wrong	Wrong
23	Large short shot	OK	OK
24	Half	Miss	OK
27	Normal	Wrong	Wrong
29	Normal	Wrong	Wrong
31	Half	OK	OK
41	Large short shot	OK	OK
43	Half	Miss	OK
44	Half	Miss	OK
49	Half	OK	OK
50	Half	Miss	OK

The results in Table 3-6 shows clearly that monitoring part quality using ram position is more reliable than using nozzle pressure. It is believed that different monitoring strategies give different results and will have their own pos and cons, therefore a new methodology was proposed based on statistic which combined different monitoring strategies for part quality monitoring. Suppose there are n monitoring systems, they will have their own monitoring result y (which is 1 for part having an abnormal condition and 0 for a normal part), the overall monitoring result Y is given by:

$$Y = \sum_{i=1}^{n} a_i(y_i) \tag{21}$$

y_i is the monitoring result of system i ;

a_i is the ***performance coefficient*** of system i calculated by:

$$\frac{C_i}{\sum_{i=1}^{n} C_i} \tag{22}$$

where C_i is the ***correct percentage*** of system i.

Y should be a value between 0 and 1.**Thresholds** (also between 0 and 1) are defined to check the quality of part, i.e.:

$Y \le threshold_1$ **: normal**;

$threshold_1 \le Y < threshold_2$ **: suspect case**;

$threshold_2 \le Y$ **: abnormal**;

For the monitoring method using estimate nozzle pressure, 13 parts were reported as abnormal and 9 of them were right, thus:

$$C_{np} = \left(9/13\right) \times 100\% = 69.23\% (or 0.6923)$$

For the monitoring system using ram position, 20 parts were reported as abnormal and 16 of them were right, thus:

$$C_{ram} = \left(16/20\right) \times 100\% = 80\% (or 0.8)$$

Moreover,

$$a_{np} = \frac{0.6923}{0.6923 + 0.8} = 0.4639 \text{, and}$$

$$a_{ram} = \frac{0.8}{0.6923 + 0.8} = 0.5361,$$

So the monitoring equation was:

$$Y = a_{np}(y_{np}) + a_{ram}(y_{ram}) = 0.4639(y_{np}) + 0.5361(y_{ram})$$

In this study, we set two thresholds, 0.4 and 0.55, such that:

$Y \leq 0.4$ means the part was **normal**;

$0.4 \leq Y < 0.55$ means the part was a **suspect case**;

$0.55 \leq Y$ means the part was **abnormal**;

Table 3-7 shows the test results of the new monitoring system using the same experiment data as nozzle pressure monitoring system:

Table.3-7: Monitoring results by the new method.

Exp. No.	Y	Meaning	Exp. No.	Y	Meaning
1	0	Normal	26	0	Normal
2	0	Normal	27	1	Abnormal
3	1	Abnormal	28	0	Normal
4	0.5631	Suspect case	29	1	Abnormal
5	0	Normal	30	0	Normal
6	0.5631	Suspect case	31	1	Abnormal
7	0	Normal	32	0	Normal
8	1	Abnormal	33	0	Normal
9	1	Abnormal	34	0	Normal
10	0.5631	Suspect case	35	0	Normal
11	0	Normal	36	0	Normal
12	0	Normal	37	0	Normal
13	0	Normal	38	0	Normal
14	0	Normal	39	0	Normal
15	1	Abnormal	40	0	Normal
16	1	Abnormal	41	1	Abnormal
17	1	Abnormal	42	0	Normal
18	0	Normal	43	0.5631	Suspect case
19	0	Normal	44	0.5631	Suspect case
20	0	Normal	45	0	Normal
21	1	Abnormal	46	0	Normal
22	0	Normal	47	0	Normal
23	1	Abnormal	48	0	Normal
24	0.5631	Suspect case	49	1	Abnormal
25	0	Normal	50	0.5631	Suspect case

The new method was more reliable than the methods before as it could not only show the normal or abnormal conditions of parts, but also gave judgments to some marginal cases.

3.4.7 Parameter Resetting using SVM and VSM

An experiment was accomplished to verify the performance of the proposed parameters resetting method. The experiment began when experimenter inputs first set of parameters to the injection molding machine and ran the process, then experimenter measured the weight of the injected part and inputed to the system. The system then suggested new set of machine parameters. Finally, experimenter followed the suggestion of the system and ran the process continuously, until the target weight wais achieved. Table 3-8 and 3-9 show the results of the experiment (Details results include in Appendix D):

Table 3-8: Training data sets for the SVR model.

Nozzle pressure (°C), x_1	**Injection pressure (bar), x_2**	**Injection Speed (%), x_3**	**Holding pressure (bar), x_4**	**Weight (g), y**
203	95	70	30	37.39
205	98	80	40	35.57
195	80	55	5	28.14
198	82	60	15	32.64

Table 3-9: Results of the tuning process (*Target weight: 33.5g±0.3*).

Iteration	**Nozzle pressure (°C),** x_1	**Injection pressure (bar),** x_2	**Injection Speed (%),** x_3	**Holding pressure (bar),** x_4	**Weight (g),** y
1	205	80	80	5	27.5
2	199	98	49	27	30.46
3	203	99	54	37	32.78
4	204	99	54	38	33.37

From the above results, it was shown that the product requirement (*33.5g±0.3*) is reached at the 4th iteration (i.e. 33.37g) and have an average standard deviation of 0.1527 (shown in Appendix D).

Chapter 4: The Remote Monitoring and Diagnosis System (RMDS)

This chapter describes the remote monitoring and diagnosis system developed in the research, which included both the hardware and software part. Reader can have a clear understanding to the system after reading this chapter.

4.1 Introduction to the Remote Monitoring and Diagnosis System

With all the essential technologies and components, it was ready to build the RMDS. The RMDS was used to monitoring the injection molding machine during the injection process and it should include two main parts: 1) Network communication, which provided communication between the injection molding machine and the host computer; 2) Monitoring software, which provided a user friendly interface for the user, conducted data mining, analyzed and provided alert functions in order to monitor the injection molding machine. Figure 4-1 shows the overview of the remote monitoring and diagnosis system.

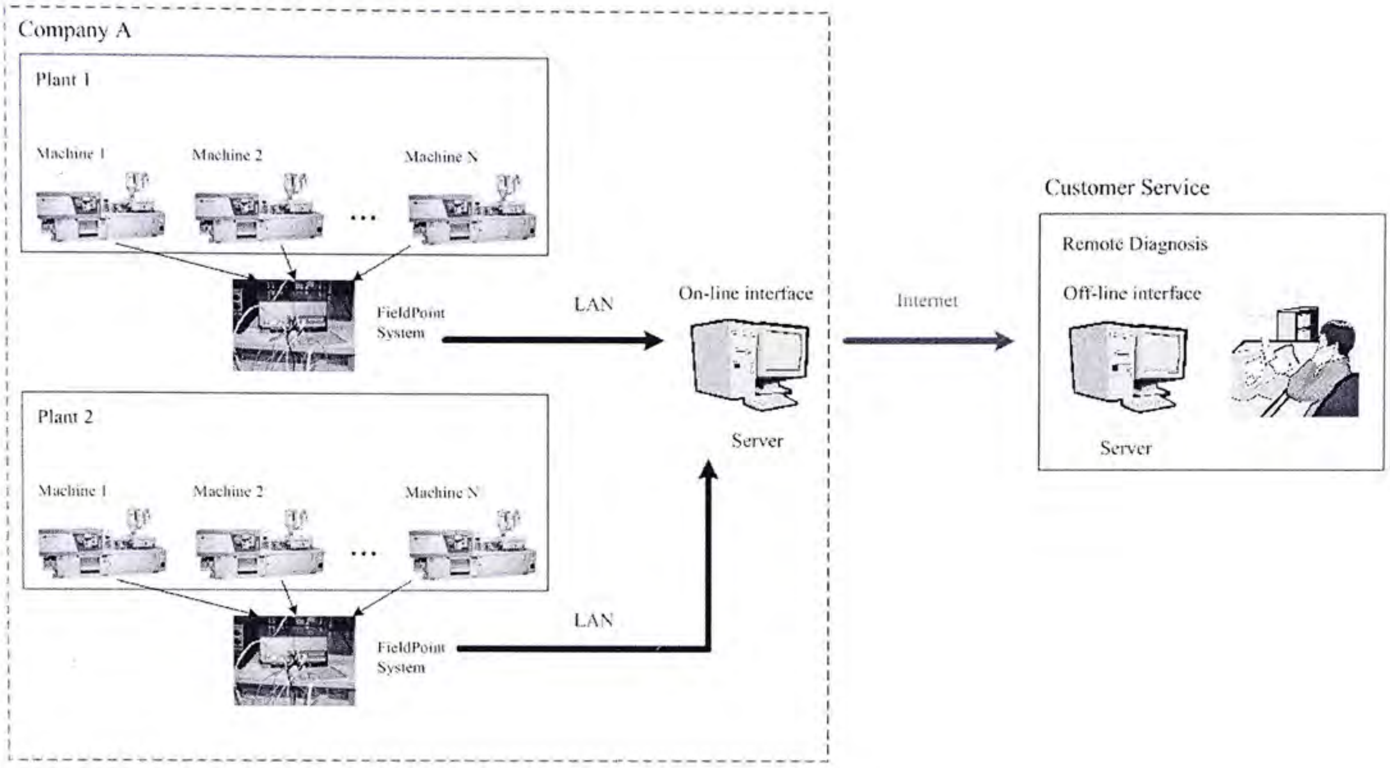

Fig.4-1: Overview of the RMDS.

For network communication between the injection molding machine and the target computer, a commercial product called FieldPoint system was chosen (Figure 4-2, model no.: NI FP-AI-110). The National Instruments FP-AI-100 Series consists of versatile analog input modules for the FieldPoint I/O system. One can used the module to monitor voltage or current loop inputs from a variety of sensors and transmitters. The NI FP-AI-110 features 16-bit, filtered, low-noise inputs. With the FieldPoint system, we can collect the analog sensor signals from those sensors, convert to digital format and pass to the network.

 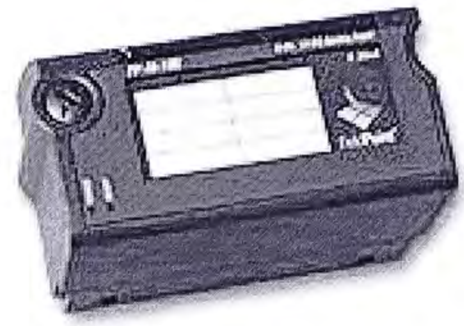

Fig.4-2: Network module *(left)* and I/O module *(right)* of FieldPoint system.

The monitoring software was written by LabVIEW, it can easily cooperate with the FieldPoint system to achieve on-line or off-line monitoring and diagnosis. The major functions of the software were: data mining, properties settings, data analysis, statistic process control and network communication, which will be covered in the following sessions one by one.

4.2 Starting Use of the Software

After starting the software, there were three choices: *"Start"*, *"Exit"* and *"Offline Running"* (Figure 4-3).

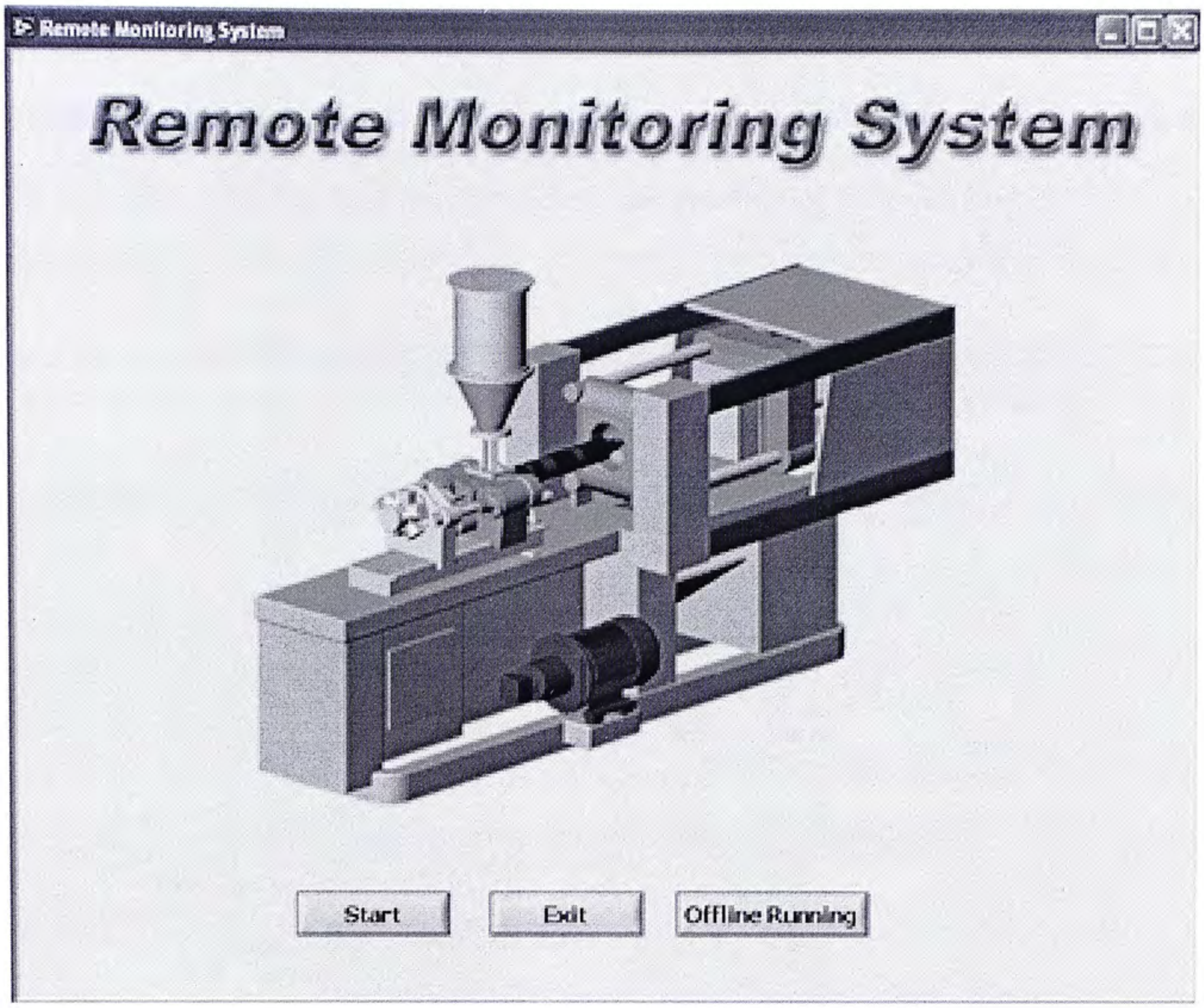

Fig.4-3: First page of the LabVIEW monitoring software.

- **Start:** Start running the software.
- **Exit:** Exit the software.
- **Offline Running:** Run the software in an offline state, this mode is for offline analysis and simulation. A data file has to load in offline running. Details will be discussed in later session.

4.3 Properties and Channel Settings

Clicking the "Start" button, a pop up window would appear which corresponding to a settings page for the company profile and channels setup (Figure 4-4). In this page, user had to input some basic information of the company:

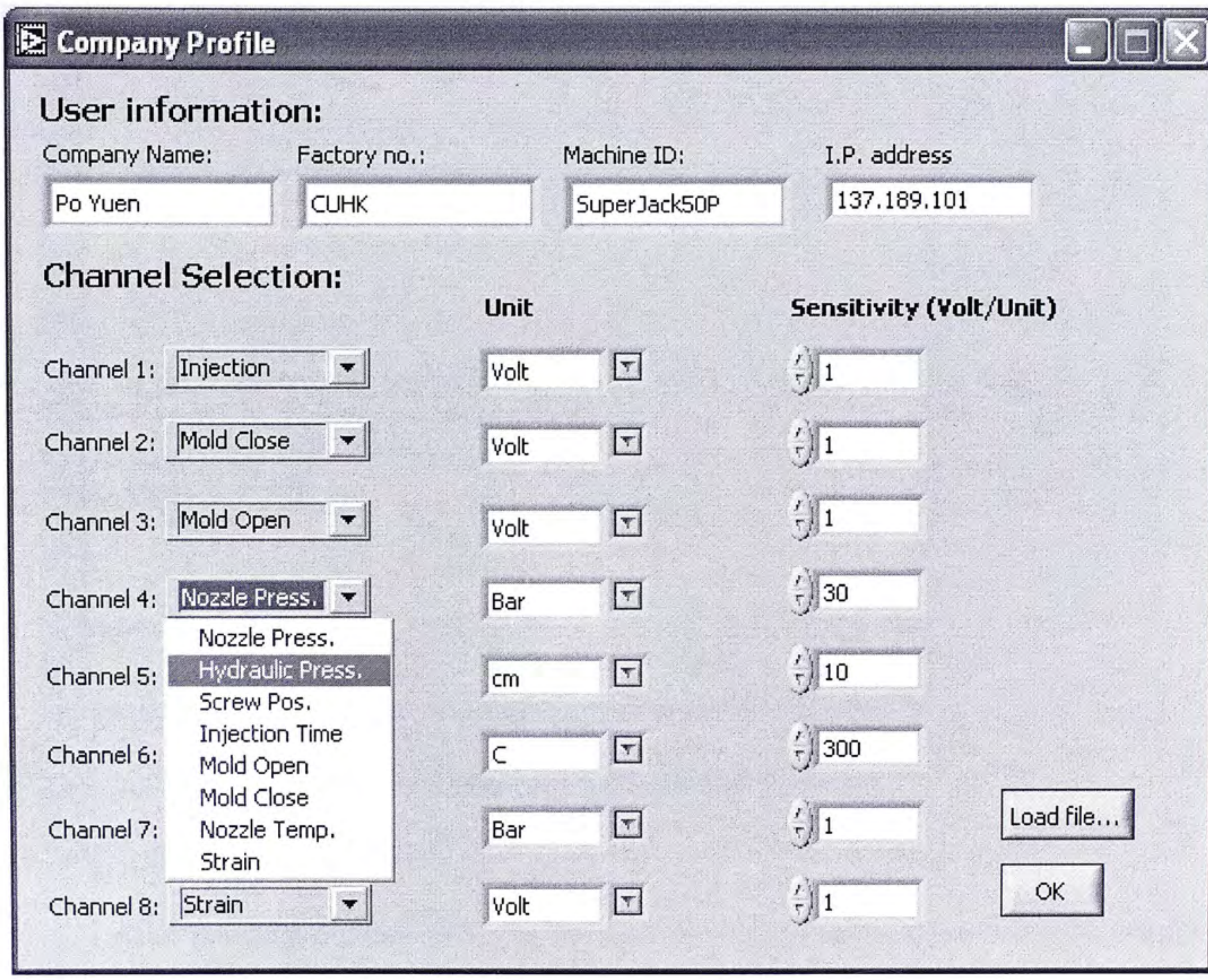

Fig.4-4: Setup page for the company profile and channels.

After setting all the channels and company profile, clicked the *"OK"* button to save the information. If the settings were the same as some previous process, user could load the settings from a saved file instead of setting them again. This was done by clicking the button *"Load file..."* (Figure4-5).

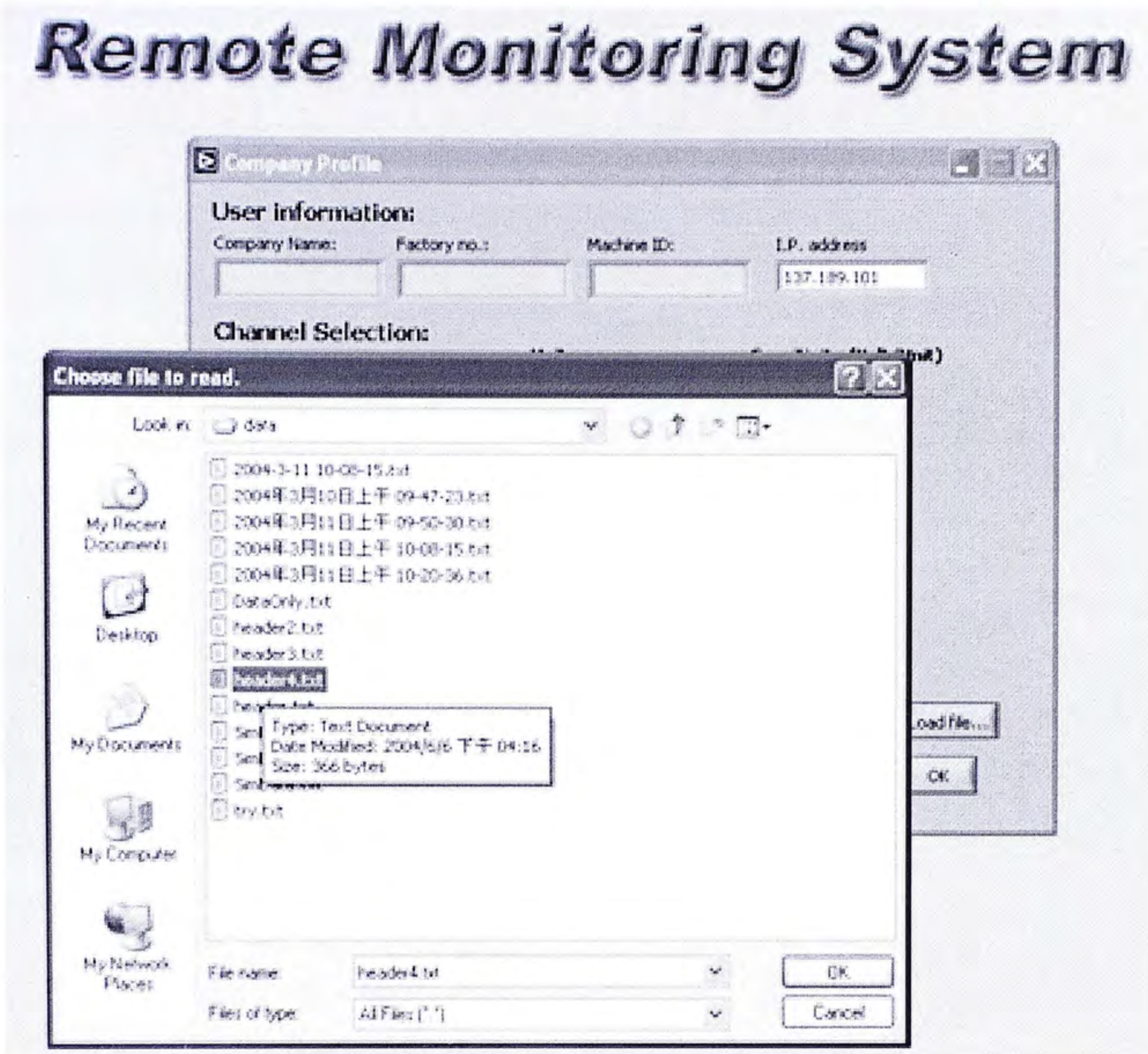

Fig.4-5: Load previous settings from file.

After defining the channels, the software was ready to use. Figure 4-6 shows the interface of the software. There were several buttons in the interface providing specific functions for the software, and will be introduced one by one.

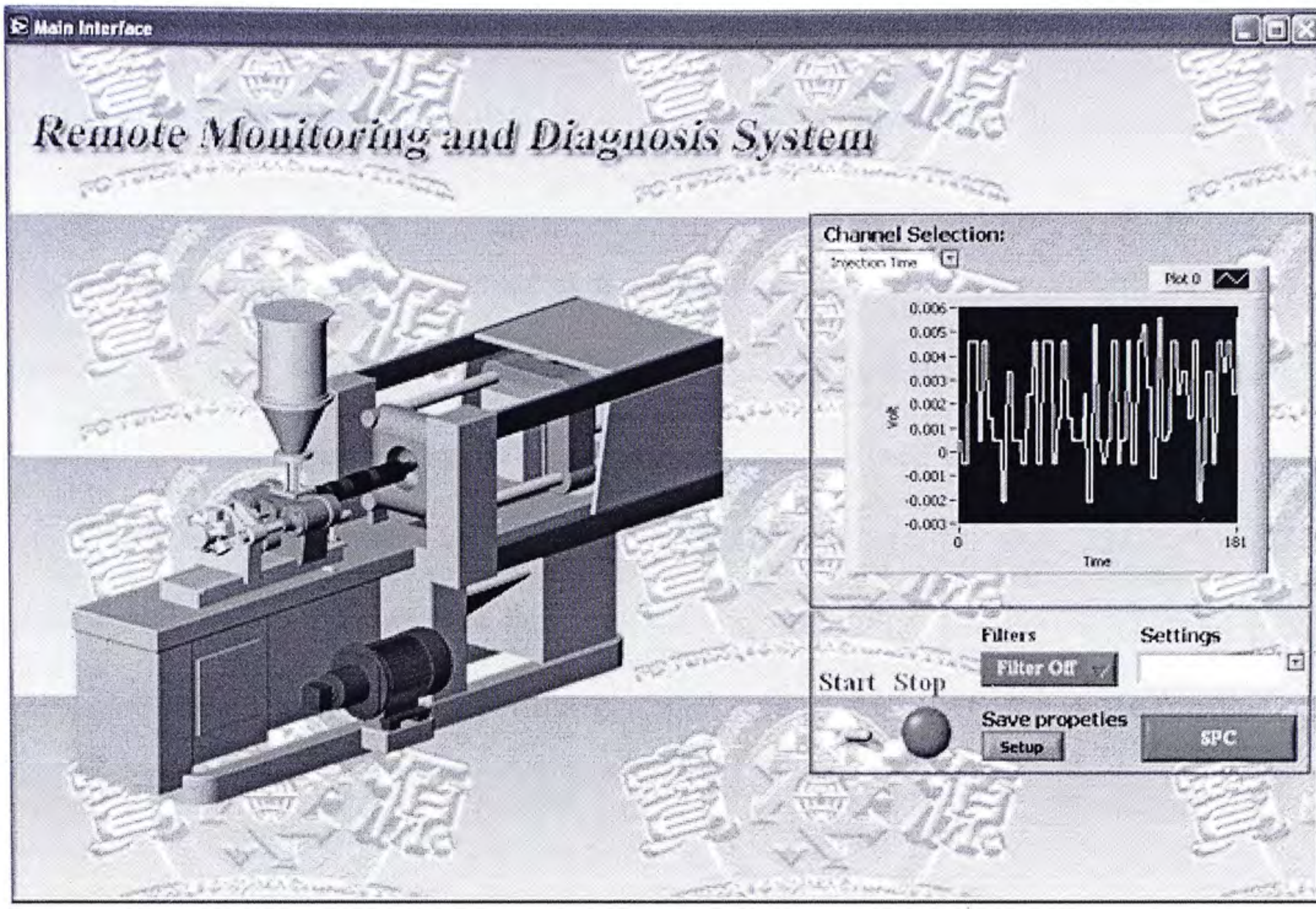

Fig.4-6: Interface of the monitoring software.

There was a control panel in the interface. The control panel was used to control the functions of the software, which included the channel selection, on and off of the system, filter selection for the signal, settings of channel, machine, saving options and the SPC. Below are some of the features:

4.3.1 Statistic Process Control (SPC)

Since the 1940s the industry has been using statistical methods to ensure the quality of both products and services at their place of origin in order to reduce errors, costs, and time to market. The aim of SPC is the systematic selection of crucial parameters from the total of all parameters involved in the process in order to control the manufacturing process with decisive parameters and appropriate measures.

The SPC of the software included a process capability analysis for the part weight. The process capability described the long-term behavior of the process in order to assess performance trends over time and provides a measure of the quality of the process. Capturing the mean values of the measured values (i.e. part weight) by way of many single spot checked and applied them as Gaussian distribution would determine the quality of the process. Capability process calculations such as *Cp* (capability process, i.e., admissible tolerance versus process distribution ratio) and *Cpk* (considers additionally the conformance of the process versus the tolerance limits) indicated both the capability for quality and repetitive accuracy of a process. (23) shows the formula of *Cp*.

$$Cp = \frac{U.S.L - L.S.L}{S.T \times P.S} \tag{23}$$

where U.S.L: Upper Spec. Limit; L.S.L: Lower Spec. Limit;

S.T: Sigma Tolerance; P.T: Process Sigma.

The higher the *Cpk* value, the more capable the process was in relation to distribution and compliance. In industrial mass production, a *Cpk* value >1.33 will show that all systematic influences are eliminated and is therefore considered the desirable characteristic. Processes that meet these requirements are classified as controlled. Alert will be given to warn the user if there are any malfunctions encountered. In the system, the part weight was predicted using the methodology described in 3.1.5. Figure 4-7 shows the SPC display window.

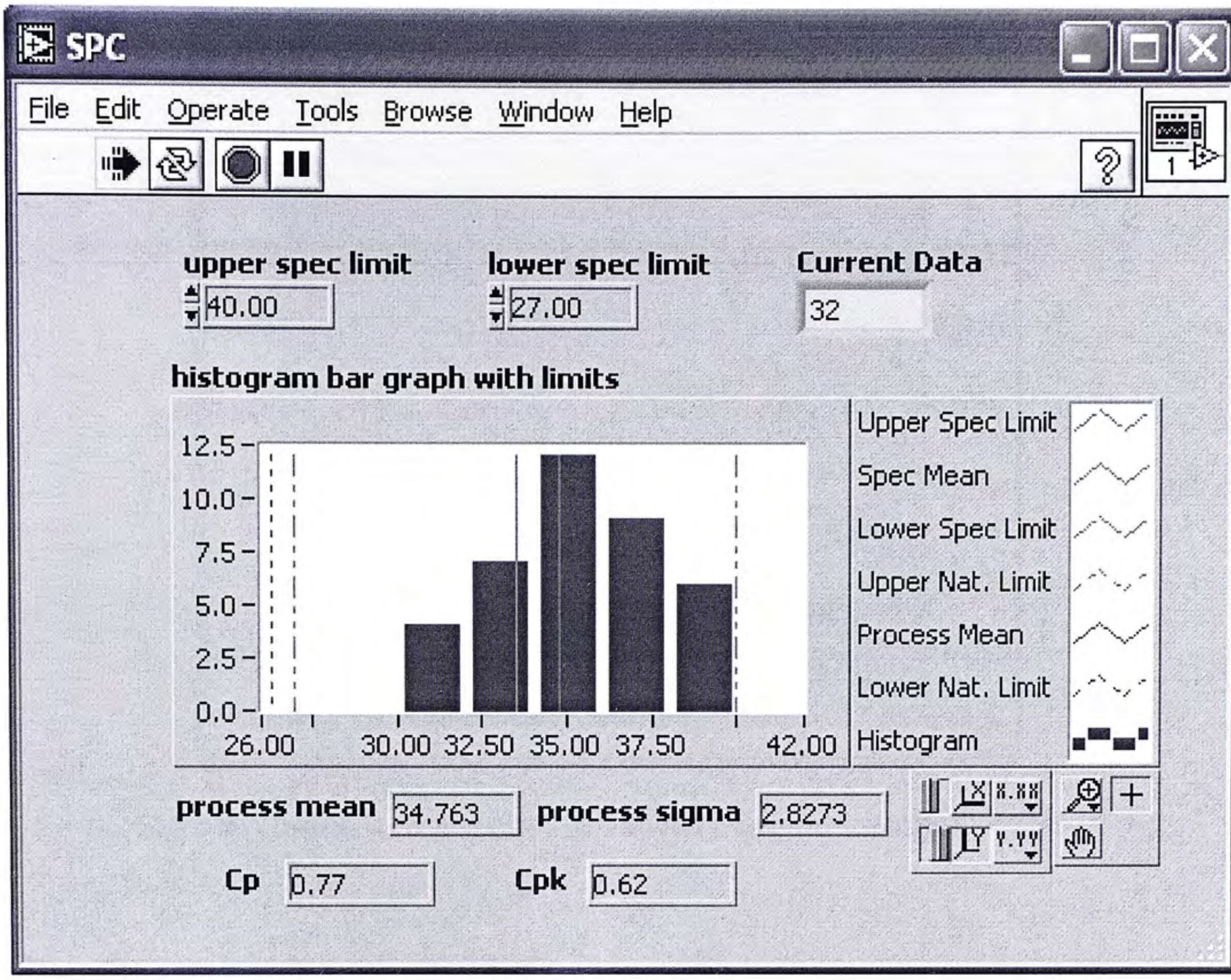

Fig.4-7: SPC display window.

4.3.2 Settings

User can view the settings of the machines, FieldPoint and company profile using the "Settings" button (Figure 4-8). They were read-only files, user had to return to the settings page if he/she wanted to change the settings.

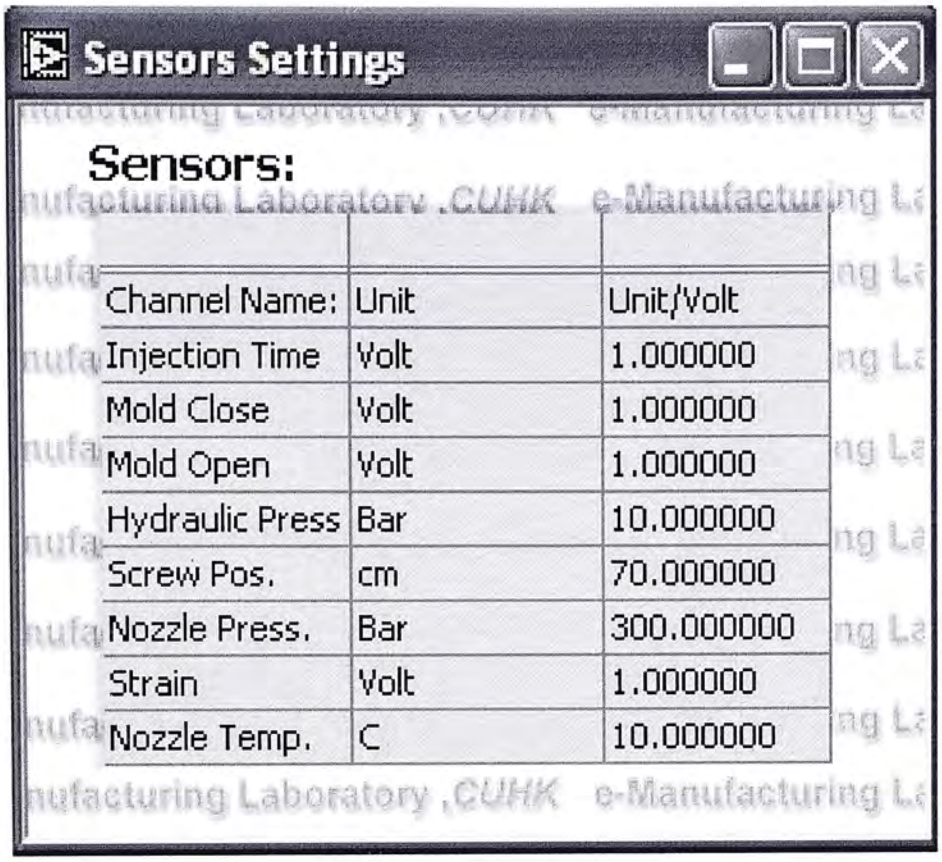

Fig.4-8: Channels settings can be viewed from the "Settings" button.

4.3.3 Viewing the signals

This was one of the major functions of the software. User could view any of the signals from the display window by choosing the corresponding channel name under the "Channel Selection" pull down menu (Figure 4-9). The channels were the same as those set by the user before in the settings page, and the signal was shown in the right scale and unit according to the sensitivity and unit name saved in the settings file. The signals were shown in real time. User could choose a filter to filter the incoming signal, they were the *"FIR filter"*, *"Chebyshev Filter"* and *"Butterworth Filter"*. User could view any of the signals immediately so that real time adjustment could be made to the machine if there were any malfunctions checked.

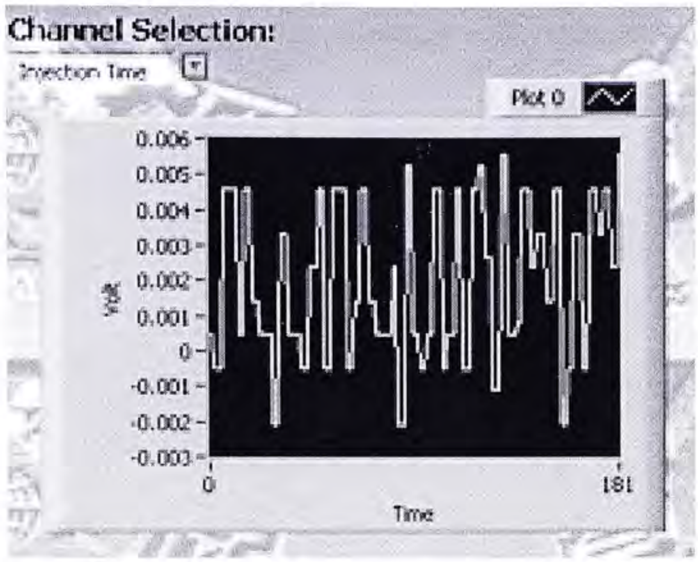

Fig.4-9: View signals from the display window.

4.3.4 Short shot monitoring

With the similarity monitoring methods described in 3.2, the RMDS would monitor the injection molding machine to see if short shot was occurred in the injected part. In case the RMDS detected a short shot occurred in the injected part, alert would be given to notice the user and the corresponding signal would be recorded.

4.3.5 Data management

User could save the signals for later used by choosing the "Save properties". A pup up window would appear (Figure 4-10). User could set the date and time of saving, trigger method and sample rate. After saving the signals, another pop up window appeared to ask if the user wanted to send the saved file to the remote server, this was optional for the user (Figure 4-11). In fact, the software was supposed to be used by the technician in factory, the saved file could help the company in data management, offline analysis could also be conducted later with the file. On the other hand, user could ask for professional opinions from the expert. That's why the software provided the upload function for the user, so that the machine making company (e.g. The Po Yuen (TO'S) Machine FTY. LTD) could provide after-sales services to their client. In case the client's injection molding machine had some problems, for example, machine failure, bad quality of injected part, etc., he/she could log several set of machine signals using the RMDS, and then upload to the machine making company to request for help.

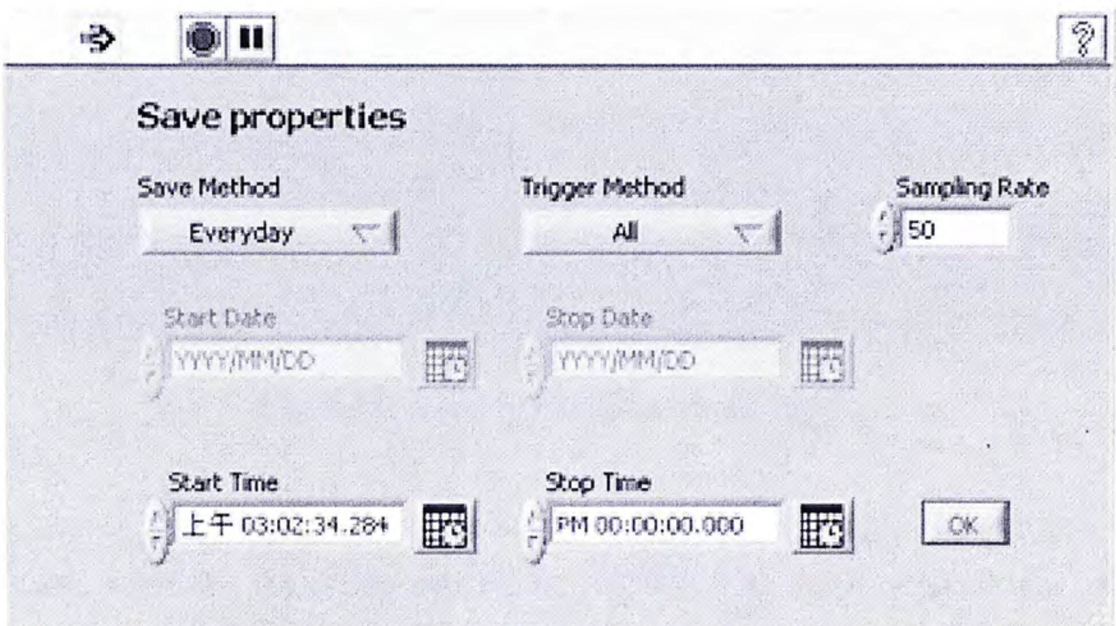

Fig.4-10: Options of saving the data.

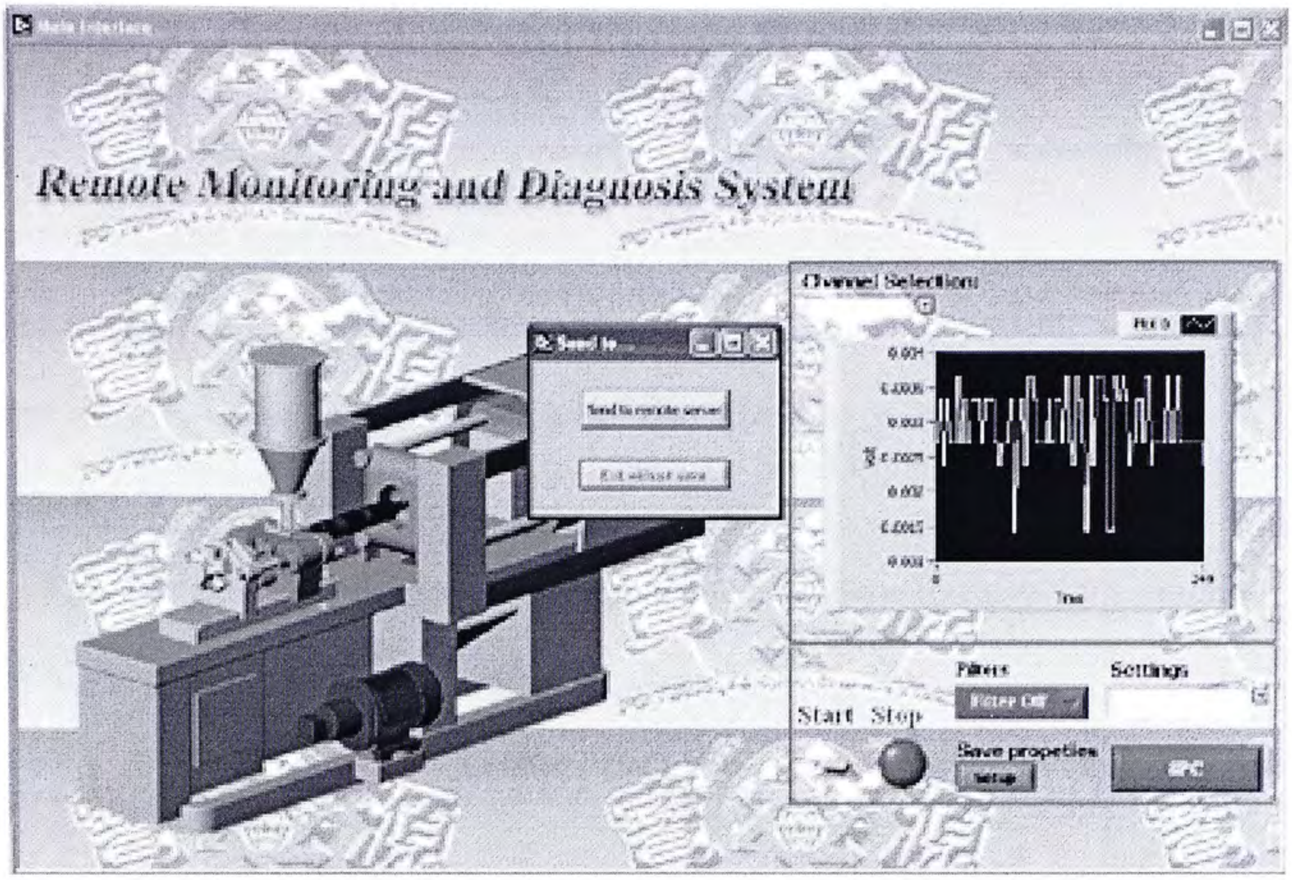

Fig.4-11: Send file to the remote server.

These were the main features of the RMDS. The software could provide basic receiving, displaying, monitoring and transferring functions well for the user. Tests have been done to confirm the fluency and workability of the software.

Chapter 5: Conclusions and Future Works

From the results of the previous chapters, we have accomplished many experiments and their results are great. In Chapter 1 and 2, a brief introduction was given to clarify objective of the research. The problems and possible solutions were stated clearly, some related works were also given to show the importance of the research.

In Chapter 3, the methods that were being used in the research were described in details, the performances were verified by experiments as well:

1. Design of Experiment (DOE) was accomplished to find out optimal settings of injection molding machine. Experiments did in the research afterwards were based on the results obtained in the DOE.
2. Radial Basis Function Neural Network (RBFNN) was used to estimate the nozzle pressure and part weight. The set-points of the training data in the RBFNN obtained through the design of experiment. It was found that the later portion of the hydraulic pressure was not sensitive for estimating the nozzle pressure. To solve the problem, ram position was introduced as input of the RBFNN. Experiments showed that using hydraulic pressure and ram position as inputs of the network was more effective. The estimated nozzle pressure hading an average root mean squared error of less than 8%, while the predicted part weight hading an average root mean squared error of 0.64g.
3. Similarity monitoring was done to monitor the short shot of injected part. Results showed that monitoring part quality using nozzle

pressure encounters problem in the case of "half" while monitoring using ram position doesn't. A new statistic-based monitoring methodology was proposed, which used both nozzle pressure and ram position as indicators for monitoring the part quality and the results is excellent. Results showed that the new proposed method could correctly monitor the normal and abnormal conditions of parts. Moreover, it could give judgments to some marginal cases.

4. A parameters resetting model based on Support Vector Machine (SVM) and Virtual Search Method (VSM) was built. The model would suggest new machine parameters according to the target output (weight). The VSM model would search for the appropriate inputs continuously, and to the physical process only when it has exhausted the virtual search. The support vector regression model would be updated afterwards. Experiments showed that the proposed parameters resetting model could provided machine settings reaching the target weight within 5 iterations.

In chapter 4, a Remote Monitoring and Diagnosis System was developed providing monitoring and diagnosis function for the injection molding machine. It was combined of the FieldPoint system and LabVIEW program. The FieldPoint system was a commercial product, which was reliable and was ready to use in the industry; the LabVIEW monitoring software was completed, providing an easy to use environment for handling the monitoring tasks. These two major parts combined to form a reliable and effective monitoring system. With the monitoring system, user could deeply understand and analyze the inside of the injection molding machine in an easy and effective way. Besides handling the monitoring tasks, the system could also help in data management and network communication, which would bring commercial benefit to the company.

The objectives of the research were achieved. A remote monitoring and diagnosis system was developed. The monitoring function of the system was effective and better than any past researches. Experiments were conducted to ensure its reliability and workability. In the coming future, the system will be used in the real industry to test its performance. We will try to install the system into different injection molding machine, therefore the functions of it can be verified clearly. On the other hand, feedbacks can be obtained from different companies and we can further improve the system. We believed that our system will bring positive impact to the plastic injection molding industry.

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Appendix A: Machine settings in the experiment

Mold Close

	Open			Close	
Pressure (bar)	35	70	20	140	
Speed (%)	80	80	30	35	
Position (mm)	230	225	10	2.5	0.2

Mold Open

	Open				Close
Pressure (bar)	22		70		100
Speed (%)	40		30	80	15
Position (mm)	230	150	70	8	0

Injection

Pressure (bar)	86
Injection delay (s)	0.5
Injection time (s)	5
Speed (%)	68

Holding

Pressure (bar)	20
Speed (%)	60
Holding time (s)	4
Actual injection stroke (mm)	60.9

Plasticizing

Auto	Position (mm)	Speed (%)	Pressure (bar)
1. Decompression	0	40	50
1. Plasticizing	14	65	60
2. Plasticizing	28	65	60
3. Plasticizing	42	65	60
4. Plasticizing	56	65	60
5. Plasticizing	70	65	60
2. Decompression	3	50	50
Total stroke	73 mm		
Plasticizing Delay	2 sec.		

Ejector Select

	Backward	Forward
Pressure (bar)	30	30
Speed (%)	40	40

Temperature

	Production	Pre-temp	Alarm Level (AL)-	Alarm Level (AL)+
Nozzle Tip	200	100	20	20
Barrel 1	200	100	20	20
Barrel 2	195	100	20	20
Barrel 3	190	100	20	20
Barrel 4	195	100	20	20

Appendix B: Measured part weight in the part weight prediction experiment

Exp. No.	Weight (g)	Runner(g)	Exp. No.	Weight (g)	Runner(g)
1	33.45	4.05	31	34.52	4.08
2	33.73	4.06	32	34.35	4.06
3	34.05	4.06	33	35.51	4.23
4	33.35	4.04	34	34.84	4.14
5	34.19	4.09	35	32.45	4.02
6	34.32	4.08	36	34.81	4.12
7	34.39	4.07	37	35.04	4.12
8	34.36	4.08	38	34.88	4.11
9	34.56	4.08	39	34.96	4.13
10	34.91	4.12	40	34.81	4.09
11	34.61	4.09	41	34.76	4.10
12	34.19	4.07	42	34.66	4.10
13	34.76	4.10	43	34.44	4.07
14	33.72	4.06	44	34.22	4.07
15	34.94	4.11	45	33.63	4.05
16	35.35	4.2	46	33.32	4.03
17	34.71	4.08	47	32.33	4.02
18	34.76	4.07	48	33.49	4.04
19	34.78	4.10	49	33.77	4.06
20	34.45	4.07	50	34.23	4.07
21	34.31	4.07	51	33.54	4.04
22	34.02	4.06	52	33.62	4.03
23	33.77	4.04	53	33.66	4.04
24	33.50	4.04	54	33.58	4.02
25	31.12	4.02	55	33.61	4.03
26	33.15	4.03	56	33.74	4.05
27	30.95	4.01	57	32.74	4.02
28	29.73	4	58	33.29	4.03
29	33.4	4.01	59	32.93	4.01
30	34.78	4.11	60	33.37	4.04

Appendix C: Measured part weight in the similarity monitoring experiment

Exp. No.	Weight (g)	Description	Exp. No.	Weight (g)	Description
1	30.15	Normal	26	30.26	Normal
2	30.22	Normal	27	29.47	Normal
3	28.10	Abnormal(S)	28	29.29	Normal
4	28.22	Abnormal(H)	29	29.54	Normal
5	29.65	Normal	30	30.17	Normal
6	28.46	Abnormal(H)	31	28.39	Abnormal(H)
7	30.57	Normal	32	29.31	Normal
8	14.11	Abnormal(VL)	33	29.44	Normal
9	24.13	Abnormal(L)	34	29.55	Normal
10	28.66	Abnormal(S)	35	29.57	Normal
11	29.57	Normal	36	29.80	Normal
12	30.28	Normal	37	29.64	Normal
13	30.27	Normal	38	29.81	Normal
14	30.44	Normal	39	29.41	Normal
15	29.39	Normal	40	29.87	Normal
16	7.02	Abnormal(VL)	41	26.13	Abnormal(L)
17	24.32	Abnormal(L)	42	29.25	Normal
18	29.45	Normal	43	28.30	Abnormal(H)
19	30.11	Normal	44	25.95	Abnormal(H)
20	30.51	Normal	45	29.44	Normal
21	28.94	Normal	46	29.67	Normal
22	29.65	Normal	47	30.00	Normal
23	22.92	Abnormal(L)	48	29.76	Normal
24	28.74	Abnormal(H)	49	28.12	Abnormal(H)
25	29.92	Normal	50	27.78	Abnormal(H)

S=small short shot
L=large short shot
VL=very large short shot
H=one side of the part has short shot

Appendix D: Results of Parameters Resetting Experiment

1st trial	2nd trial	3rd trial	Mean (g)	S.D.
37.62	37.21	37.34	37.39	0.1711
35.30	35.61	35.80	35.57	0.2061
28.09	28.03	28.30	28.14	0.1158
32.52	32.80	32.60	32.64	0.1178

Average standard deviation: 0.1527

Appendix E: List of figures

Appendix F: List of tables