MIMO Adaptive Process Control in Stamping
Using Punch Force

by
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To my wife, Jina Lee,  
son, Jiyong,  
future daughter,  
and parents
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PREFACE

This dissertation describes recent research work on the design methodologies for process control in stamping, to improve stamped part quality in the presence of operational variations. It also includes evaluation of in-process variables for the design and implementation of the stamping process controller. Using the punch force as an in-process variable, a process controller can adjust the blank holder force based on tracking a reference punch force trajectory. While previous work has shown that process control in stamping can improve part quality, there have been limitations: 1) Prior work only covers single-input single-output (SISO) stamping process modeling and control using a simple geometry (e.g., u-channel, cup, or box drawing) in laboratory-based experiments, 2) those experimental tests required manual controller fine-tuning which can be time-consuming and expensive, and 3) such a fixed-gain process controller tuned manually can reject disturbances (e.g., lubrication change and variations in material properties), but cannot produce a good stamped part in the presence of process parameter variations.

The research presented in this dissertation describes systematic design and implementation of a multi-input multi-output (MIMO) adaptive stamping process controller with production of a complex-geometry part. Manual controller fine-tuning is eliminated. The experimental results presented here show that the MIMO adaptive (i.e., both direct and indirect approaches) stamping process controller produces good tracking of the reference punch force as well as significant part quality improvement in the presence of plant variations. The study in this dissertation is based upon original
experiments performed with a novel variable blank holder force system that includes 12 hydraulic actuators to control 4 punch force outputs measured at the four corners of the press.

Chapter 1 presents the motivation for this research, a comprehensive literature review, and states research objectives and original contributions. Chapter 2 develops a fourth order linear MIMO dynamic structure which relates the blank holder forces as inputs to the punch forces as outputs for a complex-geometry part. This chapter also presents a system identification procedure, based on parameter estimation experiments, which are used to parameterize a MIMO stamping process model. Chapter 3 presents a fixed gain process controller which is tuned manually through experiment tests. Chapter 4 presents a systematic approach to the design and implementation of a direct adaptive controller (i.e., MRAC) which updates the controller gains. Also, the derivation of the parametric model for the adaptive law of a direct MRAC is presented. This chapter also presents the auto-tuning method which is useful for providing good initial gain values for use with the adaptive controller. Chapter 5 describes a systematic design approach for the indirect adaptive control (AC) which does not require the nominal process parameters and provides the estimates of process model parameters. This chapter also presents how an indirect AC, which requires the off-line computation of the controller gains via optimization due to the simple proportional plus integral (PI) control structure selected, is designed and implemented on-line using a look-up table scheme. The look-up table, which stores controller gains that are pre-computed off-line, is embedded into the indirect AC system and used to provide on-line the controller gains based on the estimated process parameters. Furthermore, the direct and indirect adaptive controls are compared
through simulation and experiments, in terms of the tracking performance as well as part quality improvement, in the presence of disturbances. Finally, Chapter 6 summarizes this research, contains important conclusions, and provides suggestions for future work.

The author hopes that this dissertation will be of interest to graduate students and researchers who have special interest in studying stamping process dynamics, modeling and control, as well as the relevant adaptive control methodology.

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CHAPTER 1

INTRODUCTION

In stamping, both manufacturing and control engineers have faced challenges to prevent stamped parts from wrinkling and tearing, to improve their dimensional accuracy (e.g., to minimize springback), and to maintain consistency in the stamping process (e.g., reduce variations in stamped part quality). In this research, a process control strategy is introduced in sheet metal stamping to improve the quality of stamped parts and the consistency of the stamping process.

1.1 Motivation

Sheet metal stamping is a primary manufacturing process for large-volume high-speed and low-cost production of components, such as panels in automobiles and home-appliances. A stamped part is made by placing a sheet of metal (the blank) between an upper die (or punch) and a lower die, which are geometric negatives of each other, and then stamping the sheet of metal using a press. A blank holder, or binder, is used to hold the edges of the sheet of metal, and to control the flow of material into the die, sometimes using drawbeads, which provide additional restraining forces on the blank. Once die design and validation are accomplished, high productivity is the hallmark of stamping operations due to their suitability for large-volume production. As shown in Figure 1.1.1, a punch (i.e., upper die) is forced towards the lower die, with the material to be drawn
placed in between. In Figure 1.1.1, $F_p$ is the punch force, $l_s$ is the material draw-in, $h$ is the punch stroke, and $F_b$ is the binder (or blank holder) force. Traditionally, stamping presses have been mechanical in design, but modern presses are often electro-hydraulic. Presses also typically have rubber, springs, and pneumatic/hydraulic pistons to passively cushion the die in a stamping press from the punch impact.

![Figure 1.1.1: Schematic of the sheet metal stamping process including process variables.](image)

As shown in Figure 1.1.2, the two main quality considerations in stamping are formability (e.g., the ability to avoid wrinkling caused by excessive local compression, and tearing caused by excessive local tension) and dimensional accuracy (e.g., reduction of springback caused by elastic recovery). In addition, consistency in terms of minimization of dimensional variations (caused by variation in lubrication, material properties, or thickness) is a key requirement in production.

Additional challenges arise from the use of new materials. For example, the need to reduce weight in automobiles, and to improve car crash performance, encourages manufacturers to choose light weight and/or stronger materials (e.g., aluminum, magnesium, and/or high strength steel alloys) in place of low carbon mild steel.
However, these alloys are not as formable as mild steel, and can produce more springback and fracture problems (Adamson et al., 1996; Anon, 2006; Lee et al., 2007). Therefore, a major challenge in manufacturing sheet metal products from such materials is the ability to consistently produce good parts, without tears, wrinkling, and minimal spring-back, using a given blank (with specified blank size, sheet thickness, and material properties) and tooling (with specified geometry).

Figure 1.1.2: Problems of part quality in the sheet metal stamping process: (a) wrinkling (b) tearing (c) springback.

1.2 Review of Related Research

This section presents a thorough review of developments in stamping process control, taking a broad view from conventional die try-out to in-process control in production. First, an overview of stamping process control is presented, including die try-out, machine control, in-process control and cycle-to-cycle control. Second, the development of different types of active blank holder force (BHF) control systems is described to focus on their objectives and performance as well as their advantages and disadvantages in terms of complexity, applicability and flexibility. Third, extensive
reviews of diverse sensors measuring stamping process variables are addressed in terms of their design and operation, including a description of their advantages and disadvantages with respect to complexity, applicability and flexibility (Lim et al., 2008a).

1.2.1 Development in Stamping Control

Die Try-out

Die try-out determines the parameters (such as die geometry and fixed BHF) that control the forming process to avoid tearing and wrinkling by physical modifications (e.g., grinding and welding) of the die surface and alteration of the BHF in sheet metal stamping. The die try-out procedure is time-consuming, with many cycles of trial-and-error. Sklad and Harris (1991) noted that most changes in stamping are connected with altering die geometry data (e.g., binder geometry and drawbeads), because part geometry data and material data are normally fixed in the stamping process. They also noted that a poorly-tuned open-loop forming process, which is close to failure, can result in frequent disruptions in manufacturing scheduling and a high scrap rate, and significantly increase costs. Therefore, finite element analysis (FEA) software tools play an important role in rapid evaluation of forming severity, with respect to fracture and wrinkling, prior to actual die manufacturing in order to reduce costs and scrap rate.

Although die try-out is costly and time-consuming, many techniques have been incorporated in die try-out, and lead time and production costs have been improved. Herderich (1990) has developed empirical equations to predict the force necessary to form sheet metal around drawbeads. He suggested useful concepts in determining BHF and the number of nitrogen gas cylinders and/or nitrogen gas pressures with respect to
quality of stamped parts. Xu et al. (2007) discussed the reduction of springback through open-loop compensation of mechanics-based springback reduction (e.g., drawbead constraint force) and geometry-based springback reduction (e.g., die face compensation).

**Machine Control**

The machine control (MC) strategy, as illustrated in Figure 1.2.1(a), is to control the BHF, $F_b$, to follow a predetermined reference trajectory. The machine control requires a predetermined reference BHF trajectory that can be obtained through experiment and/or FEA simulation. The reference BHF depends on its location on the die and is a function of the punch stroke. The punch force ($F_p$), as shown in Figure 1.2.1(a), is an output of the process and is directly associated with fracture and wrinkling. $F_p$ is affected by the BHF. Thus, the relationship between the punch force and the BHF, obtained using mathematical modeling and/or experiments, can be used to design a process controller which generates a reference BHF trajectory for the machine controller.

Experimentally, different kinds of BHF trajectories (e.g., a step change in the BHF) have been used to study their effects on produced part quality. Some of them have been demonstrated to improve formability (Ahmetoglu et al., 1992; Kergen and Jodogne, 1992; Ziegler, 1999), to reduce springback (Adamson et al., 1996; Sunseri and Cao, 1996; Siegert, 1992, 1997; Ziegler, 1999), and to improve part consistency (Adamson et al., 1996). However, these investigations have not led to methods to determine BHF trajectories to make good parts.

The optimal magnitude of the BHF was predicted to improve fracture and wrinkling problems in deep drawing (Sheng et al., 2004; Zhong-qin et al., 2007). They used FEA simulation of closed-loop control based on the wrinkling and fracture detection of sheet
metal. They showed the variable BHF profile predicted by adaptive FEA simulation, and compared it with the optimum constant BHF profile (see Figure 1.2.1(b)), in terms of formability. Using a pre-determined variable BHF profile, they formed a cup to a depth of 47mm without any failures. Compared with a cup formed by optimum constant BHF, this represented an increase of 9% in cup depth. Optimal trajectories of variable BHF by FEA simulation were also developed in (Zhong-qin et al., 2007).

The main disadvantage of machine control is that it cannot eliminate the influence of disturbances (e.g., variations in lubrication and blank thickness) on part quality and consistency (see Figure 1.2.1(a)). For example, two tests were conducted using closed-loop machine control with a predetermined BHF trajectory but with different lubrication conditions. Results showed that if a constant BHF is used, there were differences in stamped part quality in BHF for the two tests (Hsu et al., 2000).

Figure 1.2.1: Machine control: (a) adjust the BHF to achieve the reference BHF (b) determination of the BHF profile using FEA.
In-Process Control

In-process control is used to control a measurable process variable (e.g., punch force or draw-in) to follow a reference trajectory by manipulating the BHF. To implement the in-process control, a process controller and reference trajectory are needed after the monitored process variable is selected, in addition to the machine control scheme shown in Figure 1.2.2.

![Figure 1.2.2: In-process control of sheet metal forming process with reference punch force trajectory.](image)

Hardt and Fenn (1993) performed a series of constant BHF experiments to find failure height and then defined optimal tangential force (i.e., punch force) and normalized average thickness trajectories as the actual trajectories of these variables when the failure height was the largest. Then, they presented a method for in-process control of the BHF to ensure optimal forming conditions based on desired optimal trajectories. The method was implemented using closed-loop control based on process variable feedback, and subjected to experiments where various disturbances (e.g., lubrication and material change) were considered.

Siegert et al. (1997) showed that the material flow is highly dependent on the friction force between the sheet metal and the upper and lower binder. They introduced
process control using friction force as the controlled variable to avoid wrinkling and tearing during the stamping process. They also showed that the actual friction force follows the desired nominal curve of BHF. Therefore, they focused on monitoring the friction force by using a sensor, and utilized feedback control to realize the desired friction force curve over the stroke.

Bohn et al. (1998, 2000) developed a new multiple-point active drawbead forming die to improve part quality and formability with lighter material (i.e., Aluminum), using drawbead restraining force based on measuring the die shoulder force during the drawing process. In comparison to their previous work on (Michler et al., 1993, 1994; Weinmann et al., 1994), they expanded the study to include multiple-point actuation with closed-loop control and developed second-order transfer functions for modeling the drawbead hydraulic actuators. They also monitored punch stretching force and adjusted the displacement of the active drawbead to constrain material flow, thus, avoiding tearing and wrinkling during the forming process.

Hsu et al. (2000 and 2002) demonstrated that in-process control can be used to improve stamped part quality and consistency of a simple part by adjusting the BHF in forming based on tracking an optimal punch force trajectory. They pointed out that a process controller and reference punch force trajectory had to be included in the design (see Figure 1.2.2). In particular, their approach included modeling of the sheet metal forming process, design of the process controller, and determination of the optimal punch force trajectory. They achieved good results using proportional plus integral control with feedforward action (PIF) for the process controller in both simulation and experiments.
Cao et al. (2000) proposed a neural-network system, along with a stepped BHF trajectory, that was able to control springback in forming. A neural network was chosen due to its ability to handle the highly non-linear coupled effects that are found in sheet metal forming when variations in material and process parameters occur. Polynomial coefficients from curve fitting of the punch force trajectory were used as inputs into the neural network. Viswanathan et al. (2003) experimentally implemented the neural-network based process control for springback reduction during forming. They noted that neural-network control would be effective in dealing with material variations. However, for forming a complex part, they noted that more advanced sensors (e.g., local draw-in or local tangential force measurement) are needed because punch force alone may not be sufficient in identifying variations.

Lim et al. (2009a) determined that in-process control can be used to improve stamped part quality and consistency to adjust BHF, using a multi-input multi-output (MIMO) stamping process controller, with a complex-geometry part. More recently, they demonstrated a MIMO adaptive stamping process controller whose parameters are updated to accommodate changes in plant dynamics and disturbances (Lim et al., 2010b-d). They also proposed the automatic tuning method not only to easily and rapidly tune simply the process controller gains, but also to provide an appropriate initial value for the adaptive control algorithm for stamping that they developed. These studies are detailed in this dissertation.

**Cycle-to-Cycle Control**

Statistical process control methods are used to implement cycle-to-cycle control based on the dimensional measurements of stamped parts. In cycle-to-cycle control, an
important aspect is to maintain a database of process variables (e.g., material property, lubrication, BHF, punch force, draw-in and punch speed). For example, as illustrated in Figure 1.2.3, operator experience is necessary to adjust a process variable(s) at each cycle. Ultimately, the current cycle-to-cycle control, where an operator closes the loop using dimensional measurement in an otherwise open-loop process, could be improved when combined with machine control and an in-process measurement scheme.

Manabe et al. (1999, 2002, and 2008) proposed the use of a database for an intelligent sheet metal forming system to enable design of a process control system without experts who are skilled and experienced in the forming process. They developed a fuzzy-rule model which provides an easy way to optimize cycle-to-cycle control, because the deep drawing process is not only unsteady and complicated but has nonlinear characteristics. Their method resulted in around 25% reduction in production time. They were able to increase the draw-depth of an experimental cup by 0.77mm (or up to 40% drawn cup height) using their method. Moreover, in order to realize preliminary evaluation of process design and implementation, Koyama and Manabe (2003) also proposed a virtual processing algorithm for the intelligent stamping process using the fuzzy-rule model, which was based on their previous work in (Manabe et al., 2002).

Hardt and Siu (2002) proposed a single-input, single-output (SISO) control scheme based on output measurement and input change after each processing cycle. They also experimentally implemented cycle-to-cycle control of a simple bending process. Rzepniewski and Hardt (2003, 2004, and 2008) provided the extension of the cycle-to-cycle control concept to the general multiple-input multiple-output (MIMO) situation. It has been shown that properties of zero mean error and bounded variance amplification
that were seen for the SISO case can also be achieved for the MIMO case. Finally, they noted that MIMO cycle-to-cycle (or run-by-run) control is an appropriate candidate for a system having many thousands of inputs and outputs (e.g., a reconfigurable discrete forming die).

Cycle-to-cycle control itself has been used to improve stamped part quality through post-process inspection or in-process variable monitoring. However, post-process corrections can only be achieved after bad parts are produced. Ultimately, in-process control, despite its additional cost and difficulty in sensing, is needed to improve formability, dimension accuracy and consistency in production.

Figure 1.2.3: Expected evolution of cycle-to-cycle control: (a) current, (b) with machine control and (c) with in-process and machine control.
1.2.2 Active Blank Holder Force (BHF) Control Systems

This section introduces different types of active BHF control systems to improve part quality, controlling the material flow into the die cavity. Conventional passive die-cushions filled with nitrogen gas can be replaced with an active BHF control system actuated by multiple hydraulic cylinders. The objective is to improve the formability and dimensional accuracy of the stamped part by varying the BHF at different locations on the die, as well as at different times during the punch stroke.

Segmented Blank Holder System

The typical elastic binder (Doege et al., 2001) focused on generating homogeneous binder pressure on the sheet-metal blank, a segmented blank holder (or flexible binder) is able to accomplish control of one segment while not being significantly influenced by the variation and distribution of other segments.

He et al. (2001, 2003) utilized a segmented variable blank holder force (BHF) system through simulation to enhance formability of tailor-welded blanks (TWB) with thinner (i.e., 0.8 mm) and thicker (i.e., 1.5 mm) materials in box-drawing. In simulation, different segmented BHF combinations were applied to reduce the weld line movement during the forming stroke. Moreover, they conducted experiments to validate conditions for segmented BHF which were chosen using the analysis and FEA results. Those experiments showed very good formability enhancement by using variable BHF control at different locations. Based on (He et al., 2003), Chen et al. (2008) accomplished a comparison study on the effectiveness of stepped binder and weld line clamping pins on formability improvement for TWBs, evaluating them via segmented BHF drawing simulations and experiments.
Yagami et al. (2004) employed segmented blank holder modules to control the material flow into the die cavity, enhancing the effect of the BHF control and improving formability in the stamping process. They obtained fuzzy blank holder pressure (BHP) trajectories for each blank holder segment and showed that the distributed BHP method can improve wall thickness distribution.

Wang et al. (2005) developed a space variant BHF system with segmented blank holders to control the strain path during the deep drawing process. They reported that the key advantage is that strain in the forming process can be adjusted in a safe working area without fracture.

![Figure 1.2.4: Working area for pulsating BHF with amplitudes of 0kN (static case), 9kN, 13kN, 20kN; frequency 3Hz; sheet material: ZHPH (Ziegler, 1999).](image)

**Pulsating BHF Control System**

A new approach to the variation of BHF has involved pulsation. Experiments by Ziegler et al. (1999) showed that the onset of wrinkling in a blank drawn with a pulsating BHF occurs at a displacement similar to that obtained under a constant BHF equal to the
maximum force of the pulsation (see Figure 1.2.4). The reduction in the friction force achieved when the pulse reduces the BHF to below this maximum allows increased deformation to occur prior to tearing, without sacrificing effective wrinkle suppression. An example of the increase in the working window achieved with zinc-coated and phosphated steel sheets, employing a pulse frequency of approximately 3 Hz (the specific frequency itself was determined to be of little influence), is demonstrated in Figure 1.2.4.

The key objective that they tried to achieve was to avoid cracks on the surface by reducing the friction force. For example, with constant BHF, it was only possible to avoid cracks for the friction coefficient \( \mu = 0.1 \). With higher friction coefficients cracks occur. With pulsating BHF, it was possible to avoid cracks even if the friction coefficient increased up to \( \mu = 0.12 \). Ultimately, this showed that pulsating BHF helped to increase the robustness of the process and contributed to avoiding scratches on the surface of stamped parts. However, the amplitude and frequency of the pulses would need to be tuned with respect to the lubrication and material properties for a given stamping.

**Active Drawbead Control System**

Material flow in the forming process is often modified locally by the insertion of drawbeads into the tooling. In practice, the drawbead is a fixed component on the dies. However, Michler et al. (1993, 1994) and Bohn et al. (1998, 2000) implemented their control function with a set of active drawbead actuators. They constructed a multiple-action hydraulic sheet metal strip-drawing tool for the purpose of studying the effectiveness of feedback control in forming. As shown in Figure 1.2.5, a punch pulls a strip of sheet metal over a die shoulder and a controllable drawbead is located in the center of the blank holder. Both drawbead penetration and BHF are controlled while the
apparatus is measuring and recording the drawbead position, the vertical drawbead force, BHF, and the punch (strip pulling) force (i.e., measured output). In experiments, a PI controller was used, adjusting the drawbead penetration to compensate for the deviation between the reference input (i.e., desired punch force trajectory) and the measured output (i.e., actual punch force).

An active drawbead control system can achieve fast response and require smaller energy consumption than other types of active blank holder systems consisting of large inertia-based hydraulic actuators. However, this idea is difficult to implement in practice, due to complexity and cost in the production of the dies.

Reconfigurable Discrete Die

A reconfigurable forming tool attempts to use a die whose shape can be rapidly reprogrammed between forming cycles. If the die surface is in some way programmable,
then, the stamped part quality can be improved. Obviously, a key advantage of the reconfigurable die is that it rapidly enables one to regenerate new dies, whose shape is different from previous ones, with aid of die reconfiguration actuators.

Walczyk et al. (1998) and Hardt (2002) addressed the design and analysis issues involved with movable die pins, turning a matrix of die pins into a rigid tool, and the pin matrix containment frame. As illustrated in Figure 1.2.6, they proposed a feedback control scheme to monitor directly the 3D shape of the stamped part. Using this approach, the pin actuators are controlled by the shape controller until part shape errors are minimized with respect to a predetermined shape trajectory. The reconfigurable tool was combined with a three-dimensional shape-sensing device and a spatial frequency-based control law.

However, the reconfigurable discrete die may not be applicable to produce very complex part shapes. Challenges include optimizing the number of actuator pins with respect to cost and mechanical complexity.

Figure 1.2.6: Shape control system using a reconfigurable tool and spatial frequency controller (Hardt, 2002).

1.2.3 Process Variables and Sensors in Stamping

This section addresses how to measure physical quantities either on the machine or the work-piece itself in stamping. The most important constitutive relationship for the
Stamping process is stress-strain or force-displacement, the latter two quantities are most often measured. In general, monitoring process variables (e.g., punch force, draw-in, and wrinkling) in the sheet metal forming process is very important to improve stamped part quality and to reduce cost and time-consuming die-work. Thus, many researchers have focused on sensors to monitor process variables for use in control of the stamping process.

**Punch Force**

Among the process variables, punch (i.e., strip pulling) force is valuable to interpret the stress-strain curve for the material, because sheet metal pulling force is directly involved in failure (Hosford et al., 1993; Marciniak, 2002). The punch force can be measured using commercial sensors installed on the stamping press.

Michler et al. (1993, 1994) detected the punch force using a bi-directional force transducer for an adjustable drawbead system that varied drawbead penetration to control the draw-in restraining force. This behavior of the punch force is influenced to a significant extent by the drawbead restraining force.

Similar measurement of the punch force was achieved by Hsu et al. (2000 and 2002) and Lim et al. (2010a-d). They presented in-process control though adjustment of the BHF using a hydraulically controlled actuator press based on tracking a reference punch force trajectory to improve part quality and consistency. Sensing the punch force as a process variable in the forming process is easy to implement in practice. However, the measured punch force represents the resultant effect of the forming process and lacks local detail.
Mahayotsanun et al. (2009) described a mathematical framework for representing measurements from an array of punch force sensors (using pressure sensors) structurally integrated into the tool-work-piece (or upper die) interface of sheet metal operations. The pressure distribution on tool surfaces is interpolated and estimated using some techniques (e.g., Bezier surface interpolation). Thus, this work shows the solutions to two challenges: 1) How to best place the limited number of sensors in order to maximize information retrieval, and 2) how to best recreate the spatial distribution of the contact pressure from the limited number of sensors.

**Draw-In (or Material Flow-In)**

The ideal feedback measurement for in-process control of forming would be the stress and strain field throughout the sheet metal. With this information local springback can be reduced and fracture can be also prevented. Unfortunately, in-process measurements of stresses and strains are impractical. However, certain displacements can be measured. In processes where sections of material remain free of surface pressure, mechanical and optical measurement devices could be inserted to sense draw-in of the sheet metal.

Using linear variable differential transducers (LVDT), Hardt et al. (1993) measured draw-in to control the BHF in process to ensure optimal forming conditions. Then, they proved that displacement of the edge of the sheet during draw-in was not reliable because of tearing. They also proposed a method that measured the circumferential contraction of the material, in averaging all draw-in over the entire circumference of the blank.

Sunseri et al. (1996) and Siegert et al. (1997) also used an LVDT type draw-in sensor to reduce springback and wrinkling respectively. However, the LVDT requires
significant setup time in practice, and becomes too time-consuming and expensive to use in production.

A compact, economic draw-in sensor to overcome the week-point of the LVDT type sensor has been developed. Lo et al. (1999) monitored the displacement of sheet metal blank, using a reflective photoelectric encoder, which has a rotating wheel where it contacts the sheet metal. However, this sensor can detect only one direction as the sheet metal moves tangentially with respect to the rotating wheel.

Figure 1.2.7: Operating principle of transducer (b) transducer and sheet metal configuration (c) Induced voltage signal from transducer (Cao et al., 2002; Mahayotsanun et al., 2005, 2007, 2009).

Doege et al. (2002) developed a computer-mouse-like, ball sensor which is based on the mechanical transmission of the plane movement of the sheet metal onto a ball.
Using the ball sensor the material draw-in direction, material flow velocity and material flow path can be independently measured in two orthogonal directions. Doege et al. (2003) also designed a computer-mouse-like, contactless-optical sensor for online sheet metal flow measurement. This contactless-optical sensor consists of a chip in which a complementary metal oxide semiconductor (CMOS) sensor and a digital signal processor (DSP) are integrated. One point from the sheet surface is analyzed by the sensor and described at its initial position by the two pixel values (i.e., PX1 and PY1). When the object is moved, the image point moves to a different position with the pixel values (i.e., PX2 and PY2). Sensing accuracy of optical sensors in draw-in displacement was improved at each local position, compared to the contact-based draw-in sensor. However, there are still implementation difficulties and cost challenges for practical use.

Cao et al. (2002, 2005) and Mahayotsanun et al. (2005, 2007, and 2009) developed a new type of draw-in sensor which has two key advantages: 1) Ease of setup and 2) cost-effective implementation in industrial applications. The installation of LVDT and optical sensors requires either setup time with each forming cycle or intricate tooling modification. Based on the mutual inductance principle, they designed a draw-in sensor by experimenting with a prototype printed on a conventional circuit board to address the need for an affordable and accurate draw-in sensor. This design of sensor was small enough to be embedded in a die or blank holder. In the single transducer configuration the primary and secondary coils, as shown in Figure 1.2.7(a), were printed into one transducer board. Utilizing the principle of mutual inductance between the two loops, the linear draw-in of sheet metal was detected based on the uncovered area of the primary and secondary coils on the board, as shown in Figure 1.2.7(b). The linear position sensor
transmitted signals to a signal conditioning board, which amplified and filtered the induced voltage readings and these readings were sampled using a computer based data acquisition system. Thus, sheet metal draw-in can be obtained using the voltages generated by the draw-in sensor, after calibration using an LVDT, as illustrated in Figure 1.2.7(c). However, the sensor has to be calibrated for each material used and the inductive characteristics are dependent on material properties. Consequently, if this sensor is able to demonstrate endurance for a large number of stamping cycles, it may become adopted by industry due to its ease of use and low cost. In particular, thick epoxy (i.e., about 0.8~2mm) covers the top of the sensor to protect it from wearing out over many hours operation and to place constant gap between the transducer and the sheet metal. Thus, our research evaluated to use this type of the draw-in sensor for our application, due to its simplicity in use and cost-effective implementation in production. However, it had errors due to wrinkling, which creates varying gap conditions between the transducer and the blank (see Appendix A for more detail).

**Wrinkling**

The wrinkling of sheet metal is a common phenomenon which arises in forming due to locally compressive stresses. The ability to sense the occurrence of wrinkles is potentially useful in the sheet metal forming process consisting of closed-loop process control systems (e.g., active BHF).

Pereira et al. (1994) presented a method using two fiber optic displacement sensors for detecting low and high frequency wrinkling in stamping. From two parallel non-contact readings attached to the upper binder, estimation of the peak amplitude of the wrinkle was achieved by combining estimation of wrinkle frequency ($\omega$) with the

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distance between two sensors. Though this non-contact based optical wrinkle sensor would be free from the wear problem in applications, it has also a technical challenge; it is difficult to choose the optimal distance between two readings based on the smallest wrinkling frequency in order to avoid aliasing (e.g., 2 or more oscillations of wrinkling within the distance between two readings).

![Diagram of inductive displacement transducer](image)

Figure 1.2.8: A schematic of inductive displacement transducer for the measurement of the wrinkle height (Siegert et al., 1997).

The measurement of wrinkle height, as shown in Figure 1.2.8, was achieved in closed-loop stamping by applying a combination of two opposing displacement transducers, which are positioned in the upper binder and the lower binder (Siegert et al., 1997). The displacements of the two transducers can be used to measure the real wrinkle height. Changes in sheet thickness cause errors in the measurement of the height if only the displacement between upper and lower binder is measured. However, this contact-based wrinkling sensor is limited in industrial application because of friction-based endurance failures at the sensor tip that contacts the sheet, and also because wrinkle locations are not known a priori.
1.3 Process Control Design

In terms of control terminology, the closed-loop system, including the process model and the process controller, must have high performance in terms of tracking the reference trajectory (e.g., punch force) through manipulation of the input (e.g., blank holder force) regardless of disturbances and model uncertainty. To systematically develop a good stamping process controller, two tasks must be performed: One task is modeling the sheet metal forming process, model uncertainty and process disturbances. The other task is to develop a controller with high tracking performance through available controller design techniques.

1.3.1 Modeling of the Stamping Process

The control-design model of the process must be simple, yet accurate enough to capture the characteristic relationship between blank holder force and draw-in or punch force. In stamping, the modeling for control of sheet metal forming has not been adequately addressed so far. Most sheet metal forming models are based on finite element analysis, which are very complex, and therefore, not suitable for controller design (Wagoner and Chenot, 2001). Since, they developed a piecewise linear model for simulation design, however, this model cannot be used in control design.

In this research, the mechanics of the stamping process to develop a structure for such a simple control-design model is considered. This model structure is subsequently used as the basis for experimentally identified models. This is discussed in detail in Chapter 2.
1.3.2 Process Control Design in Stamping

The most popular structure for the process controller is a proportional plus integral (PI) controller, which has been successfully used for rejecting disturbances and improving robustness to model uncertainty in stamping (Cao and Boyce, 1994; Sunseri et al., 1996, Siegert et al., 1997; Ziegler, 1999; Hsu et al., 2002). A single-input single-output (SISO) process modeling and control using a proportional plus integral (PI) controller was investigated based on simple die geometry (e.g., u-channel forming) under laboratory-based tests (Siegert et al., 1997; Ziegler, 1999; Hsu et al., 2000, 2002). As part of this research, a multi-input multi-output (MIMO) PI stamping process controller with good tracking performance has, for the first time, been developed and experimentally validated (Lim et al., 2008b, 2009a, and 2010a) based on complex die geometry (e.g., a door panel of pick-up truck) in production-environment experiments. This MIMO stamping process control has been designed using estimated MIMO process models based on system identification techniques, and has been shown to improve part quality and consistency for a complex-geometry part, in the presence of plant disturbances. However, in those experimental tests controller fine-tuning based on a manual approach, which can be time consuming and expensive, was required.

Astrom et al. (1993) and Astrom and Wittenmark (1995) utilized the auto-tuning method to tune the gains of a standard PI(D) controller. Such auto-tuning can also be utilized to provide good initial values of the PI gains for the adaptive control design. In our research (Lim et al., 2010b-d) we have utilized the automatic tuning method to tune the controller gains, eliminating manual tuning, which requires costly and time-consuming effort. However, if there are unpredictable parameters changes in the
stamping process during operation, the fixed-gain PI process controller tuned by auto-
tuning will still have limitations in tracking performance in the presence of such plant parameter variations.

Consequently, in our research, the MIMO PI adaptive controller (AC), whose gains are updated to accommodate the changes in plant dynamics and disturbances for a complex-geometry part, is investigated to improve the tracking performance as well as part quality, in the presence of plant variations, by adjusting the binder forces to achieve a desired control objective. In addition, a pre-compensator based on the inverse of the closed-loop system is also included to achieve high output tracking performance.

1.4 Summary and Conclusions

Key developments in feedback control in stamping and its effect on the quality of stamped parts are summarized. The use of feedback control to improve part quality requires addressing several technical issues, including the generation of accurate reference trajectories for the control loops using FEA and/or design-of-experiments. In-process control also requires the implementation of controllers to adjust BHF and achieves the control objective of tracking the desired reference trajectories. The design of these controllers requires accurate models of the forming process. In addition, the development of reliable, cost-effective sensors to measure representative process variables is also a key technical challenge. Addressing these issues will lead to the creation of systems that combine statistical process control methods, machine control, in-process control, and cycle-to-cycle control capabilities to significantly improve part quality and consistency in stamping.
The closed-loop system, including the process model and the process controller, requires high performance tracking of the reference trajectory (e.g., punch force) through manipulation of the input (e.g., blank holder force), regardless of the disturbance and the model uncertainty. First of all, the control-design model structure, which must be simple, yet accurate enough to capture the characteristic relationship between the input and output, has been studied. Furthermore, different types of stamping process controllers using fixed gains have been designed, showing improvement in part quality and consistency for both simple and complex geometries. However, controller tuning based on a manual approach in experimental tests can be time consuming and expensive. Thus, auto-tuning methods can be used for tuning gains of the process controller. However, if there are unpredictable parameters changes in the stamping process during operation, the fixed-gain PI process controller tuned by auto-tuning, which may yet give good initial values for the adaptive control design, will still have limitations in tracking performance in the presence of such plant variations.

Consequently, an adaptive controller, whose parameters are continuously adjusted to accommodate changes in process dynamics and disturbances, is developed to improve tracking performance as well as part quality in the stamping process, in the presence of plant variations and disturbances.

1.5 Research Objectives

The main problems in stamping are to avoid wrinkling and tearing during forming, to minimize springback of the stamped part, and to reduce variations in stamped part quality. A MIMO adaptive process control approach, which can complement existing
techniques to improve part quality and consistency of stamped parts with complex-geometry parts, in the presence of plant variations, is proposed. The proposed approach is a feedback control strategy based on the adjustment of the 12 blank holder forces to control the 4 punch forces. The reason for choosing the punch force as the monitored process variable is the simplicity of its measurement and cost-effective implementation in production applications (see Section 1.2.3 and Appendix A for details).

The research objectives can be accomplished through addressing the relationship between adaptive process control and part quality for complex-geometry dies, and developing systematic design procedures for adaptive process control. The relationship between adaptive process control and part quality can be investigated through comparison of both simulation and experimental results between adaptive process control and machine control only.

Systematic development of a MIMO adaptive stamping process control can be divided into three problems areas:

1. Validation and integration of in-process sensors for the stamping process
   In-process sensors are validated and integrated with real-time data acquisition capabilities to collect data which can be used to parameterize a MIMO stamping process model using system identification techniques.

2. Modeling a MIMO sheet metal stamping process for controller design
   A suitable MIMO dynamic model structure, along with parameter estimation experiments are proposed to characterize the appropriate relationship between the binder force actuators (i.e., the inputs) and the measured punch force (i.e., the outputs) with a complex-geometry part.
3. **MIMO adaptive process controller design and implementation**

A proper MIMO stamping process controller can make the closed-loop system track the reference punch force trajectory as well as improve part quality in the presence of plant parameter variations with a complex-geometry part.

This proposed research is based upon original experiments performed with a novel system for binder force control in the stamping process, using 12 hydraulically-controlled actuators as inputs and 4 punch forces as outputs, with a complex-geometry part. Therefore, this dissertation will focus on MIMO problems. In addition to the comprehensive theoretical and simulation-based development, a key objective is to evaluate the performance of the system in a commercial environment using an actual production part.

**1.6 Original Contributions**

This research has led to the development of validated methods for practical MIMO adaptive process control in stamping. A summary of the contributions of the research is given below:

- **Development of a MIMO process model structure in stamping**
  - A fourth order linear MIMO relationship between the blank holder forces and the punch forces for a complex-geometry part.
  - This MIMO model structure is validated by using original experiments performed with a novel new design for a stamping process system that includes 12 hydraulic actuators to control the binder forces, and monitors 4 punch forces.
The results of the experiments are used, via system identification techniques, to parameterize the process MIMO model.

- **Design and implementation of a MIMO process controller**
  - A systematic design procedure involving simulation using the estimated process model is proposed and applied to design of a proportional plus integral (PI) controller including a pre-compensator for actual production.
  - A MIMO process controller is successfully designed based on the systematic design procedure, and implemented to improve part quality in real production tests based on a manual tuning approach.

- **Automatic tuning and adaptive control**
  - A simulation-based auto-tuning method, which requires the stamping of only one additional part for the purpose of plant model parameter estimation, is investigated to eliminate a manual approach to obtain the fixed PI gains.
  - The design and implementation of two MIMO adaptive process control approaches (i.e., direct and indirect), for the first time, is investigated in stamping.
  - Two MIMO adaptive process controllers are experimentally validated in terms of the tracking performance of the reference punch force as well as part quality improvements, in the presence of plant parameter variations and/or disturbances.
Application of the developed MIMO process model and process controller design procedures to actual stamping production is demonstrated to show the generality of the developed procedures.

1.7 Outline of Thesis

Chapter 1 presents the motivation for this research, a comprehensive literature review (Lim et al., 2008a), and states research objectives and original contributions. Chapter 2 develops a fourth order linear MIMO dynamic structure which relates the blank holder forces (as inputs) to the punch forces (as outputs) for a complex-geometry part. This chapter also presents a system identification procedure, based on parameter estimation experiments, which is used to parameterize a MIMO stamping process model (Lim et al., 2008b, 2009a, 2010a).

A systematic approach to designing a suitable process controller is discussed in Chapters 3, 4, and 5. Chapter 3 presents a fixed gain process controller which is tuned by trial-and-error through experimental tests. Chapter 4 presents a systematic approach to the design of a direct adaptive controller (i.e., MRAC) which updates the controller gains. In this chapter, the derivation of the parametric model for the adaptive law of a direct MRAC is presented. The filter model in the regressor of the direct MRAC uses nominal process parameters. This chapter also presents the auto-tuning method which is useful for providing good initial gain values for use with the adaptive controller (Lim et al., 2010b-c). Chapter 5 describes a systematic design approach for the indirect adaptive control which does not require the nominal process parameters and provides the estimates of process model parameters. This chapter also presents how an indirect AC, which requires
the off-line computation of the controller gains via optimization due to the simple proportional plus integral (PI) control structure selected, is designed and implemented on-line using a look-up table scheme. The look-up table, which stores controller gains that are pre-computed off-line, is embedded into the indirect AC system and used to provide the controller gains on-line based on the estimated process parameters. Furthermore, the direct and indirect adaptive controllers are compared through simulation and experiments, in terms of the tracking performance as well as part quality improvement, in the presence of disturbances (Lim et al., 2010d). Finally, Chapter 6 summarizes this research, contains important conclusions, and provides suggestions for future work.
CHAPTER 2

SYSTEM IDENTIFICATION BASED ON EXPERIMENTS

The first step in a systematic process controller design approach is process modeling.

2.1 Introduction

The modeling for control of sheet metal forming has not been adequately addressed, especially, from a control point of view. A useful process model must satisfy two requirements: 1) the control-design model of the process must be as simple as possible to be suitable for process controller design, yet 2) the process model must be accurate enough to capture the characteristic dynamic relationship between input (i.e., blank holder force) and output (i.e., punch force). Thus, these requirements are necessary for both simulation and experiments to evaluate the performance of a designed controller. Sheet metal forming models based on finite element analysis (FEA) are too complex (Wagoner and Chenot, 2001) for process controller design. Hsu et al. (2000) developed a process model which describes mathematically the relationship between the binder (or blank holder) force and the punch force, assuming that the punch force generation is a function of the blank holder force: see, for example, (Hsu et al., 1999), where such a model was developed for a single-input single-output (SISO) process. Other researchers
have developed sheet metal stamping models based on material flow data from experiments which consider the local strain (Lo et al., 1999; Doege et al., 2003). Such methods, considering both draw-in and local strain of sheet metal, can mathematically determine the elongation of a section of a radial-line out of a drawn part with respect to drawing stroke. However, only simple die geometry (e.g., \( u \)-channel forming and cup-drawing) characterized by a SISO process model in laboratory-based tests were investigated.

The purpose of this chapter is, for the first time, to develop a MIMO controller-design model structure of the sheet metal forming process for a complex-geometry part, under actual production conditions. The MIMO process model is then parameterized using system identification techniques, and then experimentally validated. The estimated MIMO process model is subsequently used as the basis for the design of the process controller. This research is based upon original experiments performed with a novel system for binder force control in stamping, using 12 hydraulically-controlled actuators.

### 2.2 Experimental System

The experimental system, with 12 hydraulic cylinders placed underneath the lower binder, which act as binder force actuators, and an Opal-RT real-time data acquisition and control system, is deployed. When the press ram compresses the hydraulic fluid in the cylinders located at the bottom of the die (see Figure 2.2.1(a)), binder forces at different locations are generated based on pressure feedback from hydraulic pressure sensors located on the hydraulic regulator unit at the back of the press (see Figure 2.2.2).
An example of one of the complex-geometry parts used for the experiments is an inner door panel for a sports-sedan (see Figure 2.2.1(b)).

More specifically, as shown in Figure 2.2.2, process input and output variables (i.e., punch stroke, actuator pressure (or binder force) and punch force) are monitored and then controlled by the real-time computer. First, the punch stroke sensor specifies the stroke of a hydraulic actuator which corresponds to the drawing depth. Second, each measured actuator pressure is converted into the blank holder force (i.e., $F_b = P \times A$, where $P$ is the hydraulic pressure and $A$ is sectional area of the hydraulic actuator piston). As shown in Figure 2.2.2, two pressure tanks, half filled with hydraulic fluid and compressed using pneumatic pressure (i.e., around 6.5 bars), are used to return the hydraulic cylinder actuator rods to their original position. Third, the punch force, which serves as the process output variable, is measured at the four corners of the press using full-bridge strain gauges that are attached to the surface of the four punch-supporting beams on the press.

The real-time system (Opal-RT HIL System) plays a key role in controlling the system and acquiring the measured data from the sensors. As shown in Figure 2.2.3, using a software layer (i.e., Python), the real-time operating computer, which is connected to the process variables, is interfaced with a laptop computer where the RT-Lab control package is installed. First, an Excel template is used to input the pre-determined binder forces for the hydraulic actuators to the software layer. Second, all system conditions (e.g., hydraulic pressure and punch force offsets, implemented controller gains, etc) are monitored and also modified using a GUI built in LabView and run in TestDrive, the interactive software of Opral-RT. Third, the designed process
controller is created in Simulink, the simulation software module of Matlab, compiled using the RT-Lab control package, and then implemented on the Opal-RT target machine through the software layer. Finally, the acquired data (e.g., binder force and punch force) are collected using the Opal-RT target machine, and then communicated to the RT-Lab control package which is installed on the laptop computer. A sample rate of 2 kHz is used for both data acquisition as well as machine controller execution. However, the process controller executes at a sample rate of 100 Hz. The experimental conditions and specifications of the sensors used in the tests are given in Table 2.2.1.

The press is a 1000-ton mechanical press which can operate at 17 strokes/minute. The material flow is controlled by a set of blank holders using the 12 hydraulic actuators. As shown in Figure 2.2.1(b), the process variables used for the experiment are the punch forces measured at the four corners of the press using standard tonnage monitors, denoted by $F_p^i$ ($i = 1, 2, 3, 4$), and the three binder forces associated with each of those punch force are denoted by $F_{bj}^i$ ($j = 1, 2, 3$). In (Lim et al, 2008, 2009a 2010a), the assumption that each punch force output is most affected by the three nearest binder forces as inputs has experimentally been verified. In addition, the configuration of the experimental system for a production test with a complex-geometry part is described in Appendix B.
Figure 2.2.1: Experimental system: (a) test die with actuators and sensors (b) a stamped part showing locations of process variables (i.e., a top-view of (a)).

Figure 2.2.2: Experimental setups for showing actuators, sensors, and real-time control system located at the rear of the test die shown in Figure 2.2.1.
Figure 2.2.3: Schematic diagram of signal connections for the experimental setup shown in Figure 2.2.2.

Table 2.2.1: Experimental conditions and process sensor specifications.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Punch speed (max.)</td>
<td>215 mm/sec</td>
</tr>
<tr>
<td>Punch displacement, $h_{\text{max}}$</td>
<td>150 mm</td>
</tr>
<tr>
<td>Data sampling rate</td>
<td>2 kHz for machine control &amp; 100 Hz for process control</td>
</tr>
<tr>
<td>Lubrication</td>
<td>Dry &amp; Ferrocote 61 MAL HCL 1</td>
</tr>
<tr>
<td>Material</td>
<td>EDDQ HD 50G50G</td>
</tr>
<tr>
<td>Blank size (L x W x thickness)</td>
<td>1640 x 984 x 0.64 &amp; 0.79 mm</td>
</tr>
<tr>
<td>Punch force sensor</td>
<td>Full-bridge strain gauge transducer</td>
</tr>
<tr>
<td>Excitation</td>
<td>Built-in 10V@125mA max</td>
</tr>
<tr>
<td>Accuracy</td>
<td>$&lt; \pm 1%$ of full scale</td>
</tr>
<tr>
<td>Binder force sensor</td>
<td>Strain gauge pressure transducer</td>
</tr>
<tr>
<td>Resolution</td>
<td>$&lt; \pm 1%$ of full scale</td>
</tr>
<tr>
<td>Punch stroke sensor</td>
<td>Linear displacement transducer</td>
</tr>
<tr>
<td>Accuracy</td>
<td>$&lt; \pm 0.005%$ of full scale</td>
</tr>
</tbody>
</table>
2.3 Experimental Data for System Identification

In this section a simple mechanics-based approach to establish a potential controller-design model structure is presented. System identification is an experimental approach to plant modeling. Data obtained from experiments is used to estimate the unknown parameters in the process model. The objective here is to parameterize transfer function models of the forming process, with input-output data from experimental die try-out tests. In addition, these experiments are used to capture the desired reference trajectories (i.e., punch force trajectories) which characterize a good part.

2.3.1 Blank Holder Force Trajectories as Input

Figure 2.3.1 shows three different types of measured blank holder force trajectories (i.e., $F_b(t)$) for one representative cylinder of the 12 hydraulic actuators. Due to space limitations, only one of the 12 binder force profiles is shown. Trajectory (1) is a constant blank holder force experiment used as a baseline. Trajectory (2) is a desired, or “optimal”, blank holder force trajectory selected by experienced operators for making a good part. Trajectory (3) is a perturbed blank holder force (with respect to the baseline) used for system identification.

2.3.2 Punch Force Trajectories as Output

Figure 2.3.2 shows experimental results for four punch force trajectories based on the three different types of blank holder force trajectories. The punch force trajectories obtained, with the desired blank holder force, will be used as the reference punch force trajectories in the subsequent design of a process controller. Note, from Figure 2.3.2, that the punch force generally increases as the punch stroke increases. Higher blank holder
force (or smaller draw-in) produces higher punch force. For example, as shown Figure 2.3.1 and Figure 2.3.2(d), during 0 – 0.4 seconds, the punch force ($F_p^d$) in the desired case is larger than in the constant case, because the binder force ($F_b^d$) in the desired case is larger than in the constant case. Also, during 0.4 – 0.7 seconds, the same trend is validated; a smaller blank holder force results in a smaller punch force. This input-output relationship will be further investigated in the following process modeling and parameter identification sections. We note that small fluctuations are observed in Figure 2.3.2 at the beginning of the stroke due to the compliance of the hydraulic actuator rods as they contact the binder right after the impact of the punch with the lower binder.

Figure 2.3.1: Commanded blank holder force trajectories (i.e., $F_b^d$) for a hydraulic actuator shown Figure 2.2.1(b).
2.4 Process Model Structure

2.4.1 Mathematical Modeling of the Stamping Process

For designing the stamping process controller, a simple controller-design model, providing a dynamic relationship between the process input (i.e., binder force) and process output (i.e., punch force) is required. Thus, the goal in modeling is not to develop a complex model suitable for simulating the stamping process, but rather a simple model structure dynamically relating input and output, with undetermined parameters that can then be experimentally evaluated.
Consider a simple one-dimensional analysis, for a cross section of the sheet metal in tension in a simple stamping process, as the sheet is being pulled into the die by the punch as in Figure 1.1.1. This is schematically illustrated in Figure 2.4.1(a), where the binder, with force $F_b(t)$, restricts the flow of material into the die. The punch stroke is denoted by $h(t)$, and pulls the element of material into the die. The contact at the binders inhibits the material flow into the die, due to the friction force given by $\mu F_b(t)$. As a consequence of the resulting deformation of the material in tension, the material draw-in, $l_s(t)$, is less than $h(t)$, i.e., $(h(t) - l_s(t)) > 0$.

For the plastic deformation of the sheet metal in tension, the stress, $\sigma$, and strain, $\varepsilon$, are related by (Hollomon, 1945; Hosford and Caddell, 1993):

$$\sigma = K \varepsilon^n \dot{\varepsilon}^m$$  \hspace{1cm} (2.1)

where $\dot{\varepsilon}$ is the strain rate, and $K$, $n$ and $m$ are material constant, work-hardening and strain rate sensitivity respectively. Linearization of Eq. (2.1) about nominal values $(\sigma_0, \varepsilon_0, \dot{\varepsilon}_0)$ yields
\[ \Delta \sigma \approx K_1 \Delta \varepsilon + K_2 \Delta \dot{\varepsilon} \]  

(2.2)

where

\[ \Delta \sigma = \sigma - \sigma_0 \]
\[ \Delta \varepsilon = \varepsilon - \varepsilon_0 \]
\[ \Delta \dot{\varepsilon} = \dot{\varepsilon} - \dot{\varepsilon}_0 \]

The relationship in Eq. (2.2), together with the element geometry, can be used to determine a restraining force, in terms of the elongation and elongation rate in the element of material, of the form:

\[ F_r = \alpha \{ h(t) - l_s(t) \} + \beta \{ \dot{h}(t) - \dot{l}_s(t) \} \]  

(2.3)

where \( \alpha \) and \( \beta \) will depend on \( K, n, m \) as well as the element geometry and contact conditions. As shown schematically in Figure 2.4.1(b), one then obtains a lumped-parameter dynamic model for the draw-in:

\[ m_s \ddot{l}_s(t) + \beta \dot{l}_s(t) + \alpha l_s(t) = \alpha \dot{h}(t) + \beta h(t) - \mu F_b(t) \]  

(2.4)

where \( m_s \) is an equivalent mass for the element under consideration.

Consider next the formulation in terms of perturbation variables, which represent changes in these variables from specified values:

\[ h(t) = h_0(t) + \delta h(t) \]
\[ l_s(t) = l_{s0}(t) + \delta l_s(t) \]
\[ F_{s0}(t) = \delta F_s(t) \]
\[ F_{p0}(t) = \delta F_p(t) \]  

(2.5)

where \( \delta F_p(t) \) denotes the punch force. The punch stroke \( h(t) \) is assumed to be prescribed, with no variation, and thus \( \delta h(t) = 0 \). Also, the restraining force, for the simple one-
dimensional geometry being considered, is equal and opposite of the punch force. Thus, 
\[ F_p(t) = -F_r(t), \]
and by Laplace transformation of Eq. (2.4) one obtains the following transfer function relating the change in binder force (input) to the change in punch force (output):

\[
\frac{\delta F_p(s)}{\delta F_b(s)} = \frac{\mu(\beta s + \alpha)}{m_s s^2 + \beta s + \alpha} = \frac{b_1 s + b_0}{s^2 + a_1 s + a_0} \tag{2.6}
\]

As illustrated experimentally in Figure 2.4.2, a sudden change of input (binder force) and output (punch force) shows qualitative agreement with model structure in Eq. (2.6). A sudden change, in binder force from a nominal value, leads to a change in the punch force with the same sign, a time lag, and overshoot. In the experiment, a small fluctuation in punch force, at the beginning of the stroke (0 - 0.1 sec), occurs due to the impact of the punch with the lower binder, as shown previously in Figure 2.3.2.

Thus, Eq. (2.6) provides the basic structure for the required controller-design model, relating the change in the manipulated binder force inputs to the resulting change in the measured punch force outputs. Note, however, that the parameters of the dynamical model in Eq. (2.6) will depend on the sheet metal properties and geometry, as well as the die and binder geometry, lubrication, etc. Consequently, the parameters in Eq. (2.6) will need to be experimentally estimated, as described in the next section. In this research, although not presented here to focus on the punch force as a process variable, the basic relationships between binder force inputs and material draw-in (i.e., Eq. (2.4)) have also been experimentally validated using both mutual inductive type (Cao et al., 2002, 2005; Mahayotsanun et al., 2005, 2007, 2009) and cable type draw-in sensors (see Appendix A for more detail).
2.4.2 Process Model Parameter Estimation (Off-Line)

Input-output data obtained from die try-out tests are used to parameterize the process models. The MIMO complete process model structure for parameter estimation consists of three separate dynamic models: machine control, process model and low-pass noise filter.

Figure 2.4.2: Qualitative validation of the control-design model structure through experiments via comparison to Eq. (2.6) of a change in binder force and the resulting punch force response.

Figure 2.4.3: Schematic diagram of process model for estimation ($Ts = 0.01$ sec).
Since the process variables are sampled in connection with the analog-to-digital conversion, Eq. (2.6) in continuous-time is converted into a transfer function for a 2nd order process model \( G_p \) in discrete-time with sampling rate \( T_s = 0.01 \text{ sec} \). As shown in Figure 2.4.3, the resulting process model structure, which characterizes the simple process dynamics relating the actual binder force \( F_{b,act} \) as an input and the actual punch force \( F_{p,act} \) as an output, is formulated with unknown parameters in discrete-time as:

\[
G_p(z) = \frac{\delta F_{p,act}(k)}{\delta F_{b,act}(k)} = \frac{b_1 z + b_0}{z^2 + a_1 z + a_0} \tag{2.7}
\]

Second, based on experimental observations, the transfer function of the 1st order machine control model \( G_m \) shown in Figure 2.4.3, which characterizes the reference binder force \( F_{b,ref} \) as an input and the actual binder force \( F_{b,act} \) as an output, is formulated as a first order transfer function with unknown parameters in discrete-time as:

\[
G_m(z) = \frac{\delta F_{b,act}(k)}{\delta F_{b,ref}(k)} = \frac{\delta_0}{z + \beta_0} \tag{2.8}
\]

The unknown parameters in the machine control models are estimated using two methods: the N4SID subspace algorithm (Overschee and Moor, 1994) and the standard least squares (LS) algorithm (Astrom et al., 1990). The machine control models obtained using these two methods are validated by matching the measured desired binder force output with the actual binder force generated by the identified machine control model with the commanded desired binder force as the input (see Figure 2.4.4(a)-(c)).
Third, the transfer function of the first order low-pass filter \( G_f \) shown in Figure 2.4.3, is given, with known parameters, in discrete-time as:

\[
G_f(z) = \frac{\delta F_{p,fil}(k)}{\delta F_{p,act}(k)} = \frac{50z}{z - 0.9048}
\]  

(2.9)

The filter is discretized using an impulse-invariant transformation with a sampling period of 0.01 second, while the machine control model utilizes a zero-order-hold (ZOH) to characterize the digital-to-analog (D-A) converter in the real-time system. As shown in Figure 2.4.3, cascading the three transfer functions in Eqs. (2.7), (2.8) and (2.9), and
using the mean machine control models, the total model structure is formulated in 
discrete-time with unknown process model parameters as:

\[
G_{\text{total}}(z) = \frac{\delta F_{p,\text{fil}}(k)}{\delta F_{b,\text{ref}}(k)} = G_p(z) \cdot G_m(z) \cdot G_f(z) \quad (2.10)
\]

or

\[
G_{\text{total}}(z) = \frac{\delta F_{p,\text{fil}}(k)}{\delta F_{b,\text{ref}}(k)} = \frac{b_1 z^2 + b_{10} z}{z^4 + a_5 z^3 + a_4 z^2 + a_3 z + a_0} \quad (2.11)
\]

Moreover, one can extend the model structure in Eq. (2.11) to the MIMO case by 
creating a 4 × 12 transfer function matrix (TFM) in Eq. (2.12), with 4-punch force \((\delta F_{p,\text{fil}})\) 
as output and 12-binder force \((\delta F_{b,\text{ref}})\) as inputs. Based on the experimentally validated 
assumption that each punch force output is heavily affected only by the three nearest 
binder force inputs (see Figure 2.2.1(b)), we constrain the TFM to a block-diagonal form 
given by

\[
\begin{bmatrix}
\delta F_{p,\text{fil}}^1(k) \\
\delta F_{p,\text{fil}}^2(k) \\
\delta F_{p,\text{fil}}^3(k) \\
\delta F_{p,\text{fil}}^4(k)
\end{bmatrix} = \begin{bmatrix}
G_1^1 & G_2^1 & G_3^1 \\
0 & G_2^1 & G_3^2 \\
0 & 0 & G_3^3 \\
0 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
\delta F_{b,\text{ref}}^1(k) \\
\delta F_{b,\text{ref}}^2(k) \\
\delta F_{b,\text{ref}}^3(k) \\
\delta F_{b,\text{ref}}^4(k)
\end{bmatrix} \quad (2.12)
\]

Experimental data show that this structure is sufficient to characterize the dynamics 
of the process from actuator reference inputs to filtered sensor outputs. Thus, the 
structure in Eq. (2.12) represents a collection of 4 MISO systems (one at each corner) 
with one punch force output and three binder force inputs. The unknown parameters in
the 4th order system models are estimated based on the experimental data using the Least Squares (LS) algorithm and are plotted in Figure 2.4.5. Each estimated model characterizes the dynamics of the process from three reference binder force (i.e., \( F_{b,ref} \)) inputs (as shown in Figure 2.3.1) to one filtered punch force (i.e., \( F_{p,fil} \)) output (as shown in Figure 2.3.2). Estimated parameters of the 4th order perturbation process models in discrete-time with respect to the each punch force output are also given in Table 2.4.1.

As shown in Figure 2.4.6 for the model validation, experimental punch forces recorded for the desired case (solid-line in Figure 2.4.6) are compared with the punch force outputs generated by estimated models (dotted-line in Figure 2.4.6) using the command binder forces in the desired case. The agreement is acceptable, for our purposes of controller design, but the discrepancies are significant. There are two major reasons why measured punch force outputs are not well matched with outputs from estimated models in these validation results. First, nonlinearity in plastic deformation was ignored in obtaining our process model structure through linearization. Second, although forming is a complex three-dimensional phenomenon, only a simple one-dimensional analysis was considered in developing the control-design model structure. However, it is shown in the next section that the use of this simple model structure for controller design is adequate for obtaining good closed-loop system performance.
Figure 2.4.5: Estimated 4th order perturbation model based on experimental data: (a) $\delta F^1_p$ (b) $\delta F^2_p$ (c) $\delta F^3_p$ (d) $\delta F^4_p$.

Table 2.4.1: Estimated parameters of the 4th order perturbation model in transfer function matrix in Eq. (2.12) with a sample rate of 100 Hz.

<table>
<thead>
<tr>
<th></th>
<th>$\delta F^1_{p,\beta}$</th>
<th>$\delta F^2_{p,\beta}$</th>
<th>$\delta F^3_{p,\beta}$</th>
<th>$\delta F^4_{p,\beta}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G_1^1(z)$ =</td>
<td>$\frac{0.8432 z^2 - 0.8321 z}{z^4 - 0.9746 z^3 + 0.3065 z^2 - 0.3469 z + 0.1798}$</td>
<td>$\frac{0.2462 z^2 - 0.1468 z}{z^4 - 0.7203 z^3 - 0.1166 z^2 - 0.2076 z + 0.1942}$</td>
<td>$\frac{0.1526 z^2 - 1.479 z}{z^4 - 0.9746 z^3 + 0.3065 z^2 - 0.3469 z + 0.1798}$</td>
<td>$\frac{0.1353 z^2 - 0.0927 z}{z^4 - 0.7203 z^3 - 0.1166 z^2 - 0.2076 z + 0.1942}$</td>
</tr>
<tr>
<td>$G_1^2(z)$ =</td>
<td>$\frac{2.095 z^2 - 1.586 z}{z^4 - 0.9746 z^3 + 0.3065 z^2 - 0.3469 z + 0.1798}$</td>
<td>$\frac{0.8538 z^2 - 0.7037 z}{z^4 - 0.7203 z^3 - 0.1166 z^2 - 0.2076 z + 0.1942}$</td>
<td>$\frac{1.526 z^2 - 1.479 z}{z^4 - 0.9746 z^3 + 0.3065 z^2 - 0.3469 z + 0.1798}$</td>
<td>$\frac{0.1353 z^2 - 0.0927 z}{z^4 - 0.7203 z^3 - 0.1166 z^2 - 0.2076 z + 0.1942}$</td>
</tr>
<tr>
<td>$G_1^3(z)$ =</td>
<td>$\frac{0.4912 z^2 - 0.2313 z}{z^4 - 1.403 z^3 + 0.3936 z^2 + 0.1452 z - 0.05513}$</td>
<td>$\frac{0.2685 z^2 - 0.1701 z}{z^4 - 1.621 z^3 + 0.6777 z^2 + 0.06901 z - 0.06487}$</td>
<td>$\frac{0.333 z^2 - 0.03505 z}{z^4 - 1.403 z^3 + 0.3936 z^2 + 0.1452 z - 0.05513}$</td>
<td>$\frac{0.4632 z^2 - 0.4214 z}{z^4 - 1.621 z^3 + 0.6777 z^2 + 0.06901 z - 0.06487}$</td>
</tr>
<tr>
<td>$G_1^4(z)$ =</td>
<td>$\frac{0.333 z^2 - 0.03505 z}{z^4 - 1.403 z^3 + 0.3936 z^2 + 0.1452 z - 0.05513}$</td>
<td>$\frac{0.2685 z^2 - 0.1701 z}{z^4 - 1.621 z^3 + 0.6777 z^2 + 0.06901 z - 0.06487}$</td>
<td>$\frac{0.9474 z^2 - 0.66 z}{z^4 - 1.403 z^3 + 0.3936 z^2 + 0.1452 z - 0.05513}$</td>
<td>$\frac{0.4632 z^2 - 0.4214 z}{z^4 - 1.621 z^3 + 0.6777 z^2 + 0.06901 z - 0.06487}$</td>
</tr>
</tbody>
</table>
2.4.3 Preliminary Experiments with Process Variables

As described in the previous section, the control-design model of stamping in Eq. (2.7) relates the binder force (i.e., input variable) and the punch force (i.e., output variable). The punch force varies with any change in the binder force. The punch force is also influenced by disturbances (e.g., lubrication and thickness change), under the same binder force conditions. For example, as illustrated in Figure 2.4.7 for a representative test, when there is lubricant on the sheet metal, the punch force output is smaller than under non-lubricated conditions, with the same binder forces. Furthermore, the punch force also varies when a thicker (i.e., 0.79 mm) blank is used, as compared to a blank of nominal thickness (i.e., 0.64 mm), with the same binder forces and lubrication conditions.
Figure 2.4.7 shows not only that more lubrication results in a lower punch force because of reduced friction/restraining force, but also that a thicker material results in a larger punch force because of increased friction/restraining force. Thus, plant disturbances directly affect the material flow during the stamping process, leading to degradation of part quality. These disturbances are captured in punch force data, consequently, the punch force can be measured and used as a process variable to provide real-time feedback on part quality consistency in the presence of disturbances.

![Diagram showing punch force changes](image)

Figure 2.4.7: The changes in the punch force due to plant disturbances (e.g., lubrication and thickness changes), with the same binder forces condition.

### 2.5 Discussion

For designing the stamping process controller, a simple controller-design model, providing one-dimensional dynamic relationship between the binder force and the punch force, was addressed. As shown previously in Figure 2.4.6, the key reason why validation results follow the data poorly may be fact that nonlinearities in the forming process were
ignored, and a simple control-design model was obtained via linearization. Thus, the research does not expect high model fidelity. However, the model captures the input-output dynamic behavior for small perturbations, showing the qualitative agreement (see Figure 2.4.2) in experimental validation for the linear relationship between the binder force and the punch force. Indeed, this is what is needed for process controllers design, and the resulting controller, which will be described in following chapters, performs well.

The research made a decision for considering only the three nearest actuators for each corner punch force. For a solid die, each binder force, of course, affects all punch force outputs. However, based on model validation procedures using experimental data for the binder forces and punch forces, the case of the three nearest inputs for each output in terms of estimation accuracy was determined to be better than the case of six or twelve inputs for each punch force output. This input and output grouping leads to a set of MISO systems (one at each corner) rather than a fully controlled MIMO system.

The punch force as a process variable to control was selected due to its simplicity to use. Based on preliminary tests using the punch force (see Figure 2.4.7) with the same binder force conditions, the punch force was strongly sensitive to plant disturbances (e.g., lubrication and material thickness change). For example, if the material is thicker than nominal, a larger punch force output occurs. Then, the process controller, which will be described in following chapters, tracks the reference punch force output by decreasing the binder force. In the case of increased lubrication (or if a smaller punch force is detected), then again, the process controller to track the punch force reference adjusts the binder force by increasing it, to reduce material draw-in, and therefore, the punch force increases.
2.6 Summary and Conclusions

Modeling of the sheet metal forming process is required for systematic process controller design. In this chapter the development of a simple dynamic input-output controller design model for MIMO process control in stamping is, for the first time, described. First, the structures of the process models are derived in Eqs. (2.7) and (2.11) respectively: one provides the relationship between the actual blank holder force as an input and the actual punch force as an output, the other provides the whole system structure which has the relationship between the reference blank holder force an input and the filtered punch force as an output. The key features of this chapter are: 1) the development of 2nd order perturbation linear process model is based on the plastic deformation of the sheet metal in tension (Hollomon, 1945; Hosford and Caddell, 1993; Marciniak, 2002), 2) a 4th order model structure includes machine control, process control, and low-pass filter dynamics, 3) these model structures are used to formulate a MIMO model structure as a block-diagonal transfer function matrix, and 4) the parameters of the MIMO model structures are experimentally determined and validated using system identification techniques.

The novel experimental system used in this research has 12 hydraulic actuators which enable the blank holder force to be controlled at different locations, and to be varied during the punch stroke. Furthermore, four punch force sensors built into the press enable the measurement of process output responses to changes in the blank holder forces and plant disturbances. This system allows one to develop, for the first time, a MIMO process model for stamping. In the following chapters, the MIMO process model developed herewith will be used as the basis for designing a MIMO process controller
which adjusts blank holder forces to follow desired reference trajectories for the measured process output, namely, punch force.
The tracking performance of the process controller determines both part quality and consistency. The process controller design must achieve a high tracking performance regardless of plant disturbances (e.g., lubrication change and variations in blank size and thickness), to ensure that stamped parts consistently meet quality metrics.

3.1 Introduction

Die design, using the finite element analysis (FEA) and die try-out, which involves grinding and welding of the die to ensure that the parts produced meet specifications, are time-consuming tasks. Moreover, engineers in the forming industry also face challenging production problems due to process variability. To improve part quality (e.g., eliminating wrinkling, tearing, and springback), with given materials and a conventional press, the original die dimensions based on the part geometry data (e.g., product shape designed by a product designer using computer-aided-design tools) are changed (e.g., working the die/binder geometry or drawbead) (Sklad et al., 1991). Both die design and die try-out depend heavily on the experience of experts (Manabe et al., 2002).

Controlling the flow of sheet metal via controllable multi-cylinder blank holder actuators reduces die-try out time by cutting down on die rework (e.g., grinding and
welding) (Kergen et al., 1992; Siegert et al., 1997; Lo et al., 1999; Hsu et al., 2002; Doege et al., 2001, 2002, 2003). Researchers have developed different types of active blank holder systems (e.g., segmented/pulsating blank holder system and reconfigurable discrete die) to improve stamped part quality in forming (Michler et al., 1993, 1994; Walczyk et al., 1998; Ziegler, 1999; Doege et al., 2001).

A press with a computer-controlled hydraulic blank holder is capable of controlling the binder force to track a predetermined blank holder force trajectory during forming. As shown previously by the inner loop in Figure 1.2.2, this type of control is referred to as “open-loop” or “machine” control. Previous research has shown that machine control can improve material formability, reduce springback, and improve part consistency (Adamson et al., 1996; Sunseri et al., 1994) and can be combined with FEA approach to determine desirable blank holder force references (Sheng et al., 2004; Sunseri et al., 1996; Wang et al., 2005). However, machine control cannot maintain performance with regard to disturbances occurring during production. Such disturbances can include change in material properties (e.g., formability, blank size, and sheet thickness), change in tooling (e.g., die wear), and variation in lubrication (Hardt, 1993; Hardt et al., 1993; Hsu et al., 2000; Yagami et al., 2004).

As illustrated in Figure 1.2.2, for process control, a measurable process variable (e.g., punch force, $F_p$) is made to track a reference trajectory (i.e., reference punch force, $F_{p,ref}$) through manipulation of a control variable (i.e., binder force, $F_b$). The process controller is designed to automatically generate the necessary binder force commands (i.e., $F_{b,ref}$) for the machine controller to maintain the tracking error between $F_p$ and $F_{p,ref}$ as small as possible in the presence of disturbances. Thus, the closed-loop system,
including the process model and the process controller, can achieve high performance tracking of the reference punch force trajectory through manipulation of the binder force regardless of the disturbances. Previous work has shown the effectiveness of process control in sheet metal forming. For example, single-input single-output (SISO) process modeling and control using a proportional plus integral (PI) controller was investigated based on simple die geometry (e.g., u-channel forming) under laboratory-based tests (Siegert et al., 1997; Bohn et al., 1998, 2000; Ziegler, 1999; Hsu et al., 2000, 2002). However, multi-input multi-output (MIMO) process control with a complex-geometry part for high-volume production has not been studied. The purpose of this chapter is to present a systematic approach to the design and implementation of a suitable MIMO process controller.

3.2 MIMO Stamping Process Model Structure

For the design of the MIMO process control, a MIMO process model was described previously in Section 2.4.

3.3 MIMO Stamping Process Controller Structure

For the MIMO system given by the block-diagonal form in Eq. (2.12), four SIMO proportional plus integral (PI) controllers are implemented using Opal-RT’s RT-LAB and The Mathworks’ Simulink/Real-Time Workshop® in the experimental real-time system.

The SIMO process controller at each corner in discrete-time is given by

\[
\underline{u}(k) = F_{b}(k) = \left( K_p + K_i \frac{1}{z-1} \right) \left\{ F_{r,ref}(k) - F_p(k) \right\} 
\]

(3.1)
where $F_{p, \text{ref}}(k) - F_p(k)$ is the error between the reference punch force and the measured punch force at each corner. $K_p$ is the vector of proportional control gains, and $K_i$ is the vector of integral control gains.

The block diagram of the SIMO process controller at each corner is shown in Figure 3.3.1. The $4^{th}$ order estimated perturbation models in Table 2.4.1 are used to design the PI process controller gains.

To design the SIMO PI controller based on the MISO perturbed process model at each corner, five steps are followed:

- **Step 1**: Determine PI control gains based on a linear process model by using the root-locus design method to evaluate how the PI controller gains influence the closed-loop pole locations.

- **Step 2**: Investigate the gain margin (GM) and phase margin (PM) using a frequency-response design method (e.g., Bode plot). Based on the PI controller gains determined from Step 1, stability margins (i.e., GM and PM) are
investigated for several cases described in Table 3.4.1. It is recommended to provide gain margins not less than 6 dB, and phase margins not less than $\pi/6$ (Safonov, 1980). A sample result in Figure 3.3.2, shows a controller design where GM is greater than 60 dB and PM is greater than $\pi/2$.

- **Step 3**: Check system transient performance (e.g., rise time and settling time) based on three cases of different PI controller gains determined from Step 1, using the closed-loop step response. For example, settling time of Case I and Case II is less than 0.05 sec (see Figure 3.3.3a).

- **Step 4**: Perform simulations based on three cases of PI controller gains, with experimentally determined reference punch forces. This step is used to assess the tracking performance of the controller while ensuring that the control signals meet the binder force saturation constraints (minimum 0 tons and maximum 16 tons) (see Figure 3.4.1 for the simulated output and Figure 3.4.2 for the simulated inputs).

- **Step 5**: Perform the experiments with the selected gains for the PI process controller. Then, investigating the tracking performance as well as stamped part quality, PI process controller gains are fine-tuned through experiments based on a manual approach (or trial-and-error).
Figure 3.3.2: Frequency response analysis based on the PI control gains for the punch force (i.e., $F_p^1$).

Figure 3.3.3: Simulation results with step reference input: (a) simulated output (i.e., $F_p^1$) (b) – (d) simulated inputs (i.e., $F_{b1}$, $F_{b2}$, and $F_{b3}$ respectively).
3.4 Simulations

3.4.1 Simulation Results

Simulation is used to validate the performance of the PI process controller based on the estimated perturbation process models in Table 2.4.1. The simulation models use the perturbed binder forces ($\delta F_{bj}^i$) as inputs, the perturbed punch force ($\delta F_p^i$) as output, and the perturbed punch force ($\delta F_{p,ref}^i$) as the reference. The perturbations are with respect to baseline binder force inputs. The total simulated punch force ($F_p^i$), reference punch force ($F_{p,ref}^i$) and binder forces ($F_{bj}^i$) for each corner $i$ ($i = 1, 2, 3, 4$) are respectively given by

\[ F_p^i = F_{p,base}^i + \delta F_p^i \]
\[ F_{p,ref}^i = F_{p,base}^i + \delta F_{p,ref}^i \]
\[ F_{bj}^i = F_{bj,base}^i + \delta F_b^j \quad j = 1, 2, 3 \quad (3.2) \]

where $F_{p,base}^i$ is the measured-baseline of the punch force corresponding to the baseline binder forces, $F_{bj,base}^i$, which is set to a constant value of 16-tons for all 12 actuators. Figure 3.4.1 shows the simulation results for punch force as output using the PI process controller based on the process models. Based on these simulation results, good experimental tracking performance is expected. Simulation and experimental results are compared with respect to the three binder forces associated with each punch force shown in Figure 3.4.2. Due to space limitations, simulated and measured binder forces are shown only for the one corner of punch force output (i.e., $F_p^i$). Although there are differences between simulated binder forces and experimentally measured binder forces, the simulated binder force trajectories are similar to the measured binder force.
trajectories. The high-frequency oscillatory behavior at the end of the punch stroke arises from an implementation issue in the reference punch force signal generation which is being corrected for future experiments. However, these oscillations are at a frequency that is sufficiently high as to not affect the stamping process, as evidenced by the fact that they are filtered out by the process dynamics in the punch force output.

Table 3.4.1: Cases of PI process controller gains for simulation and experiment.

<table>
<thead>
<tr>
<th>Plaut model</th>
<th>Cases</th>
<th>$K_p$ gains (1 x 3)</th>
<th>$K_i$ gains (1 x 3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulation</td>
<td>All models</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(δ$P_{p1} \sim δP_{p4}$)</td>
<td>Case I</td>
<td>[0.3 0.3 0.3]</td>
<td>[0.01 0.01 0.01]</td>
</tr>
<tr>
<td></td>
<td>Case II</td>
<td>[0.4 0.4 0.4]</td>
<td>[0.02 0.02 0.02]</td>
</tr>
<tr>
<td></td>
<td>Case III</td>
<td>[0.5 0.5 0.5]</td>
<td>[0.03 0.03 0.03]</td>
</tr>
<tr>
<td>Experiment</td>
<td>$F_{p1}$</td>
<td>[0.4 0.2 0.6]</td>
<td>[0.01 0.01 0.01]</td>
</tr>
<tr>
<td></td>
<td>$F_{p2}$</td>
<td>[0.1 0.15 0.15]</td>
<td>[0.01 0.01 0.01]</td>
</tr>
<tr>
<td></td>
<td>$F_{p3}$</td>
<td>[0.6 0.2 0.4]</td>
<td>[0.01 0.01 0.01]</td>
</tr>
<tr>
<td></td>
<td>$F_{p4}$</td>
<td>[0.15 0.15 0.1]</td>
<td>[0.01 0.01 0.01]</td>
</tr>
</tbody>
</table>

Figure 3.4.1: Simulation results of punch force as output tracking reference punch force: (a) $F_{p1}$, (b) $F_{p2}$, (c) $F_{p3}$, (d) $F_{p4}$.
3.5 Experiments

3.5.1 Experimental Setup

Experimental setup was previously shown in Section 2.2.

3.5.2 Experimental Results

Experimental tests using the MIMO PI process controller designed through simulation is performed with the nominal material and test conditions. Experimental results using the MIMO PI process controller and the reference punch force trajectories are shown in Figure 3.5.1. As illustrated in Figure 3.5.2, it is noted that the process controller (PC) enables accurate punch force output tracking by manipulation of the binder forces. The experimental results shown here demonstrate the effectiveness of the
process controller under two extreme conditions. In the first test, all the binder force actuators are initially set to generate 8 tons, a situation in which the total binder force is below the desired or “optimal” setting and results in wrinkling, without process control. However, the process controller automatically corrects the binder force based on punch force measurements to eliminate the wrinkles. In the second test, all the binder force actuators are initially commanded to generate 16 tons, a situation in which the total binder force is above the desired or “optimal” setting and results in tearing without process control. The rationale behind these tests is that if the process controller is able to correct for these extreme variations, it will be able to correct for the smaller punch-force trajectory deviations observed due to in-process variations arising from disturbances.

Figure 3.5.1: Experimental results of punch force as output tracking reference punch force with high binder forces (i.e., 16 tons) initially commanded: (a) $F_p^1$ (b) $F_p^2$ (c) $F_p^3$ (d) $F_p^4$.
Figure 3.5.2: Improved part quality comparisons: (a) wrinkling problem with constant 8-ton binder force, without PC (b) tearing problem with constant 16-ton binder force, without PC (c) improved part, with PC for complex part geometry (i.e., double-door panel).

The results show that the process control is highly effective in reducing the two problems of wrinkling and tearing. First, Figure 3.5.2(a) illustrates the wrinkling problem; this can occur not only because of low binder forces (i.e., 8 tons), but also because of excessive lubrication allowing too much material flow-in, even with the same blank holder force conditions. Second, Figure 3.5.2 (b) shows the tearing problem; this can occur not only because of high binder forces (i.e., 16 tons), but also because of thicker material causing the binder to hold the blank tighter and restrict material flow, as a result of variations in blank sheet production. Thus, although the binder forces have
been initially commanded to a constant value of 8 tons (or 16 tons), Figure 3.5.2(c) demonstrates that the MIMO process control adjusts the binder forces to track the reference punch force trajectories, thus eliminating wrinkling or tearing. Consequently, the MIMO process control is shown to correct these defects by appropriately regulating the material draw-in in the presence of stamping process disturbances.

However, the MIMO process controller gains, which were designed through simulation, were tuned experimentally by the manual approach, which requires costly and time-consuming effort in an actual production runs.

### 3.6 Discussion

As shown in Figure 3.4.1 and Figure 3.4.2, even though the output trajectory seems well followed, the highly oscillatory behavior of the blank holder force (or inputs) was observed in both simulation and experiments. The problem was in the generation of the reference trajectory in the real-time system which resulted in a noisy signal at the end of the stroke. However, note that the high-frequency oscillations at the end of the stroke were outside the bandwidth of the forming process and had no noticeable effect on the quality of the part.

### 3.7 Summary and Conclusions

In this chapter a MIMO stamping process control has been designed using a systematic approach and shown to improve part quality and consistency for a complex-geometry part using nominal material and test conditions. For the first time, a MIMO PI stamping process controller with good tracking performance has been developed and
experimentally validated. Moreover, comparing constant blank holder force setups, stamped part quality accomplished by fixed gain process controller, which adjusts blank holder forces, is significantly improved. However, controller fine-tuning based on manual approach in experimental tests can be time consuming and expensive. Thus, in the following chapters, an auto-tuning method, which tunes the PI process controller gains without manual tuning effort and also provides an appropriate initial value for the implementation of adaptive control, will be investigated.

With fixed gain stamping process controller, there were limited investigations showing results based on two extreme cases with constant binder forces. For example, the case of low binder forces (i.e., 8 tons) was used to simulate excessive lubrication allowing too much material flow-in. On the contrary, the case of high binder forces (i.e., 16 tons) was used to simulate thicker material causing the binder to hold the blank tighter and restrict material flow. Hence, a more realistic investigation in terms of the tracking performance as well as part quality is described in the Chapter 4 and 5 with an adaptive process controller that is used to compensate for intentionally introduced lubrication and material thickness changes that cause variations in the plant dynamics.
CHAPTER 4

MIMO DIRECT ADAPTIVE PROCESS CONTROL

An adaptive process controller whose parameters are continuously adjusted to accommodate changes in process dynamics and disturbances can improve the tracking performance as well as part quality in the presence of plant parameter variations. Automatic controller tuning method can improve the previously investigated fixed gain process controller tuned by a manual approach, and in addition, provide good initial values for implementation of adaptive control.

4.1 Introduction

The control of material flow into the die cavity is crucial for part quality and consistency in the presence of disturbances. Adjustable binder force systems, with or without drawbeads, are used to control the material flow in stamping. As illustrated previously in Figure 1.2.2, a process controller is used to control a measurable process variable (e.g., punch force, $F_p$) that provides feedback on the part quality, and track a reference trajectory (i.e., reference punch force, $F_{p,\text{ref}}$) which characterizes a good part, through adjustment of a control variable (i.e., binder force, $F_b$). The “machine control” described previously becomes an inner-loop of this process control loop. The process controller is designed to automatically generate the necessary binder force command (i.e., $F_{b,\text{ref}}$) for the machine controller to maintain the tracking error between $F_p$ and $F_{p,\text{ref}}$ as small as possible in the presence of disturbances. Thus, process control can achieve high
performance tracking of the reference punch force trajectory through manipulation of the binder force regardless of the disturbances, when compared to machine control by itself. A single-input single-output (SISO) process modeling and control using a proportional plus integral (PI) controller was investigated based on simple die geometry (e.g., u-channel forming) under laboratory-based tests (Siegert et al., 1997; Ziegler, 1999; Hsu et al., 2000, 2002). More recently, a multi-input multi-output (MIMO) PI stamping process controller with good tracking performance has, for the first time, been developed and experimentally validated (Lim et al., 2008, 2009a, 2010a). This MIMO stamping process control has been designed using estimated MIMO process models based on system identification techniques, and has been shown to improve part quality and consistency for a complex-geometry part (i.e., a door panel of pick-up truck) in the presence of plant disturbances. However, in those experimental tests controller fine-tuning based on a manual approach, which can be time consuming and expensive, was required.

Figure 4.1.1: Design methods for tuning, and fine-tuning process controllers: (a) auto-tuning with relay feedback (b) model reference adaptive control.
Thus, in this research, two approaches to reduce the manual tuning effort for the MIMO process controller, namely, automatic controller tuning (or auto-tuning) and adaptive control (i.e., direct MRAC) are addressed. Industrial experience has clearly indicated that auto-tuning is a highly desirable and efficient method for PID controller tuning (Astrom et al., 1993, 1995). As shown in Figure 4.1.1(a), auto-tuning is a method to determine the process controller gains based on the observation that a process model has limit cycle oscillations with a specific period and amplitude in the output \( y \) under relay feedback. Controller gains are then calculated in terms of the period and amplitude of the output oscillation based upon an empirical rule-based table (i.e., Ziegler-Nichols ultimate stability method), which will be detailed in following section. However, if there are unpredictable parameters changes in the stamping process during operation, the fixed-gain PI process controller tuned by auto-tuning will still have limitations in tracking performance in the presence of such plant variations.

Given these variations, the purpose of this chapter is also to address the design and implementation of a MIMO adaptive process controller whose parameters are continuously adjusted to accommodate changes for a complex-geometry part, in process dynamics and disturbances. The adaptive controller updates the gains of the MIMO PI process controller (which are initially set to the values obtained from auto-tuning) to minimize tracking error, in the presence of plant parameter variations.

Adaptive control has been extensively studied during the last three decades for diverse applications (e.g., aircraft, automotive, and machine tools). Typically using a model reference control structure and normalized adaptive laws based upon a gradient or recursive least squares on-line estimation (Lauderbaugh and Ulsoy, 1989; Astrom and
Wittermark, 1995), the design and analysis of continuous- and discrete-time robust MRAC with normalized adaptive laws has been described in detail (Goodwin and Sin, 1984; Sun and Ioannou, 1992; Ioannou and Sun, 1989, 1996). Furthermore, in order to make adaptive control more attractive for practical implementation by effectively bounding control inputs, researchers have developed algorithms using constrained estimation (Goodwin and Sin, 1984; Chia et al., 1991), and have performed sensitivity and robustness analyses (Ardalan and Adali, 1989). In addition, in order to achieve high output tracking performance, pre-compensator or feedforward controllers based on the inverse of the closed-loop system or of the plant model have been studied (Tomizuka, 1987; Devasia, 2002; Karimi et al., 2008).

In this research a discrete-time MRAC process controller is, for the first time, studied in stamping process control. It makes real-time adjustments to the binder force command based on feedback from the measurable process variable (i.e., punch force) in the presence of plant disturbances (e.g., lubrication and material thickness change). As shown in Figure 4.1.1(b), a direct MRAC structure includes a pre-compensator and minimizes the error between the reference model output ($y_m$) and the process model output ($y$). The reference model specifies the desired tracking performance of the closed-loop system, and the process model output represents the measured punch force in the presence of process parameter variations and disturbances.

4.2 Automatic Tuning Based on Relay Feedback

The basic idea for auto-tuning the process controller is the observation that many processes have limit cycle oscillations under relay feedback with step inputs (Astrom and
Wittenmark, 1995). As shown in Figure 4.2.1, when the output lags behinds the input by \(-\pi\) radians, the closed-loop system, which includes an ideal relay as shown in Figure 4.1.1(a), will oscillate with ultimate period \((T_u)\) and amplitude \((a)\). From the Fourier series expansion of the periodic relay output \((u)\), the amplitude can be considered to be the result of the primary harmonic of the relay output. Therefore, the ultimate gain, \(K_u\), can be obtained from the describing function approximation:

\[
K_u = \frac{4d}{\pi a}
\]

(4.1)

where \(d\) is the magnitude of the relay and \(a\) is the amplitude of the output oscillation. Consequently, \(T_u\) and \(K_u\) can be used directly to obtain the controller gains. Based on the original Ziegler-Nichols tuning rules (Zielger and Nichols, 1942), \(K_P\) and \(K_I\), expressed in terms of \(K_u\) and \(T_u\), are given by \(K_P = 0.4\times K_u\) and \(K_I = K_P/(0.8\times T_u)\).

In order to tune the PI gains numerically based on these rules, two parameters (i.e., \(a\) and \(T_u\)) of the output oscillation corresponding to a step command input (i.e., \(u_c\)), as shown Figure 4.1.1(a), are obtained through simulation, and the ultimate gain \((K_u)\) is calculated using \(a\) (amplitude) and \(d\) (relay height) from Eq. (4.1). Three transfer functions, or MISO estimated process models for each corner (see Table 2.4.1), are used as the three different process models in Figure 4.1.1(a). Thus, three sets \(\{(K_{P1}, K_{I1}), (K_{P2}, K_{I2}), (K_{P3}, K_{I3})\}\) of fixed gains of the SIMO PI process controller in Eq. (3.1) are simply tuned by three sets of \(T_u\) and \(K_u\) based on simulations using three transfer functions (or process models) for the punch force in each corner. Simulation and experimental validation of this controller is described in Section 4.5 and 4.6, along with a comparison with the adaptive process controller that is described in the next section.
4.3 Prior Information for Adaptive Control in Stamping

Many adaptive control schemes (both direct and indirect) require a priori information about the process dynamics and utilize a pre-determined controller structure. As described in previous chapters, system identification based on standard least squares (LS) algorithm was used to parameterize the plant dynamics of a MIMO linear sheet metal stamping using input (i.e., binder force) and output (i.e., punch force) data from experiments. Furthermore, the simulation-based auto-tuning, also referred to as the pre-tune mode, was introduced to obtain the controller gains, which were also used as appropriate initial values for the design of the adaptation law in the direct AC (i.e., MRAC). Moreover, disturbances (e.g., lubrication and thickness change), which affect not only the process variable (i.e., punch force) but also part quality, were addressed (Lim et al., 2010b-d).
4.3.1 Experimental Setup

Experimental setup and conditions were described previously in Section 2.2.

4.3.2 MIMO Perturbation Process Model Structure

The MIMO perturbation process modeling for the MIMO controller design was described previously in Section 2.4.

4.3.3 MIMO Stamping Process Controller Structure

The MIMO PI stamping process controller structure was described previously in Section 3.3.

4.3.4 Plant Disturbances in Stamping

The disturbances in the stamping process were described in Section 2.4.3 and also shown in Figure 2.4.7.

4.4 Design and Implementation of Direct MRAC

The direct model reference adaptive control (MRAC) approach dominates the adaptive control literature, due to the simplicity of its design as well as its robustness properties in the presence of process modeling errors (Astrom and Wittenmark, 1995; Ioannou and Sun, 1988, 1989, and 1996). The basic structure of a direct MRAC is shown in Figure 4.1.1(b). The reference model is chosen to generate the desired performance of the closed-loop system, \( y_m \), which the measured plant output, \( y \) (or the punch force), has to track. The tracking error, \( e = y - y_m \), represents the deviation of the process model output from the desired punch force trajectory. In this section, the design and implementation of a direct MRAC process controller, which updates its controller gains
to make the measured punch force \( y \) track the reference model output \( y_m \) as closely as possible in the presence of plant dynamics variations and disturbances, including a consideration of constraints in the recursive least squares (RLS) adaptation algorithm, is described.

### 4.4.1 Direct MRAC Process Controller Structure

**Process Model** The MISO estimated linear process model with the same denominator in discrete-time (decoupled MIMO transfer function matrix in Eq. (2.12) for each corner output) or \( y_i \) \((i = 1, 2, 3, 4)\), is given as

\[
y_i(k) = \frac{B_i(z)u_i(k)}{A_i(z)} + \frac{B_i(z)u_i(k)}{A_i(z)} + \frac{B_i(z)u_i(k)}{A_i(z)}
\]

where

\[
B_i(z) = b_{j1}z^2 + b_{j0}z \quad j = 1, 2, 3
\]

\[
A_i(z) = z^4 + a_{i3}z^3 + a_{i2}z^2 + a_{i1}z + a_{i0}
\]

\[
y_i = \delta F_{p,fil}
\]

\[
\begin{bmatrix}
u_i \\
u_i \\
u_i
\end{bmatrix} = \begin{bmatrix}
\delta F_{h_{1,ref}} \\
\delta F_{h_{2,ref}} \\
\delta F_{h_{3,ref}}
\end{bmatrix}
\]

All estimated parameters of the perturbation process model using system identification techniques were shown previously in Table 2.4.1.

**Control Law** The control law with a SIMO PI controller, and a pre-compensator shown in Figure 4.1.1(b), to generate the reference input \( r_i \) is given as

\[
u_i(k) = C_i(z)\{r_i(k) - y_i(k)\} \quad i = 1, 2, 3, 4
\]

where
and the SIMO PI controller parameters are related to the original $K_P$ and $K_I$ gains as:

$$s_{ji}^j = K_{Pj}^j \text{ and } s_{jo}^j = K_{Ij}^j - K_{Pj}^j, \quad j = 1, 2, 3$$

(4.4)

The optimal values of these controller parameters are unknown, as the plant parameters vary from their nominal estimated values due to operational variation. Thus, the controller parameters $s_{ji}^j$ and $s_{jo}^j$ in Eq. (4.3) are replaced by their estimates $\hat{s}_{ji}^j(k)$ and $\hat{s}_{jo}^j(k)$ from the adaptation algorithm, to generate the control input as:

$$u_i^j(k) = \frac{\hat{s}_{ji}^j(k)z + \hat{s}_{jo}^j(k)}{z - 1} \left\{ r_i^j(k) - y_i^j(k) \right\}, \quad j = 1, 2, 3$$

(4.5)

**Reference Model** In the direct MRAC case, a reference model specifies the desired performance of the closed-loop system. In this study, as shown in Figure 4.1.1(b), the reference model in discrete-time was selected to be for each corner $i = 1, 2, 3, 4$:

$$\frac{y_i^j(k)}{r_i^j(k)} = \frac{B_{m}^j(z)}{A_{m}^j(z)} = \frac{b_{m1}^j z^3 + b_{m2}^j z^2 + b_{m3}^j z}{z^3 + a_{m1}^j z^2 + a_{m2}^j z^2 + a_{m3}^j z + a_{m0}^j}$$

(4.6)

where this model has the same structure as the closed-loop system with a fixed-gain PI controller, and is obtained by combining Eq. (4.2) and (4.3) with the values of $s_{ji}^j$ and $s_{jo}^j$ set to their values obtained from auto-tuning, and by using the nominal process model parameters, which will be shown in Eq. (4.10) and Eq. (4.11) in detail. The reference model based on the gains chosen using auto-tuning satisfies the step
response specifications required for the stamping process, with a settling time of less than 0.1 second and an overshoot of less than 20%.

**Assumptions** In order to meet the model reference control objective with an adaptive control law which is implementable, the plant model and the reference model need to satisfy the following assumptions respectively (Ioannou and Sun, 1988, 1996): First, the numerator \((B_i^j(z))\) of the plant model as shown Eq. (4.2) must be a monic Hurwitz polynomial (i.e., minimum-phase). As shown in Table 2.4.1, all the estimated process models are minimum-phase systems based on a sample rate of 100 Hz. Second, \(A_m^i\) and \(B_m^i\) of the reference model must be also monic Hurwitz polynomials. In other words, the locations of poles and zeros of the reference models are inside the unit circle in the z-plane. Finally, the relative degree (i.e., 2) of the reference model shown in Eq. (4.6) must be the same as the relative degree of the plant model (i.e., 2) in Eq. (4.2).

**Adaptive Law** The adaptive law for generating \(s_{j1}^i(k)\) and \(s_{j0}^i(k)\) at time-step \(k\) is developed by viewing the problem as an on-line estimation problem for \(s_{j1}^i\) and \(s_{j0}^i\). This is accomplished by obtaining an appropriate parameterization for the MISO process model in Eq. (4.2) for on-line estimation, in terms of the unknown parameters \(s_{j1}^i\) and \(s_{j0}^i\).

Based on the parameterization of the process model shown in Eq. (4.2), in terms of the unknown controller parameters \(s_{j1}^i\) and \(s_{j0}^i\), the parametric model for the estimates of \(s_{j1}^i\) and \(s_{j0}^i\) is derived as follows.

Adding and subtracting \(u_j^i(k)\) from Eq. (4.3) into Eq. (4.2) yields,
\[ y' = \frac{B_i^i (C_i^i - C_i^i) + B_{i+1}^i (C_{i+1}^i - C_i^i) + B_{i+2}^i (C_{i+2}^i - C_{i+1}^i)}{A^i} (r^i - y') + \frac{B_{i+3}^i u_{i+3}^i + B_{i+4}^i u_{i+4}^i + B_{i+5}^i u_{i+5}^i}{A^i} \]

or

\[ \left( \frac{A^i + B_{i+1}^i C_{i+1}^i + B_{i+2}^i C_{i+2}^i + B_{i+3}^i C_{i+3}^i}{A^i} \right) y' = \frac{B_i^i C_{i+1}^i + B_{i+1}^i C_{i+2}^i + B_{i+2}^i C_{i+3}^i}{A^i} r^i - \frac{B_i^i C_{i+1}^i + B_{i+1}^i C_{i+2}^i + B_{i+2}^i C_{i+3}^i}{A^i} (r^i - y') + \frac{B_{i+3}^i u_{i+3}^i + B_{i+4}^i u_{i+4}^i + B_{i+5}^i u_{i+5}^i}{A^i} \]

Multiplying Eq. (4.8) on both sides by \( \frac{A^i}{A^i + B_{i+1}^i C_{i+1}^i + B_{i+2}^i C_{i+2}^i + B_{i+3}^i C_{i+3}^i} \), it follows that

\[ y' = \frac{B_i^i C_{i+1}^i + B_{i+1}^i C_{i+2}^i + B_{i+2}^i C_{i+3}^i}{A^i + B_{i+1}^i C_{i+1}^i + B_{i+2}^i C_{i+2}^i + B_{i+3}^i C_{i+3}^i} r^i - \frac{B_i^i C_{i+1}^i + B_{i+1}^i C_{i+2}^i + B_{i+2}^i C_{i+3}^i}{A^i + B_{i+1}^i C_{i+1}^i + B_{i+2}^i C_{i+2}^i + B_{i+3}^i C_{i+3}^i} (r^i - y') + \frac{B_{i+3}^i u_{i+3}^i + B_{i+4}^i u_{i+4}^i + B_{i+5}^i u_{i+5}^i}{A^i + B_{i+1}^i C_{i+1}^i + B_{i+2}^i C_{i+2}^i + B_{i+3}^i C_{i+3}^i} \]

Note that, based on Figure 4.1.1(b), since \( A^i(z) \in \mathbb{R}^1 \), \( B_j^i(z) \in \mathbb{R}^{3\times3} \) and \( C_j^i(z) \in \mathbb{R}^{3\times1} \) are defined for each corner \( i \) shown in Eq. (4.2) and (4.3) respectively, and thus, the closed-loop transfer function is given by

\[ \frac{y'(k)}{r'(k)} = \frac{B_i^i C_{i+1}^i + B_{i+1}^i C_{i+2}^i + B_{i+2}^i C_{i+3}^i}{A^i + B_{i+1}^i C_{i+1}^i + B_{i+2}^i C_{i+2}^i + B_{i+3}^i C_{i+3}^i} \]

Hence, the reference model which specifies the desired performance of the closed-loop system has the form shown in Eq. (4.10), i.e.,
and is obtained by using the controller parameters from auto-tuning in $C^i_j$, and the nominal estimated plant parameters in $B^i_j$ and $A^i$. Thus, if $A^i_m = A^i + B^i_1 C^i_1 + B^i_2 C^i_2 + B^i_3 C^i_3$ and $B^i_m = B^i_1 C^i_1 + B^i_2 C^i_2 + B^i_3 C^i_3$ Eq. (4.9) can written as

$$y^i = \frac{B^i_m}{A^i_m} r^i - \frac{B^i_1 C^i_1 + B^i_2 C^i_2 + B^i_3 C^i_3}{A^i_m} (r^i - y^i) + \frac{B^i_1 u^i_1 + B^i_2 u^i_2 + B^i_3 u^i_3}{A^i_m}$$

(4.12)

or

$$e^i = - \frac{B^i_1 C^i_1 + B^i_2 C^i_2 + B^i_3 C^i_3}{A^i_m} (r^i - y^i) + \frac{B^i_1 u^i_1 + B^i_2 u^i_2 + B^i_3 u^i_3}{A^i_m}$$

(4.13)

where $y^i_m = \frac{B^i_m}{A^i_m} r^i$ is as given in Eq. (4.11), and then tracking error is defined as $e^i = y^i - y^i_m$. If $C^i_1$, $C^i_2$, and $C^i_3$ as given previously in Eq. (4.3) and then replaced by the estimated controller gains (i.e., $\hat{s}^i_{j1}$ and $\hat{s}^i_{j0}$, $j = 1, 2, 3$), are substituted into Eq. (4.13),

$$e^i = - \frac{B^i_{1}}{A^i_m} \left( \frac{\hat{s}^i_{j1} z + \hat{s}^i_{j0}}{z-1} \right) (r^i - y^i) - \frac{B^i_{2}}{A^i_m} \left( \frac{\hat{s}^i_{21} z + \hat{s}^i_{20}}{z-1} \right) (r^i - y^i) - \frac{B^i_{3}}{A^i_m} \left( \frac{\hat{s}^i_{31} z + \hat{s}^i_{30}}{z-1} \right) (r^i - y^i)$$

$$+ \frac{B^i_{1} u^i_1 + B^i_{2} u^i_2 + B^i_{3} u^i_3}{A^i_m}$$

(4.14)

Thus, Eq. (4.14) can be written in the parametric model form for adaptive updates in the direct MRAC as

$$e^i = (\Theta^i \phi^T + u^i_j) \quad i = 1, 2, 3, 4$$

(4.15)
where

\[ \theta^i = \left[ \hat{s}_{11}^i, \hat{s}_{10}^i, \hat{s}_{21}^i, \hat{s}_{20}^i, \hat{s}_{31}^i, \hat{s}_{30}^i \right] \]

\[ \phi^{iT} = \begin{bmatrix} -z & B_1^i \\ z & 1 \\ -z & 1 \\ -z & B_2^i \\ z & 1 \\ -z & B_3^i \\ z & 1 \\ -z & 1 \end{bmatrix} \begin{pmatrix} r^i - y^i \end{pmatrix} \]

\[ u_f^i = \frac{B_j^i u_i^i + B_j^i u_i^j + B_j^i u_3^j}{A_m^i} \]

where \( B_j^i \) and \( A_m^i \) are given in Eq. (4.2) and Eq. (4.11) respectively.

The adaptation algorithm, based on the parametric model above, used the RLS algorithm with exponential forgetting (Astrom and Wittenmark, 1995). The controller parameters, \( \theta^i \), are estimated recursively:

\[ \dot{\theta}^i(k) = \dot{\theta}^i(k-1) + P^i(k) \phi^i(k) \left[ \dot{\epsilon}^i(k) - \left( \phi^{iT}(k) \dot{\theta}(k-1) + u_f^i(k-1) \right) \right] \]

\[ P^i(k) = \left[ P^i(k-1) - \frac{P^i(k-1) \phi^i(k) \phi^{iT}(k) P^i(k-1)}{\lambda \dot{\theta}(k-1) + \phi^{iT}(k) P^i(k-1) \phi^i(k)} \right] / \lambda \]

where \( \dot{\epsilon}^i(k) \) is the estimation error and \( \dot{\epsilon}^i(k) = y^i(k) - y_m^i(k) \) is the tracking error for each corner \( i \) \( (i = 1, 2, 3, 4) \). The forgetting factor, \( 0 < \lambda \leq 1 \), has the interpretation that
if $\lambda = 1$ the algorithm reduces to the standard RLS algorithm and as $\lambda$ gets smaller the algorithm “discards” older data more quickly.

**Pre-Compensator** For improved tracking performance, the inverse dynamics of the reference model shown in Eq. (4.6) are utilized in the pre-compensator (see Figure 4.1.1(b)), and then delayed by two time steps, in order to make the pre-compensator causal. Thus, the transfer function of the pre-compensator, or $G_{pc}(z)$, is expressed as:

$$
G_{pc}(z) = \frac{r^i(k)}{y_{ref}^i(k)} = \frac{1}{z^d} \frac{A^i_m(z)}{B^i_m(z)}
$$

(4.17)

where $z^d$ represents a $d$-step delay (i.e., $d = 2$ here) used to make the pre-compensator causal. As described previously in the assumptions, $B^i_m(z)$ is a monic Hurwitz polynomial which guarantees the stability of the pre-compensator.

In addition, note that the estimated plant model and the auto-tuned gains are used for two purposes in the MRAC scheme: (1) to initialize the gains of the adaptive controller and generate the required regressor vectors, and (2) to define the reference model. Clearly, if the actual plant is exactly the same as the estimated model, the reference model and plant outputs will be equal and the controller parameters will not be updated, resulting in closed-loop performance identical to that of the reference model, which is demonstrated below in Figure 4.4.1.

### 4.4.2 Robustness of the MRAC to Parameters Variations

The robustness of the direct MRAC to process model perturbations, which represent unexpected plant dynamics changes and/or a slowly time-varying system, is considered using a simulation-based approach. The RLS adaptation algorithm, which is designed
using both nominal plant model coefficients and auto-tuned PI gains, is also a critical part of the MRAC controller that depends on the plant model. Thus, in order to analyze robustness of the RLS adaptation algorithm with respect to plant parameter variations, the estimated process model coefficients in simulation are perturbed to study the resulting closed-loop performance.

The performance of the RLS algorithm can be analyzed by considering tracking error and estimation error variations caused by unexpected process dynamics changes. Eq. (4.6) can be rewritten using prime notation to denote plant variations as

$$\theta'(k) = \theta'(k-1) + P'(k)\phi'(k) \left\{ e'(k) - \left( \phi'^T(k)\theta'(k-1) + u'(k-1) \right) \right\}$$

and the tracking error variation can be given as

$$\delta e'(k) = e'(k) - e''(k)$$

where $e'(k)$ is the tracking error without plant variation, and $e''(k)$ is the tracking error with plant variations. Also, the estimation error variation can be obtained as

$$\delta\epsilon'(k) = \epsilon'(k) - \epsilon''(k)$$

where $\epsilon'(k)$ is the estimation error without plant variation, and $\epsilon''(k)$ is the estimation error with plant variations.

For robustness analysis of the RLS algorithm, randomly chosen process models, which vary within ±30% of each estimated process model parameter shown in Table 2.4.1, are used. These are given in Table 4.4.1, and are assumed to be the maximum
expected perturbations, based upon multiple sets of parameters obtained from numerous experiments using different dies, materials and presses.

Table 4.4.1: Process model parameters shown in Eq. (4.2) having variations.

<table>
<thead>
<tr>
<th>Pu.ch Force</th>
<th>$a_1$</th>
<th>$a_2$</th>
<th>$a_1$</th>
<th>$a_0$</th>
<th>$b_{11}$</th>
<th>$b_{10}$</th>
<th>$b_{21}$</th>
<th>$b_{20}$</th>
<th>$b_{31}$</th>
<th>$b_{30}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta F_{p1}$</td>
<td>w/o variation</td>
<td>-0.5096</td>
<td>-0.2098</td>
<td>-0.3753</td>
<td>0.2832</td>
<td>0.7704</td>
<td>-0.7176</td>
<td>0.570</td>
<td>-0.255</td>
<td>-0.8177</td>
</tr>
<tr>
<td></td>
<td>w/ variation</td>
<td>-0.581</td>
<td>-0.272</td>
<td>-0.331</td>
<td>0.241</td>
<td>0.852</td>
<td>-0.781</td>
<td>0.412</td>
<td>-0.352</td>
<td>0.723</td>
</tr>
<tr>
<td>$\delta F_{p2}$</td>
<td>w/o variation</td>
<td>-0.7203</td>
<td>-0.1166</td>
<td>-0.2076</td>
<td>0.1942</td>
<td>0.2462</td>
<td>-0.1468</td>
<td>0.8538</td>
<td>-0.7037</td>
<td>0.1353</td>
</tr>
<tr>
<td></td>
<td>w/ variation</td>
<td>-0.652</td>
<td>-0.141</td>
<td>-0.243</td>
<td>0.231</td>
<td>0.352</td>
<td>-0.242</td>
<td>0.742</td>
<td>-0.634</td>
<td>0.251</td>
</tr>
<tr>
<td>$\delta F_{p3}$</td>
<td>w/o variation</td>
<td>-1.403</td>
<td>0.3936</td>
<td>0.1452</td>
<td>-0.0553</td>
<td>0.4912</td>
<td>-0.2313</td>
<td>0.333</td>
<td>-0.03505</td>
<td>0.9474</td>
</tr>
<tr>
<td></td>
<td>w/ variation</td>
<td>-1.531</td>
<td>0.442</td>
<td>0.121</td>
<td>-0.061</td>
<td>0.553</td>
<td>-0.335</td>
<td>0.253</td>
<td>-0.045</td>
<td>0.853</td>
</tr>
<tr>
<td>$\delta F_{p4}$</td>
<td>w/o variation</td>
<td>-1.621</td>
<td>0.6777</td>
<td>0.06901</td>
<td>-0.06487</td>
<td>0.7219</td>
<td>-0.5878</td>
<td>0.2685</td>
<td>-0.1701</td>
<td>0.4632</td>
</tr>
<tr>
<td></td>
<td>w/ variation</td>
<td>-1.543</td>
<td>0.732</td>
<td>0.0721</td>
<td>-0.0573</td>
<td>0.654</td>
<td>-0.621</td>
<td>0.341</td>
<td>-0.241</td>
<td>0.532</td>
</tr>
</tbody>
</table>

Figure 4.4.1: Simulated results based on process model variations: (a) punch force (i.e., $\delta F_{p}^{1}$) (b) tracking and estimation errors.
Figure 4.4.1, for the punch forces (i.e., \( F_p^1 \)) of one corner, shows how the filter in the regressor vectors with fixed coefficients in the RLS algorithm affects the tracking and estimation performances in the presence of plant parameter variations. First of all, as shown in Figure 4.4.1, good tracking performance with relatively large plant parameter variations of 30% is achieved with small tracking errors (i.e., less than 5% of the punch force output). Perfect tracking (or \( y = y_m \)) is obtained only without plant variation where the reference model is the same as the closed-loop transfer function involving the process model and MRAC with controller parameters set to the values obtained from auto-tuning. Figure 4.4.1 (b) shows the tracking and estimation error variations (see Eq. and) due to changes in the model dynamics. Similar analyses of the MRAC for the other three corners showed similar results.

4.4.3 Constrained Parameter Estimation

For systems that are time-varying or nonlinear, constrained parameter estimation, based on experimental data or other \textit{a priori} knowledge, can reduce or eliminate problems, such as temporary estimation gain bursting, large transients and offset due to disturbances (Goodwin and Sin, 1984; Chia et al., 1991). Instead of using unconstrained estimates for \( \theta^i \) in Eq. (4.16), the constraints on individual controller parameters (i.e., adaptive controller gain bounds) can be utilized as follows:

\[
\theta_{n,c}^i = \begin{cases} 
\theta_{n,\min}^i & \text{if } \theta_n^i < \theta_{n,\min}^i \\
\theta_n^i & \text{if } \theta_{n,\min}^i \leq \theta_n^i \leq \theta_{n,\max}^i \\
\theta_{n,\max}^i & \text{if } \theta_n^i > \theta_{n,\max}^i 
\end{cases} \quad n = 1, \ldots, 6 \quad (4.21)
\]
where the subscript \( c \) specifies that \( \theta_i^c \) is the \textit{constrained} solution for each of the controller parameters denoted by \( n \) (i.e., \( n = 1, 2, \ldots, 6 \)) in each corner \( i \). As shown in Figure 4.4.2, the PI controller gains estimated using the constrained algorithm are bounded, while the controller gains updated using the unconstrained algorithm show large transients in simulation. Therefore, as shown in Figure 4.2.1, the constrained estimation algorithm not only enables the punch force output to achieve better tracking of the measured reference punch force than the unconstrained estimates, but also ensures that no mechanical damage is caused by over-driving the actuators.

![Figure 4.4.2: Comparison of estimated controller gains using the RLS algorithm: (a) unconstrained (b) constrained.](image-url)
Figure 4.4.3: Simulation results for punch force output tracking performance with two estimation algorithms: unconstrained and constrained.

In this simulation the auto-tuned PI gains described previously are used as initial values of the process controller gains in the RLS algorithm, and estimated process models are used as the process model. Initial values of the covariance matrix \( P^i \) (see Eq. (4.16)) are set to \( 10^{-2} \times I(n,n) \) where \( I \) is the identity matrix and \( n \) (i.e., \( n = 6 \)) is the number of controller gains for each corner output.

4.5 Simulations

4.5.1 Simulation Results

Simulation is used to validate the performance of the two PI process controllers (i.e., auto-tuned and direct MRAC process controller) based on the estimated perturbation process models, with randomly-assigned process model parameter variations to represent
changes in plant dynamics. The simulation models use the perturbed binder forces ($\delta F_{b_i}$) as inputs, the perturbed punch force ($\delta F_{p_i}$) as output, and the desired perturbed punch force ($\delta F_{p_{i,ref}}$) as the reference (or desired punch force) for each corner $i$. The simulation model was shown previously in Figure 4.1.1(b).

The three binder forces ($F_{b_{ij}}, j = 1, 2, 3$) associated with each punch force corner, $i$, ($i = 1, 2, 3, 4$) are updated to minimize the difference between $F_{p_i}$ and $F_{p_{i,ref}}$, by adding or subtracting the perturbed binder forces ($\delta F_{b_{ij}}$), which are produced by the process controller. Thus, the total binder forces, $F_{b_{ij}}$, in both simulation and experiment are given by

$$F_{b_{ij}} = F_{b_{ij,offset}} + \delta F_{b_{ij}} \quad j = 1, 2, 3$$

(4.22)

where $F_{b_{ij,offset}}$ are pre-determined nominal binder forces for each corner, $i$, and are shown in Figure 4.5.1. As described previously, the machine control (MC) alone (without the process controller) generates these pre-determined nominal binder forces, even in the presence of disturbances.

Note that the reference punch force trajectories ($F_{p_{i,ref}}$) are obtained by recording the punch forces generated using the pre-determined nominal binder forces which are determined by experienced die-makers to make a good part using the material with nominal properties and under normal operating conditions for each punch force corner $i$.

Figure 4.5.2 shows the simulation results with the punch force as output and the binder force as input, using the fixed-gain auto-tuned PI process controller and the direct
MRAC PI process controller based on the process models, which include 30% changes in the parameters as plant variations. In Figure 4.5.2, when the controlled punch force becomes smaller than the reference punch force (e.g., at the beginning and the end of the stroke), both PI process controllers enable the punch force to track the reference punch force by adjusting the binder forces. The performance of the two controllers in the presence of actual plant variations and disturbances in the form of intentionally introduced lubrication and material thickness changes is described in the next section on experimental validation.

Figure 4.5.1: The pre-determined nominal binder force trajectories (i.e., $F_{bj,\text{offset}}$) for each corner output $i$: (a) $i = 1$ (b) $i = 2$ (c) $i = 3$ (d) $i = 4$. 
Figure 4.5.2: Simulation results comparing two process controllers (i.e., the auto-tuned fixed PI controller and the direct MRAC): (a) punch force (i.e., $F_p^1$) (b) binder forces associated with the punch force.

4.6 Experiments

4.6.1 Experimental Setup

The experimental setup and conditions were previously described in Section 2.2.
4.6.2 Experimental Validation

The two MIMO PI process controllers (i.e., fixed-gain PI obtained by auto-tuning and direct MRAC PI process controller) described above were implemented on the experimental system. Their performance was compared to the performance of the machine control (MC) only (i.e., without process control (PC)) with fixed pre-determined binder forces commands ($F_{b,j,offset}$ in Eq. (4.22)), in terms of deviation from the reference punch force, and in terms of part quality, in the presence of disturbances.

Lubrication Change

The first disturbance that we consider is lubrication change. Figure 4.6.1 shows the tracking performance of the punch force for the test cases, and illustrates stamped part quality comparison for those cases in the presence of lubrication change. Due to space limitations results are presented for only one corner of the punch forces (i.e., $F_{p}^{i}$). However, all corners of the punch forces and part quality for all corners were investigated and showed similar trends. Figure 4.6.1 (a) shows that with only machine control, (i.e., without process control) there is a clear difference between the reference punch force which characterizes a good part in the absence of the extra lubrication and the measured punch force in the presence of the extra lubrication. Figure 4.6.1 (c) shows that extra lubrication results in significant wrinkling, caused by greater material flow. The desired part quality, characterized by the reference punch force, is shown in Figure 4.6.1 (b). In Figure 4.6.1(a), (d), and (e), it can be seen that the MRAC process controller provides the best tracking performance of the reference trajectory as well as part quality improvement in the presence of lubrication change. The fixed-gain auto-tuned PI process controller
also enables the punch force to track the reference punch force, but with some oscillation throughout the punch stroke under the excessive lubrication condition. Thus, the above experimental results, using a complex-geometry part, show that the MIMO process controller, designed through simulation, is quite effective in improving part quality in the presence of lubrication change.

**Material Thickness Variation**

The second disturbance that we consider is material thickness variation. With thicker material (i.e., 0.79 mm) compared to the nominal (i.e., 0.64 mm), Figure 4.6.2 shows that the two process controllers effectively track the reference punch force, which was determined using the nominal material. Again, as shown in Figure 4.6.2, machine control alone (i.e., without process control), which has fixed pre-determined desirable binder forces, cannot minimize the error between the reference punch force and the measured punch force. However, the direct MRAC process controller shows good tracking performance of the measured reference punch force by adjusting the three associated binder forces (see Figure 4.6.2 (b)) from their nominal values (i.e., $F_{bi, offset}^i$). For example, when the measured punch force is greater than the reference punch force, at around 2.5 inches of punch stroke, the MRAC process controller drastically reduces the binder forces in order to minimize the difference between the reference $F_p^2$ and measured $F_p^2$. The fixed-gain auto-tuned PI process controller performs less effectively with material thickness change, and shows excessive oscillations.
Figure 4.6.1: Experimental results in the presence of lubrication change: (a) the punch force (i.e., $F_p^1$) (b) dry condition and (c) - (e) excessive lubricated condition.
Figure 4.6.2: Experimental results in the presence of material thickness variation: (a) punch force (i.e., $F_p^2$) (b) binder forces (i.e., $F_{b4} \triangleq F_{b1}^2$, $F_{b5} \triangleq F_{b2}^2$ and $F_{b6} \triangleq F_{b3}^2$).
4.7 Discussion

We noted that the reference punch force trajectory ($F_{p,\text{ref}}^i$) for each corner $i$ was obtained by recording the punch force generated using the pre-determined binder forces which were determined by experienced die-makers to make a good part, and qualified by visual inspection. In other words, we only depended on their naked eyes to check stamped part quality. However, white light and laser 3-dimensional (3-D) scanning tools exist to offer accurate 3-D measurements of stamped parts (Hardt, 2002) and provide quantitative assessments of part quality. For example, as shown previously in Figure 4.6.1, although the direct MRAC process controller accomplished much better tracking of the reference punch force trajectory than the fixed PI process controller, the stamped part quality for both process controllers looks similar based on 2-D pictures (see Figure 4.6.1(d) and (e)). In order to obtain an accurate evaluation of part quality, a 3-D scan would be necessary. However, the required equipment was not available for this study.

The MIMO direct MRAC stamping process controller was experimentally validated in terms of the tracking performance of the reference punch force as well as part quality improvement, in the presence of plant variations and/or disturbances. For the design of the direct MRAC, the reference model (including inverse dynamics of the reference model or pre-compensator) and appropriate initial values of PI gains are obtained using the estimated process parameters and initial values of controller gains tuned by auto-tuning method. However, the direct MRAC stamping process controller can benefit from simplification of the design procedures for more user-friendly implementation in a production environment. Thus, in future, the objective of removing the system identification and simulation-based auto-tuning procedures from the direct MIMO PI
adaptive control implementation should be accomplished. Consequently, if the nominal values of the process parameters and the controller gains are used for the design of direct MRAC in stamping, its design simplicity without system identification and auto-tuning procedures can make the direct MRAC a cost-effective, user-friendly method to improve part quality in production.

4.8 Summary and Conclusions

The results presented in this chapter show that a “machine control only” strategy can be improved upon using the process controllers, in the presence of disturbances, in terms of both tracking performance and part quality. A simulation-based auto-tuning method, which requires the stamping of only one additional part for the purpose of plant model parameter estimation, has been investigated to eliminate a manual approach to obtain fixed PI gains. Furthermore, auto-tuning provides an effective way to initialize the design and implementation of an adaptive stamping process controller, based on the MRAC approach. The direct MRAC stamping process controller works much better than the fixed PI process controller based on auto-tuning; however, the auto-tuning method is useful for providing good initial gain values for use with the adaptive controller.

In this chapter, the research has described, for the first time, the design and implementation of a MIMO direct MRAC stamping process controller, and experimentally validated the tracking performance of the reference punch force as well as part quality improvement, in the presence of plant variations and/or disturbances. The direct MRAC stamping process controller, which includes a pre-compensator, provided excellent tracking performance, and resulted in good part quality, even in the presence of
significant disturbances (i.e., dry versus lubricated or almost 25% increase in thickness). The use of the constrained RLS algorithm for the MRAC yielded better adaptation results, eliminating problems related to large transients. Finally, the results presented show that use of nominal parameter values based on system identification in the pre-compensator, and for the filter in the regressor vector for MRAC, is effective.
CHAPTER 5

MIMO INDIRECT ADAPTIVE PROCESS CONTROL

This chapter compares the design, implementation and performance of direct and indirect adaptive control (AC) to improve part quality in the stamping process in the presence of disturbances. As described previously in Chapter 4, the direct AC filter uses nominal process parameters, and so requires some knowledge of the process. Consequently, an indirect AC, which does not require the nominal process parameters, is also considered.

5.1 Introduction

An adaptive controller (AC) is defined as a controller with adjustable control parameters (or gains) and an adaptation law for adjusting the control parameters to achieve a desired control objective. In indirect AC the process parameters are estimated on-line and used to calculate the controller gains. However, in direct AC the controller gains are directly adjusted (or adapted) on-line without intermediate computations involving process parameter estimates.

In a recent study (Lim et al., 2010b-c), automatic tuning (auto-tuning) and direct AC of stamping were addressed. The auto-tuning was used not only to reduce the effort in tuning the controller gains, but also to determine good initial values of the controller gains for use with a direct AC. As shown in Figure 5.1.1(a), the direct AC, or model
reference adaptive control (MRAC), was used to adaptively update the controller gains (which are initially set to the values obtained from auto-tuning) to minimize the tracking error between the reference model output ($y_m$) and the process output ($y$), in the presence of disturbances. The direct MRAC scheme has been shown to meet the performance requirements which include stability and asymptotic tracking, for minimum-phase systems. However, in general, a parameterization for process parameter estimation in the adaptive law is not possible for nonminimum-phase systems with direct MRAC (Astrom and Wittenmark, 1995; Ioannou and Sun, 1988, 1989, and 1996). In addition, since the regressor vector in the adaptation algorithm for the direct MRAC uses the nominal values of the process parameters, the robustness and sensitivity analysis of the direct MRAC to process model perturbations, which represent unexpected plant dynamics changes and/or a slowly time-varying system, has been considered in (Lim et al., 2010b).

On the other hand, indirect AC, which provides estimates of the process parameters and thus does not require the nominal process parameters, is applicable to both minimum- and nonminimum-phase systems. The indirect AC uses process observation with on-line estimates of process parameters, and then it is necessary to introduce safeguards to make sure that all conditions required for the controller design method are fulfilled (Astrom and Wittenmark, 1995). For example, it may be necessary to test whether the estimated process model is minimum-phase or whether there are common factors in the estimated polynomials. In addition, with indirect AC, solutions for the adaptation mapping between the estimated process parameters ($\theta(t)$) and the controller parameter ($\theta_c(t)$), defined by an algebraic equation $\theta_c(t) = f(\theta(t))$, cannot be guaranteed to exist at each time ($t$), thus, giving rise to two potential issues: *loss of stabilizability* and *non-uniqueness*. 
Many studies have considered the stabilizability issue using various ideas. One possibility is to modify the adaptation algorithm so that the parameter estimates are projected into a given fixed constrained region (Goodwin and Sin, 1984; Kreisselmeier, 1985; Chia et al., 1991). For example, it may be sufficient to project into a set such that $\theta_{min} \leq \theta(t) \leq \theta_{max}$. Another idea is to add a so-called leakage term to the adaptation law to keep the estimates near a priori estimates. The idea behind leakage is to modify that adaptive law so that the time derivative of the Lyapunov function, which is used to analyze the adaptive scheme, becomes negative in the space of parameter estimates when these parameters exceed certain bounds (Ioannou and Kokotovic, 1983). A third method is to introduce a dead-zone in the estimator, switching off the parameter estimation if the error is too large (Astrom and Wittenmark, 1995; Ioannou and Sun, 1996). However, the ideas introduced above require prior knowledge to select constraints and bounds, and require satisfying a persistent excitation criterion.

The non-uniqueness problem arises where a unique solution of the algebraic equation in the adaptation law does not exist, regardless of prior knowledge. To guarantee existence and uniqueness of solutions to the algebraic mapping equation requires various assumptions in the process model (i.e., $G_p(z) = B(z)/A(z)$) as shown in Figure 5.1.1 and the controller structure (i.e., $G_c(z) = S(z)/R(z)$) (Astrom and Wittenmark, 1995; Ioannou and Sun, 1996). For example, the polynomials $A$ and $B$ are required to be coprime, with the assumption that $A$ is monic. In addition, the degrees of the polynomials $R$ and $S$ in the controller must be constrained with respect to the degrees of the process polynomials $A$ and $B$. Consequently, if $R$ and $S$ are selected for a certain control structure, without consideration of such constraints on the degrees of $R$ and $S$, then the adaptation
law for adjustment of the controller gain from the process parameter may require an optimization procedure (Astrom and Wittenmark, 1995).

![Diagram of adaptive process control methods](image)

Figure 5.1.1: Design methods for adaptive process controllers: (a) direct model reference adaptive control (MRAC) (b) indirect method using look-up table.

In this chapter, indirect AC, which provides estimates of the process parameters and is applicable to both minimum- and nonminimum-phase systems, is addressed. For our application, a proportional plus integral (PI) controller, which has been successfully used for rejecting disturbances and improving robustness to model uncertainty in stamping (Sunseri et al., 1996; Hsu et al., 2002), is selected. Furthermore, in a recent study Lim et al. (2010b-c) utilized the auto-tuning method to tune the gains of a standard PI controller. Such auto-tuning can also be utilized to provide good initial values of the PI gains for a direct adaptive controller. However, the simple PI control structure selected for our indirect adaptive controller requires an optimization approach for the computation of the
controller gains, and is thus not amenable to on-line implementation. Hence, an indirect AC using a look-up table scheme, which updates the controller gains on-line based on the process parameter estimates, is, for the first time, introduced and evaluated. Noting that simple control structures (e.g., P, PI and PID) are used in many control applications, the proposed look-up table-based indirect AC described in following sections should be of wide interest.

As shown in Figure 5.1.1(b), the look-up table is used to obtain the controller gains, $\theta_c(t)$, in terms of the estimated parameters, $\theta(t)$. This is done on-line, as part of the indirect AC which estimates the process parameters $\theta(t)$. The look-up table itself is created off-line using optimization to solve the adaptation mapping, $\theta_c(t) = f(\theta(t))$, which has a non-unique solution due to the selection of a simple PI control structure for our application. Then, this functional relationship is discretized in the look-up table via a number of break points within a given constrained (or projected) range based on prior knowledge obtained from experiments. Subsequently, this indirect AC, with various levels of process parameter discretization in the look-up table, is investigated in simulations. However, due to extensive memory requirements in real-time implementation, a smaller look-up table is used in the experiments. This look-up table-based indirect AC is compared with direct MRAC in terms of tracking performance as well as part quality, in the presence of plant parameter variations. In addition, in order to achieve high output tracking performance (Tomizuka, 1987; Devasia, 2002; Karimi et al., 2008), a pre-compensator based on the inverse of the closed-loop system is also included.
5.2 Indirect Adaptive Control Using Look-Up Table

5.2.1 On-Line Plant Parameter Estimation

For the indirect AC shown in Figure 5.1.1(b), process parameters are estimated on-line based on the observation of the input ($u$) and output ($y$) in experiments. Based on the unknown parameters and measurements for each corner output $i$, the regression model of the MISO plant transfer function as shown previously in Eq. (4.2) is given by

$$
y^i(k + 4) = -a^i_3 y^i(k + 3) - a^i_2 y^i(k + 2) - a^i_1 y^i(k + 1) - a^i_0 y^i(k) + \{b^i_1 u^i(k + 2) + b^i_0 u^i(k + 1) + b^i_1 u^i(k + 2) + b^i_0 u^i(k + 1)\}$$  \hspace{1cm} (5.1)

Expressing the future output in Eq. (5.1) in terms of current and past inputs and outputs, it follows that

$$
y^i(k) = -a^i_3 y^i(k - 1) - a^i_2 y^i(k - 2) - a^i_1 y^i(k - 3) - a^i_0 y^i(k - 4) + \{b^i_1 u^i(k - 2) + b^i_0 u^i(k - 3) + b^i_1 u^i(k - 2) + b^i_0 u^i(k - 3)\}$$  \hspace{1cm} (5.2)

Using the regression model in Eq. (5.2), the parametric model for process parameter estimation is formulated in terms of estimated parameters (i.e., $\hat{a}^i_3, ..., \hat{a}^i_0, \hat{b}^i_{11}, ..., \hat{b}^i_{30}$) as

$$y^i = \theta^{iT} \phi^i$$  \hspace{1cm} (5.3)

where

$$\theta^{iT} = \begin{bmatrix} \hat{a}^i_3, ..., \hat{a}^i_0, \hat{b}^i_{11}, ..., \hat{b}^i_{30} \end{bmatrix}$$

$$\phi^i = \begin{bmatrix} -y^i(k - 1), ..., -y^i(k - 4), u^i(k - 2), ..., u^i(k - 3) \end{bmatrix}^T$$

Recursive computation for indirect AC, based on the parametric model above, uses the RLS algorithm with exponential forgetting. The process parameters, $\theta'$, are estimated recursively using the estimation error, $e^i = y^i - \hat{y}^i$: 

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\[
\theta'(k) = \theta'(k-1) + P'(k)\psi'(k) - \left( \frac{\phi(k)\theta'(k-1)}{\lambda I + \phi'(k)P'(k-1)\phi(k)} \right)
\]  
(5.4)

\[
P'(k) = \left[ P'(k-1) - \frac{P'(k-1)\phi'(k)\phi(k)\psi(k)\psi(k)P'(k-1)}{\lambda I + \phi'(k)P'(k-1)\phi(k)} \right] / \lambda
\]

### 5.2.2 Adaptation Law Using Pole Placement

Referring to Figure 5.1.1(b), \( A^i \in R^1, B_j^i \in R^{1x3} \) and \( C_j^i \in R^{3x1} \) are defined previously in Eq. (4.2) and (4.3) for each corner \( i \). Thus, the closed-loop transfer function in discrete-time is given by

\[
y'(k) = \frac{B_j^i(z)C_j^i(z) + B_j^i(z)C_j^i(z) + B_j^i(z)C_j^i(z)}{A^i(z) + B_j^i(z)C_j^i(z) + B_j^i(z)C_j^i(z) + B_j^i(z)C_j^i(z)}
\]

(5.5)

Hence, the closed-loop characteristic polynomial is:

\[
A^i + B_j^iC_j^i + B_j^iC_j^i + B_j^iC_j^i = A^i
\]

(5.6)

Substituting \( A^i, B_j^i \) and \( C_j^i \) given in Eq. (4.2) and (4.3) respectively into Eq. (5.6), the closed-loop characteristic polynomial, based on on-line estimated parameters in Eq. (5.3) and the controller gains given previously in Eq. (4.3), becomes

\[
A^i(z) \triangleq z^5 + a_{c4}^iz^4 + a_{c3}^iz^3 + a_{c2}^iz^2 + a_{c1}^iz + a_{c0}^i
\]

(5.7)

where

\[
a_{c4}^i = \hat{a}_3^i - 1
\]

\[
a_{c3}^i = \hat{a}_3^i - \hat{a}_3^i + \hat{b}_{11}^is_{11} + \hat{b}_{21}^is_{21} + \hat{b}_{31}^is_{31}
\]

\[
a_{c2}^i = \hat{a}_2^i - \hat{a}_2^i + \hat{b}_{11}^is_{11} + \hat{b}_{21}^is_{21} + \hat{b}_{31}^is_{31} + \hat{b}_{10}^is_{10} + \hat{b}_{20}^is_{20} + \hat{b}_{30}^is_{30}
\]

\[
a_{c1}^i = \hat{a}_1^i - \hat{a}_1^i + \hat{b}_{11}^is_{11} + \hat{b}_{21}^is_{21} + \hat{b}_{31}^is_{31} + \hat{b}_{10}^is_{10} + \hat{b}_{20}^is_{20} + \hat{b}_{30}^is_{30}
\]

\[
a_{c0}^i = -\hat{a}_0^i
\]
Assuming that the desired closed-loop poles are placed at five locations (i.e., \( p_d^i, d = 1, ..., 5 \)) in the \( z \)-plane, the desired closed-loop characteristic polynomial is given by

\[
A_d'(z) = (z - p_1^i)(z - p_2^i)(z - p_3^i)(z - p_4^i)(z - p_5^i) = z^5 + l_4' z^4 + l_3' z^3 + l_2' z^2 + l_1' z + l_0'
\] (5.8)

where all of the desired poles in discrete-time lie inside the unit circle. The five desired poles are grouped as two dominant poles (i.e., \( p_{1,2}^i \) in \( z \)-plane) and three fast (or non-dominant) poles (i.e., \( p_{3,4,5}^i \) in \( z \)-plane). The two dominant poles are selected based on specifications for the stamping process, i.e., a settling time of less than 0.1 second and an overshoot of less than 20%.

The controller gains (i.e., \( s_{j1}^i \) and \( s_{j0}^i, j = 1, 2, 3 \)) are determined by matching coefficients of the two polynomials in Eq. (5.7) and Eq. (5.8) respectively. Thus,

\[
\begin{align*}
z^4 & : -(p_1^i + p_2^i + p_3^i + p_4^i + p_5^i) = \hat{a}_4^i - 1 \\
z^3 & : (p_1^i p_2^i + p_1^i p_3^i + p_1^i p_4^i + ... \cdots) = \hat{a}_3^i - \hat{a}_2^i + \hat{b}_{10}^i s_{10}^i + \hat{b}_{21}^i s_{21}^i + \hat{b}_{31}^i s_{31}^i \\
z^2 & : -(p_1^i p_2^i p_3^i + p_1^i p_2^i p_4^i + p_1^i p_3^i p_4^i + ... \cdots) = \hat{a}_2^i - \hat{a}_1^i + \hat{b}_{10}^i s_{10}^i + \hat{b}_{21}^i s_{21}^i + \hat{b}_{31}^i s_{31}^i + \hat{b}_{50}^i s_{50}^i + \hat{b}_{50}^i s_{50}^i \\
z^1 & : (p_1^i p_2^i p_3^i p_4^i + p_1^i p_2^i p_3^i p_5^i + ... \cdots) = \hat{a}_1^i - \hat{a}_0^i + \hat{b}_{10}^i s_{10}^i + \hat{b}_{20}^i s_{20}^i + \hat{b}_{30}^i s_{30}^i \\
z^0 & : -(p_1^i p_2^i p_3^i p_4^i p_5^i) = -\hat{a}_0^i
\end{align*}
\] (5.9)

In Eq. (5.9), there are six unknown controller gains (i.e., \( s_{j1}^i \) and \( s_{j0}^i, j = 1, 2, 3 \)), but only five linear equations.

In general, such linear systems can be solved using a generalized inverse (or pseudo-inverse). Note that Eq. (5.9) can be expressed as \( Ax = b \), where \( x \) is the vector of unknown controller gains (i.e., \( [s_{11}^i, ..., s_{30}^i]^T \)) and \( A \) is a coefficient matrix. However, the
$5 \times 6$ matrix $A$ is not full rank (i.e., $\text{rank}(A) = 3$) because there are no unknowns (i.e., $s_i^{1}, \ldots, s_i^{30}$) in the $z^d$ and $z^0$ coefficients in Eq. (5.9). Thus, determining the controller gains, in terms of the estimated process parameters and the desired poles, requires an optimization procedure as follows (Quintana-Ortí et al., 1998).

### 5.2.3 Optimization Approach

The error for each term shown in Eq. (5.9) is defined as

$$
\gamma'_{1} = \hat{a}'_{1} - 1 + \left( p'_1 + p'_2 + p'_3 + p'_4 + p'_5 \right) \\
\gamma'_{2} = \hat{a}'_{2} - \hat{a}'_{3} + \hat{b}'_{1}s_{1} + \hat{b}'_{2}s_{2} + \hat{b}'_{3}s_{3} - \left( p'_1 + p'_2 + p'_3 + p'_4 + p'_5 \ldots \right) \\
\gamma'_{3} = \hat{a}'_{3} - \hat{a}'_{2} + \hat{b}'_{1}s_{1} + \hat{b}'_{2}s_{2} + \hat{b}'_{3}s_{3} + \hat{b}'_{4}s_{4} + \hat{b}'_{5}s_{5} + \ldots + \left( p'_1 + p'_2 + p'_3 + p'_4 + p'_5 \ldots \right) \\
\gamma'_{4} = \hat{a}'_{4} - \hat{a}'_{3} + \hat{b}'_{1}s_{1} + \hat{b}'_{2}s_{2} + \hat{b}'_{3}s_{3} + \hat{b}'_{4}s_{4} + \hat{b}'_{5}s_{5} + \ldots + \left( p'_1 + p'_2 + p'_3 + p'_4 + p'_5 \ldots \right) \\
\gamma'_{5} = -\hat{a}'_{4} + \hat{b}'_{2}s_{2} + \hat{b}'_{3}s_{3} + \hat{b}'_{4}s_{4} + \hat{b}'_{5}s_{5} + \ldots + \left( p'_1 + p'_2 + p'_3 + p'_4 + p'_5 \ldots \right) \quad (5.10)
$$

Then, based on both the desired poles (i.e., $p'_d$, $d = 1, 2, 3, 4, 5$) and the estimated plant parameters (i.e., $\hat{A}'$ and $\hat{B}'$, $j = 1, 2, 3$), the sum of the squares of the five errors (i.e., $\gamma'_k = f(\hat{a}'_i, \ldots, \hat{b}_{30}'s_{30}'$, $k = 0, 1, 2, 3, 4$) can be minimized to find the controller gains (i.e., $s'_{j_1}$ and $s'_{j_0}$, $j = 1, 2, 3$) for each corner output $i$, i.e.,

$$
\min_{s'_{j_1}, s'_{j_0}} \left\{ (\gamma'_0)^2 + (\gamma'_1)^2 + (\gamma'_2)^2 + (\gamma'_3)^2 + (\gamma'_4)^2 \right\} \quad (5.11)
$$

Thus, the computation of the controller gains requires an optimization approach, which is not amenable to on-line implementation. Consequently, the adaptation mechanism using a look-up table scheme, which updates on-line the controller gains on-line based on the process parameter estimates is developed and evaluated.
5.2.4 Adaptation Mechanism Using Look-Up Table

As shown in Figure 5.1.1(b), the controller gains, which are calculated off-line via optimization and are stored in a look-up table, can be selected on-line based on the values of the estimated plant parameters. The look-up table is generated via optimization and implemented as follows:

**Step 1:** Generate a mesh size (i.e., discretization) for the process parameters. The process parameters need to have a certain number of discrete values within appropriate bounds based on prior knowledge. For example, the process parameters (i.e., $\hat{a}^i_1, ..., \hat{b}^i_{j_0}$) are bounded within a certain variation (i.e., $\pm 2\delta$ or $\pm 20\%$) where $\delta$ is the variation of each discretized parameter, using $n$ (e.g., $n = 3$ or 5) discretized points around the nominal values (i.e., $\bar{a}^i_1, ..., \bar{b}^i_{j_0}$) of the parameters. Such discretized sets of bounded process parameters used to generate the look-up tables are shown in Table 5.2.1. Subsequently, the closed-loop performance of the look-up table will be investigated and compared in terms of the number of discrete break points $n$.

**Step 2:** Choose the desired pole locations for optimization. To obtain solutions for the controller gains (i.e., $s^i_{j_1}$ and $s^i_{j_0}$) via optimization (see Eq. (5.11)), first of all, the five desired poles in the $z$-plane must be specified. Two dominant poles (i.e., $0.62 \pm 0.2i$) and three fast, or non-dominant, poles (i.e., $0.05$, $0.1$ and $0.12$) are obtained in the $z$-plane via optimization, which minimizes the sum of the squares of the first and fifth errors (i.e., $\gamma^i_4$ and $\gamma^i_0$) respectively in Eq. (5.10), because there
are no unknowns (i.e., $s_{11}^i, \ldots, s_{30}^i$) in the $z^4$ and $z^0$ coefficients in Eq. (5.9). These satisfy system specifications required for the stamping process, i.e., a settling time of less than 0.1 second and an overshoot of less than 20%.

Table 5.2.1: Discretized sets of the bounded process parameters used in the look-up table.

<table>
<thead>
<tr>
<th>Plant parameter</th>
<th>$n = 3$</th>
<th>$n = 5$</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{a}_3^i$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\hat{a}_3^i(1)$</td>
<td>$\bar{a}_3 - 2\delta$</td>
<td>$\bar{a}_3 - 2\delta$</td>
<td>...</td>
</tr>
<tr>
<td>$\hat{a}_3^i(2)$</td>
<td>$\bar{a}_3$</td>
<td>$\bar{a}_3$</td>
<td>...</td>
</tr>
<tr>
<td>$\hat{a}_3^i(3)$</td>
<td>$\bar{a}_3 + 2\delta$</td>
<td>$\bar{a}_3 + 2\delta$</td>
<td>...</td>
</tr>
<tr>
<td>$\hat{a}_3^i(4)$</td>
<td>$\bar{a}_3$</td>
<td>$\bar{a}_3$</td>
<td>...</td>
</tr>
<tr>
<td>$\hat{a}_3^i(5)$</td>
<td>$\bar{a}_3$</td>
<td>$\bar{a}_3$</td>
<td>...</td>
</tr>
</tbody>
</table>

| $\hat{b}_{30}^i$ |         |         |     |
| $\hat{b}_{30}^i(1)$ | $\bar{b}_{30} - 2\delta$ | $\bar{b}_{30} - 2\delta$ | ... |
| $\hat{b}_{30}^i(2)$ | $\bar{b}_{30}$ | $\bar{b}_{30}$ | ... |
| $\hat{b}_{30}^i(3)$ | $\bar{b}_{30} + 2\delta$ | $\bar{b}_{30} + 2\delta$ | ... |
| $\hat{b}_{30}^i(4)$ | $\bar{b}_{30}$ | $\bar{b}_{30}$ | ... |
| $\hat{b}_{30}^i(5)$ | $\bar{b}_{30}$ | $\bar{b}_{30}$ | ... |

**Step 3:** Perform the optimization so that the look-up table stores the controller gains (i.e., $s_{j_1}^i$ and $s_{j_0}^i$) based on both the discretized sets of process parameters and the given desired poles. This was accomplished using the standard function `fminsearch` in Matlab for unconstrained optimization (Lagarias et al., 1998): This function starts at given initial values and then finds local minima of the given error equations (i.e., $\gamma_3^i, \gamma_2^i$, and $\gamma_1^i$). Thus, prior information for the controller gains, obtained using auto-tuning, is used for initial values for the optimization.
Step 4: Formulate the look-up table based on the discretized values of the estimated process parameters. This was accomplished using the standard Simulink block (i.e., look-up table (n-D) in Matlab). As shown in Figure 5.2.1, the standard look-up table block generates an output value \( s_{i1} \) by comparing the block inputs \( (\hat{a}_1,\hat{a}_2,\ldots,\hat{b}_{31},\hat{b}_{30}) \) with the discretized set parameters. The look-up table evaluates a sampled representation of a function in \( m \) variables (i.e., the estimated process parameters or \( m = 10 \) here) by linear interpolation between samples to give an approximate value. For example, one of the controller gains can be approximated by

\[
s_{i1} = \hat{f}(x_1,x_2,\ldots,x_m) = \hat{f}(\hat{a}_1,\hat{a}_2,\ldots,\hat{b}_{31},\hat{b}_{30})
\]

where \( m \) is the number of estimated parameters. The data parameter in the look-up table (see) is defined as a set of output values that correspond to its rows, column, and higher dimensions (or pages) with the \( n \)th discretized set parameter shown in Table 5.2.1. As shown in Table 5.2.2, the first \( (\hat{a}_1) \) input identifies the first dimension (row) break points, the second \( (\hat{a}_2) \) input identifies the second dimension (column) break points, the third input \( (\hat{a}_i) \) identifies the third dimension (or page) break points, and so on (see Simulink block look-up table in Matlab for more detail). Table 5.2.2 shows, for two different discretization values \( n \) (i.e., \( n = 3 \) and 5), the values of \( s_{i1} \) (one of the six controller gains for each corner \( i \)) based on the 10 estimated process parameters. In Table 5.2.2, \( \hat{a}_1 \) (first) and \( \hat{a}_2 \) (second) inputs specify row and column discretized points respectively, and the 8 other inputs
specify their first value (i.e., $\hat{a}_1^i(1),...,\hat{b}_{30}^i(1)$) of discretized points. Due to space limitations all values cannot be shown. However, all of the different values for are calculated via optimization based on the first, second or third values of discretized points for the 8 other inputs. Thus, the data parameters in the look-up tables require a large memory size which will be discussed in following section.

Table 5.2.2: An example of the controller gain (i.e., $s_{11}^i$) stored in the look-up table based on two different discretizations (i.e., $n = 3$ and 5) for variations of two plant parameters.

<table>
<thead>
<tr>
<th>Break points ($n = 3$)</th>
<th>Column ($\hat{a}_2^i$)</th>
<th>$\hat{a}_2^i(1)$</th>
<th>$\hat{a}_2^i(2)$</th>
<th>$\hat{a}_2^i(3)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{a}_1^i(1)$</td>
<td>$\bar{a}_1^i - 2\delta$</td>
<td>0.152</td>
<td>0.166</td>
<td>0.178</td>
</tr>
<tr>
<td>$\hat{a}_1^i(2)$</td>
<td>$\bar{a}_1^i$</td>
<td>0.152</td>
<td>0.153</td>
<td>0.166</td>
</tr>
<tr>
<td>$\hat{a}_1^i(3)$</td>
<td>$\bar{a}_1^i + 2\delta$</td>
<td>0.172</td>
<td>0.152</td>
<td>0.153</td>
</tr>
</tbody>
</table>

$n = 3$

<table>
<thead>
<tr>
<th>Break points ($n = 5$)</th>
<th>Column ($\hat{a}_2^i$)</th>
<th>$\hat{a}_2^i(1)$</th>
<th>$\hat{a}_2^i(2)$</th>
<th>$\hat{a}_2^i(3)$</th>
<th>$\hat{a}_2^i(4)$</th>
<th>$\hat{a}_2^i(5)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{a}_1^i(1)$</td>
<td>$\bar{a}_1^i - 2\delta$</td>
<td>0.152</td>
<td>0.153</td>
<td>0.166</td>
<td>0.171</td>
<td>0.178</td>
</tr>
<tr>
<td>$\hat{a}_1^i(2)$</td>
<td>$\bar{a}_1^i - \delta$</td>
<td>0.151</td>
<td>0.152</td>
<td>0.158</td>
<td>0.153</td>
<td>0.172</td>
</tr>
<tr>
<td>$\hat{a}_1^i(3)$</td>
<td>$\bar{a}_1^i$</td>
<td>0.152</td>
<td>0.151</td>
<td>0.153</td>
<td>0.152</td>
<td>0.166</td>
</tr>
<tr>
<td>$\hat{a}_1^i(4)$</td>
<td>$\bar{a}_1^i + \delta$</td>
<td>0.161</td>
<td>0.155</td>
<td>0.152</td>
<td>0.151</td>
<td>0.158</td>
</tr>
<tr>
<td>$\hat{a}_1^i(5)$</td>
<td>$\bar{a}_1^i + 2\delta$</td>
<td>0.172</td>
<td>0.161</td>
<td>0.152</td>
<td>0.155</td>
<td>0.153</td>
</tr>
</tbody>
</table>

$n = 5$
5.2.5 Simulation with Look-Up Table

Simulation is used to validate the performance of the look-up table scheme in Figure 5.1.1(b), based on the estimated perturbation process models, with randomly-assigned process model parameter variations to represent changes in plant dynamics. The simulations are performed in terms of three cases: (1) Case A is the original indirect AC based on optimization without using a look-up table. This case is not for the real-time implementation in experiments, but for validation of look-up table performance. (2) Case B is for a look-up table with $n = 3$. (3) Case C is for a look-up table $n = 5$. Linear interpolation in the look-up tables is used to pick an appropriate controller gain between values of the controller gains based on the estimated process parameters. Case A (i.e., off-line optimization) uses the original values of the PI controller gains based on the estimated plant parameters, without any interpolation.
Figure 5.2.2: Simulated results of the controller gains based on three cases (i.e., (1) Case A: with off-line optimization (2) Case B: with look-up table and \( n = 3 \) (3) Case C: with look-up table and \( n = 5 \)): (a) \( K_{p1} \) \( \triangleq s_{11} \), (b) \( K_{p2} \) \( \triangleq s_{21} \), (c) \( K_{p3} \) \( \triangleq s_{31} \), (d) \( K_{i1} \) \( \triangleq s_{11} + s_{10} \), (e) \( K_{i2} \) \( \triangleq s_{21} + s_{20} \), (f) \( K_{i3} \) \( \triangleq s_{31} + s_{30} \).

As shown in Figure 5.2.2, the look-up table using \( n = 5 \) (Case C) is closer to Case A than \( n = 3 \) (Case B) in the look-up table. In particular, Figure 5.2.2(a), (b) and (e) show the expected results that the look-up table with \( n = 5 \) is closer to the values from the optimization than the look-up table with \( n = 3 \). In addition, as shown in Figure 5.2.3, the tracking performance of the punch force with \( n = 5 \) in the look-up table is slightly better than the look-up table with \( n = 3 \).
Figure 5.2.3: Simulation results for perturbed punch force output tracking performance comparing $n = 3$ and $n = 5$ in the look-up table.

However, the case with 5 discretized points requires extensive memory. Specifically, for each corner $i$, the number of data points required is $l \times n^2 \times n^m$, where $l$ is the number of the controller gains (or the number of look-up tables), $n$ is the number of discretization points, and $m$ is the number of plant parameters. For $n = 5$ this becomes $1.5 \times 10^9$, while with $n = 3$ the memory requirement is $3.2 \times 10^6$ points, for $l = 6$, and $m = 10$. However, due to memory limitations in the real-time control computer, even a look-up table with 3 discretized points could not be accommodated in experiments. Consequently, a smaller look-up table (i.e., $n = 2$) was used in the experiments (memory requirement is for $2.5 \times 10^4$ points). It is compared with the direct AC in terms of the tracking performance as well as part quality, in the presence of disturbances, in a subsequent section.
In this simulation the estimated process parameters using system identification are used as initial values of the process parameters in the RLS algorithm, and estimated process models are used as the process model. Initial values of the covariance matrix $P^i$ (see Eq. (5.4)) are set to $10^3 \times I(m,m)$ where $I$ is the identity matrix and $m$ (i.e., $m = 10$) is the number of the process parameters for each corner. In simulations, normally distributed random numbers (with a variance less than 1% of output ($y$)), are added to the input ($u$) to satisfy persistent excitation conditions.

5.3 Simulations

5.3.1 Simulation Results

Simulation conditions for indirect AC using the look-up table are the same as the direct AC described previously in Section 4.5.1. Simulation is used to validate and compare the performance of the two adaptive PI process controllers (i.e., direct and indirect) based on the estimated perturbation process models, with randomly-assigned process model parameter variations to represent changes in plant dynamics. The simulation models use the perturbed binder forces ($\delta F^i_{bj}$) as inputs, the perturbed punch force ($\delta F^i_p$) as output, and the desired perturbed punch force ($\delta F^i_{p,ref}$) as the reference (or desired punch force) for each corner $i$. The simulation models were previously shown in Figure 5.1.1.

The three binder forces ($F^i_{bj}, j = 1, 2, 3$) associated with each punch force corner, $i$, ($i = 1, 2, 3, 4$) are updated to minimize the difference between $F^i_p$ and $F^i_{p,ref}$, by adding or subtracting the perturbed binder forces ($\delta F^i_{bj}$), which are produced by the process
controller. Thus, the total binder forces, \( F_{bj}^i \), in both simulation and experiment are given previously in Eq. (4.22). The pre-determined nominal binder forces for each corner, \( i \), and were shown previously in Figure 4.5.1. As described previously, the machine control (MC) alone (without the process controller) generates these pre-determined nominal binder forces, even in the presence of disturbances.

Again, note that the reference punch force trajectories (\( F_{p,ref}^i \)) are obtained by recording the punch forces generated using the pre-determined nominal binder forces which are determined by experienced die-makers to make a good part using the material with nominal properties and under normal operating conditions for each punch force corner \( i \).

Figure 5.3.1 shows the simulation results with the punch force as output and the binder force as input, using the direct AC (i.e., MRAC) and the look-up table-based indirect AC (i.e., \( n = 3 \)). These simulations include 20\% variation in the process parameters. In Figure 5.3.1, both process controllers track the punch force by adjusting the binder forces. Due to space limitations results are presented for only one corner of the punch forces (i.e., \( F_p^i \)). However, all corners of the punch forces were investigated and showed similar trends.

The performance of the two controllers in the presence of actual plant variations and disturbances in the form of intentionally introduced lubrication and material thickness changes is described in the next section on experimental validation.
Figure 5.3.1: Simulation results comparing two process controllers (i.e., direct and indirect AC with \( n = 3 \) in the look-up table): (a) punch force (i.e., output or \( F_p^1 \)) (b) binder forces associated with \( F_p^1 \).

5.4 Experiments

5.4.1 Experimental Validation

Direct and indirect AC process controllers described above were implemented on the experimental system. Their performance was compared to the performance of the machine control (MC) only (i.e., without process control (PC)) with fixed pre-determined
binder forces commands \( F_{b_j,\text{offset}}^i \) in Eq. (4.22), in terms of deviation from the reference punch force, and in terms of part quality, in the presence of disturbances.

**Lubrication Change**

The first disturbance that we consider is lubrication change. Fig. 10 shows the tracking performance of the punch force for the test cases, and illustrates stamped part quality comparison for those cases in the presence of lubrication change. Due to space limitations results are presented for only one corner of the punch forces (i.e., \( F_p^i \)). However, all corners of the punch forces and part quality for all corners were investigated and showed similar trends.

Figure 5.4.1(a) shows that with only machine control, (i.e., without process control) there is a clear difference between the reference punch force which characterizes a good part in the absence of the extra lubrication and the measured punch force in the presence of the extra lubrication. Figure 5.4.1(e) shows that extra lubrication results in significant wrinkling, caused by greater material flow. The desired part quality, characterized by the reference punch force, is shown in Figure 5.4.1(b). In Figure 5.4.1(a), (c) and (d), it can be seen that the direct MRAC process controller provides the best tracking performance of the reference trajectory as well as significant part quality improvement in the presence of lubrication change. The look-up table-based indirect AC process controller with \( n = 2 \) also enables the punch force to track the reference punch force, but with some oscillation throughout the punch stroke under the excessive lubrication condition. Note that part quality is improved with both AC methods over the MC only case. Thus, the above experimental results, using a complex-geometry part, show that the direct MRAC process
controller outperforms the look-up table-based indirect AC with \( n = 2 \) in terms of the tracking of the reference punch force trajectory, while both process controllers effectively improve part quality in the presence of lubrication change.

Figure 5.4.1: Experimental results in the presence of lubrication change: (a) the punch force (i.e., \( F_p^1 \)), and for indirect AC with \( n = 2 \) (b) dry condition and (c) - (e) excessive lubricated condition.
Figure 5.4.2: Experimental results in the presence of material thickness variation: (a) punch force (i.e., $F_p^2$), and for indirect AC with $n = 2$ (b) binder forces (i.e., $F_{b4} \equiv F_{b1}^2$, $F_{b5} \equiv F_{b2}^2$ and $F_{b6} \equiv F_{b3}^2$).
Material Thickness Variation

The second disturbance that we consider is material thickness variation. With thicker material (i.e., 0.79 mm) compared to the nominal (i.e., 0.64 mm), Figure 5.4.2 shows that the two process controllers effectively track the reference punch force, which was determined using the nominal material. Again, as shown in Figure 5.4.2, machine control alone (i.e., without PC) cannot minimize the error between the reference punch force and the measured punch force. However, the direct MRAC process controller also shows good tracking performance of the measured reference punch force by adjusting the three associated binder forces (see Figure 5.4.2(b)). For example, when the measured punch force is greater than the reference punch force, at around 2.5 inches of punch stroke, the direct MRAC process controller drastically reduces the binder forces (i.e., $F_{b4} \triangleq F_{b1}^2$, $F_{b5} \triangleq F_{b2}^2$, and $F_{b6} \triangleq F_{b3}^2$) in order to minimize the difference between the reference $F_p^2$ and measured $F_p^2$. However, the indirect AC process controller based on a look-up table with $n = 2$ performs less effectively with material thickness change, and shows excessive oscillations. Due to memory limitations, the indirect AC with a smaller look-up table ($n = 2$) is used in the experiments, where it is outperformed by the direct AC.

Again, as described previously, the performance of the look-up table-based indirect AC is restricted, due to memory limitations of the real-time control computer. Required memory sizes of the look-up table are proportional to not only the number of discretizations for the plant parameters, but also the number of plant parameters as well as the number of the controller gains. However, in this paper the results presented, for the first time, show a novel methodology where indirect AC requires an optimization
approach to obtain the solution (i.e., the controller parameter) to the adaptation mapping equation, due to certain constraints (e.g., constrained structures in the controller and/or the process model). Clearly, the adaptive controller parameters generated via optimization, which is not amenable to real-time implementation, can be embedded into the indirect AC in the form of a look-up table based on the estimated parameters, and implemented in real-time production runs. Such an approach can be expected to become more attractive in the future, as memory becomes cheaper and faster.

5.5 Discussion

Initially, to study the look-up table method, a 1st order SISO process model having 2 estimated parameters combined with a SISO PI control structure was considered. The SISO PI process controller gains obtained via off-line optimization were tuned manually and then stored in the look-up table, with 3 or 5 discretized points for the two process parameters. In other words, every possible case for the discretized points of two process parameters was considered one-by-one to obtain the PI gains via the optimization. However, for our stamping application, it was not practical to calculate the controller gains manually to generate the look-up table for each corner. Consequently, the process used to generate the look-up tables of the controller gains via off-line optimization was automated. This automation, which computes every case for the discretized points (e.g., \( n = 3 \) or 5) of the 10 estimated parameters, and generates SIMO PI controller gains matrix (see Table 5.2.2) for the look-up table, makes the look-up table scheme feasible, even with large number of discretized points for the process parameters (see Appendix C for detail programming code).
In addition, simulations with indirect AC using the look-up table method show it works well. However, the size of the look-up table becomes a critical issue for real-time implementation. Thus, the performance in experiments, which will be shown in the next section, is not as good as desired due to the limit of $n = 2$. Ultimately, indirect AC with the look-up table may be more attractive in the future as memory for real-time computer control continues to become cheaper and faster.

### 5.6 Summary and Conclusions

A comparison between direct and indirect adaptive control (AC) in stamping in terms of the design, implementation, tracking performance and improvement in part quality is presented. Both simulation and experimental results in the presence of disturbances and process variations are included. As described previously in Chapter 4, a MIMO direct AC (i.e., MRAC) stamping process controller works well. However, the adaptation algorithm for the direct AC requires the nominal process parameters and requires that the plant satisfy certain conditions such as being minimum phase. Consequently, an indirect AC, which does not need the nominal process parameters, is considered as a potential alternative. However, depending on the control structure, indirect AC may require one to find controller gains using an optimization approach, which is difficult to do in a real-time implementation. Thus, the indirect AC using a look-up table scheme is proposed.

In this chapter, the research has described, for the first time, the design and implementation of a look-up table-based indirect AC, which updates the controller gains on-line using a look-up table generated via off-line optimization. The indirect AC, with a sufficiently high level of discretization (i.e., $n = 3$ or 5) for the estimated process
parameters in the look-up table, performs well in simulations. However, the size of the
look-up table becomes an issue for real-time implementation. Thus, performance of
indirect AC, with a lower level of discretization (i.e., $n = 2$) for the estimated process
parameters in a look-up table, is not as good as the direct AC. In the future, indirect AC
with the look-up table may become more attractive as memory for real-time computer
control continues to become cheaper and faster.
CHAPTER 6

SUMMARY AND CONCLUSIONS

The main challenges in stamping are to avoid wrinkling and tearing during the process and to minimize springback of the stamped parts. Also, an additional requirement is to reduce variations in stamped part quality dimensions in the presence of plant dynamics changes and disturbances. An adaptive control approach which can complement existing techniques to improve part quality and consistency in the presence of disturbances (e.g., lubrication and material thickness change) has been developed and demonstrated. The purpose of this dissertation is to present the systematic analysis and design of a MIMO stamping process controller to improve part quality and consistency with a complex-geometry part, in the presence of plant variations. The problems can be separated into two main parts: (a) MIMO process modeling including system identification, and (b) MIMO process controllers design and implementation for a real part production.

6.1 Summary

The first step in a systematic approach to controller design is modeling. In Chapter 2, a MIMO stamping process model structure was developed. For designing the stamping process controller, a simple controller-design model structure, providing a dynamic relationship between the process input (i.e., binder force) and process output (i.e., punch force) was obtained. Then, a 4th order model structure to include machine control, process
control, and low-pass filter dynamics was formulated. Furthermore, this 4th order model structure was expanded into a MIMO model structure as a block-diagonal transfer function matrix. Consequently, these parameters of the MIMO model structures were experimentally determined and validated using system identification techniques. In addition, two different configurations (i.e., for die try-out and for production) of the experimental setups were also discussed in Section 2.2 and Appendix B respectively.

In Chapter 3, using a MIMO stamping process model described in Chapter 2, a systematic design and implementation of a MIMO fixed gain process controller was addressed to improve part quality for a complex-geometry part. An appropriate MIMO PI process controller for a real part production has been designed using the proposed design procedures through simulation and fine-tuned through experiments, with a 4th order linear perturbation model and reference punch force trajectories. Under low and high constant blank holder force conditions, experimental results using fined-tuned MIMO PI process controller showed good tracking performance.

In Chapter 4, a simulation-based auto-tuning method, which required the stamping of only one additional part for the purpose of process parameter estimation, has been studied to remove the manual tuning effort for tuning MIMO process controller gains. Furthermore, design and implementation of a direct adaptive control (i.e., MRAC) has been investigated to improve the tracking performance as well as part quality in the presence of plant variations, utilizing the auto-tuning method which provided an appropriate initial controller gains. The reference model which specifies the desired closed-loop system was obtained using the estimated nominal process parameters.
The adaptation algorithm in the design of the MIMO direct adaptive control (AC) described previously in Chapter 4 required the nominal process parameters. Thus, in Chapter 5, a MIMO indirect AC, which does not need the nominal process parameters or provides on-line estimates of process parameters, has been investigated as a potential alternative. However, depending on the control structure, indirect AC may require one to find controller gains using an optimization approach, which is difficult to do in real-time implementation. Thus, the design and implementation of the look-up table-based indirect AC has been, for the first time, proposed. The look-up table-based indirect AC was implemented to update the controller gains on-line using a look-up table generated via off-line optimization for a real part production. The comparison between direct and indirect AC was accomplished in terms of tracking performance as well as part quality, in the presence of plant variations. The indirect AC, with sufficiently high level of discretization (i.e., $n = 3$ or 5) for the estimated process parameter in the look-up table, performs well in simulation. However, due to memory limitations for real-time implementation, the performance of indirect AC, with a lower level of discretization (i.e., $n = 2$) for the estimated process parameters in the look-up table, was not as good as the direct AC.

6.2 Conclusions

The study presented in this dissertation shows that the development of a MIMO process model structure as well as the systematic design and implementation of a MIMO adaptive process controller for real part production runs can significantly contribute to improved-stamping. First, based on a thorough review of the literature related to this
proposed research, evaluation of in-process sensors (e.g., draw-in and punch force) suitable for process control was performed. Second, a MIMO control-design model that is generalized for any stamping process and captures the dynamics relationship between the binder force and the punch force was presented. Furthermore, the developed MIMO process model is broadly applicable for MIMO process controller design. Third, the systematic design and implementation procedure for a MIMO fixed PI process controller that can effectively lead to an appropriate stamping process controller was established. However, fine-tuning these controller gains through experiments has required a manual procedure, which is costly and time-consuming. Thus, to eliminate such a manual tuning effort as well as to provide appropriate initial values to the design of adaptive control, the auto-tuning method is utilized. Finally, the MIMO adaptive process control approaches which were, for the first time, developed and implemented in this stamping application have achieved part quality improvement and good tracking performance, in the presence of plant disturbances. Specifically, the direct MRAC stamping process controller, which included a pre-compensator (based on the inverse dynamics of the reference model), provided excellent tracking performance, and resulted in good part quality, even in the presence of significant disturbances (e.g., dry versus excessive lubrication or a 25% increase in thickness). The results showed that use of the nominal parameter values based on system identification in the reference model (or the pre-compensator) and for the filter in the regressor vector for MRAC, is effective for real part production. On the other hand, based on results presented previously in Chapter 5, the indirect AC with look-up table was a novel methodology that can be used where indirect AC requires an optimization approach to obtain the solution of the adaptation mapping equation, due to certain
constraints (e.g., constrained structures in the controller and/or the process model. Thus, in the future, indirect AC with the look-up table may become more attractive as memory for real-time computer control continues to become cheaper and faster.

6.3 Topics for Future Work

The direct MRAC designed through simulation performed very well in experimental results for real part production. However, system identification and auto-tuning were required, and are not user-friendly procedures for a real production environment. Even though it was not reported in this dissertation, we recently evaluated the feasibility of removing the system identification and auto-tuning steps from the direct MRAC implementation through simulation. This simplified design of the direct MRAC uses the nominal values of the estimated process parameters and the auto-tuned controller gains obtained from combined data sets from our experiments with different dies and presses as well as different complex part geometries. The simulation results are very promising, and future experiments with the simplified direct MRAC appear to be warranted.
APPENDICES
APPENDIX A

EVALUATION OF IN-PROCESS SENSORS

In this Appendix, based on a comprehensive literature review, as described previously in Section 1.2.3, we present a comparative study of in-process sensors (i.e., draw-in, punch force, and wrinkling) which can potentially be used for process variable(s) measurement. Our evaluation of in-process sensors for use in process control is summarized.

A.1 Draw-In Sensor

I. Mutual Inductance-Based Type. Cao et al. (2002, 2005) and Mahayotsanun et al. (2005, 2007, and 2009) developed a new type of draw-in sensor which has two key advantages: 1) Ease of setup and 2) cost-effective implementation in industrial applications. Thus, we evaluated the use of this type of the draw-in sensor for our research, due to its simplicity in use and cost-effective implementation in production.

The design of this sensor is small enough to be embedded in a die or blank holder. In the single transducer configuration the primary and secondary coils, as shown previously in Figure 1.2.7(a), are printed onto one transducer circuit board. Utilizing the principle of mutual inductance between the two loops, the linear draw-in of the sheet metal is detected based on the uncovered area of the primary and secondary coils on the board, as shown previously in Figure 1.2.7(b). The linear position sensor transmits
signals to a signal conditioning board, which amplifies and filters the induced voltage readings and these readings are sampled using a computer based data acquisition system. Thus, sheet metal draw-in can be obtained using the voltages generated by the draw-in sensor, after calibration using an LVDT, as illustrated previously in Figure 1.2.7(c).

As shown in Figure A.1.1, the inductive type of draw-in sensor (developed by Northwestern University and labeled NW in the legend for Figure A.1.1(c)) is experimentally validated by comparing it with a cable type sensor which will be described in the next section. Figure A.1.1(a) shows the experimental setup. The inductive type sensor (NW) is mounted on the top the edge of the die with epoxy for protection, and the cable type draw-in sensor (i.e., Celesco cable type), whose cable is hooked with a hole on the blank sheet, is also attached to the die. Then, as shown in
Figure A.1.1(b)-(c), the two generated voltages, which are proportional to material draw-in (or flow-in) displacement during the forming stroke, are compared. However, the inductive transducer displays two hump-like features, which are caused by gap change between the sheet metal and the transducer. The cable type draw-in sensor displays a linear voltage signal based on the draw depth in forming. As shown in Figure A.1.1(b), in particular, if there was wrinkling (i.e., which typically occurred at the outer edge of blank) during the punch stroke, the induced voltage generated by gap change between sheet metal and transducer would vary. Thus, it was difficult to detect true draw-in displacement during the stroke with the inductive sensor.

II. Cable Type. As described in the previous section, the cable type draw-in sensor was working properly to measure the material displacement during the punch stroke, while a newly developed draw-in sensor (i.e., NW) did not seem appropriate for our application in terms of practically, given that wrinkling can occur at the location of the sensor. As shown in Figure A.1.2, the cable type draw-in sensor is installed using a supporting bracket and connecting bar, which is connected the cable and also supported by a coil spring for making the tip of a connecting bar contact tightly with the edge of blank sheet (see Figure A.1.2(b)).

As shown in Figure A.1.3, however, one of the cable type draw-in sensors, which are mounted at four different locations on the edges of die, has a potential challenge: when a drawbead of the die is very close to the edge of sheet metal, the upper drawbead (or male part) pushes the tip of the sheet metal upward. Thus, the draw-in sensor signal (i.e., sensor #4) may capture incorrect values of material flow-in (the flat region in Figure A.1.3, where the connecting bar could be stuck between the blank and the lower die).
Figure A.1.2: Installation of the cable type draw-in sensor using the supporting bracket and the connecting bar supported by coil spring.

Figure A.1.3: Experimental validation of the cable type draw-in sensor.
**Discussion and Remarks.** Although this challenge in draw-in measurement can be addressed using a longer connecting bar attachment to the blank to prevent the blank from lifting during the punch stroke, there are still limitations for use in production runs. In stamping production runs, many dies with unique geometries must be replaced quickly to produce different kinds of stamped parts. However, this cable type draw-in sensor requires time-consuming installation effort and cost in actual high-volume production operations.

### A.2 Punch Force Sensor

The punch force (or tonnage monitoring) sensor in forming process is easy to be implemented in practice, and does not require a high level of installation effort and cost. Thus, in this research, the punch force measurement is used for process control. All evaluation and validation results are presented previously throughout the chapters. However, the punch force still has limitations, such as the lack of local detail for complex parts.

### A.3 Wrinkling Sensor

As discussed previously in Section 1.2.3 as part of the literature review, both contact and non-contact types of wrinkling sensors are costly and require time-consuming installation effort. Thus, in this research we did not evaluate the wrinkling sensor.
APPENDIX B

DEPLOYMENT OF SYSTEM CONFIGURATIONS

In our research, two types of system configurations were used in the experiments: 1) for the die try-out tests and 2) for the high-volume production runs.

B.1 System Configuration for Die Try-Out

For the die try-out test, the system configuration which was deployed at a die-try company (i.e., Troy Design and Manufacturing or TDM, one of the industrial partners in the research project) was described previously in Section 2.2.

B.2 System Configuration for High-Volume Production

The system configuration for high-volume production runs for a complex-geometry was deployed at a production company (i.e., Ogihara America Corporation or OAC) which is one of the industrial partners in the research project. Most of system components (e.g., hydraulic actuator, process variable sensors, and real-time computer) are the same as described previously in Section 2.2. In Ogihara the material is fed automatically using robots which requires the system to be ready for the next hit in about 2 second to ensure fast production, while at TDM the material is fed manually. Thus, it is important to quickly move the active binder force system as well as the dies. Thus, the compactness of the system was enhanced by modifying some components. For example, hydraulic pressure reservoirs, using compression with pneumatic pressure (i.e., around 6.5 bars) for
returning the hydraulic actuator rods to their home positions are deployed. Furthermore, the hydraulic actuators installed inside of the lower die are on a movable platform, which makes the entire system easy to move into the production line, and also to remove from production after the runs are completed.

The experimental validation based on the fixed gain process controller tuned by auto-tuning method was performed using the prototype of production system for a complex-geometry part to improve part quality. The results were quite similar to the experimental results shown previously in Section 3.5. However, due to the difficult economic situation, after completing the experiments using the fixed gain process controller, OAC informed us that they could not provide test resources any longer. Thus, we performed our final tests with the MIMO adaptive process controllers, which are described previously in Chapter 4 and 5, using the prototype system developed for production stamping at TDM.

![Prototype of system configuration for high-volume production.](image)

Figure B.2.1: The prototype of system configuration for high-volume production.
APPENDIX C

PROGRAMMING CODE

C.1 Look-Up Table Generation via Optimization

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Control Method: Look-Up table-based indirect self-tuning regulator
% MISO 4th order model + SIMO PI control + Pre-compensator
% September 15, 2009
% Lim, Yongseob (PhD candidate)
% Mechanical Engineering @ University of Michigan, Ann Arbor.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%% Fp1 corner with MISO PI indirect adaptive control.
% Table #1: Kp1_Fp1 or s11 (controller gain, Kp1)
% Table #2: Ki1_Fp1 or s11 + s10 (controller gain, Ki1)
% Table #3: Kp2_Fp1 or s21 (controller gain, Kp2)
% Table #4: Ki2_Fp1 or s21 + s20 (controller gain, Ki2)
% Table #5: Kp3_Fp1 or s31 (controller gain, Kp3)
% Table #6: Ki3_Fp1 or s31 + s30 (controller gain, Ki3)

%% Estimated (or nominal) process parameter (Fp1 corner)
% a3_Fp1 = -0.5096; a2_Fp1 = -0.2098;
% a1_Fp1 = -0.3753; a0_Fp1 = 0.2832;
% b11_Fp1 = 0.7704; b10_Fp1 = -0.7176;
% b21_Fp1 = 0.37;   b20_Fp1 = -0.255;
% b31_Fp1 = 0.8177; b30_Fp1 = -0.6751;

%% Nominal process parameter range (Fp1 corner)
% Matrix row (page #1) variation in a3:
% -0.53(min.)<= a3_Fp1 <= -0.49(max.) (delta = 0.02)
% Matrix column (page #1) variation in a2:
% -0.22(min.)<= a2_Fp1 <= -2.0(max.) (delta = 0.01)
% Variation in a1 (or page #2):
% -0.39(min.)<= a1_Fp1 <= -0.37(max.) (delta = 0.01)
% Variation in a0 (or page #3):
% 0.27(min.)<= a0_Fp1 <= 0.29(max.) (delta = 0.01)
% Variation in b11 (or page #4):
% 0.71(min.)<= b11_Fp1 <= 0.81(max.) (delta = 0.05)
% Variation in \( b_{10} \) (or page #5):
% \(-0.7\text{ (min.)} \leq b_{10}\_Fp1 \leq -0.6\text{ (max.)} \) (delta = 0.05)
% Variation in \( b_{21} \) (or page #6):
% \(0.33\text{ (min.)} \leq b_{21}\_Fp1 \leq 0.43\text{ (max.)} \) (delta = 0.05)
% Variation in \( b_{20} \) (or page #7):
% \(-0.3\text{ (min.)} \leq b_{20}\_Fp1 \leq -0.2\text{ (max.)} \) (delta = 0.05)
% Variation in \( b_{31} \) (or page #8):
% \(0.77\text{ (min.)} \leq b_{31}\_Fp1 \leq 0.87\text{ (max.)} \) (delta = 0.05)
% Variation in \( b_{30} \) (or page #9):
% \(-0.73\text{ (min.)} \leq b_{30}\_Fp1 \leq -0.63\text{ (max.)} \) (delta = 0.05)

%% Calculation and generating the Look-Up table

% Define initial values of estimated process parameters.
% \( a_{3}\_Fp1 = -0.53; \ a_{2}\_Fp1 = -0.22; \ a_{1}\_Fp1 = -0.39; \ a_{0}\_Fp1 = 0.27; \)
% \( b_{11}\_Fp1 = 0.71; \ b_{10}\_Fp1 = -0.7; \)
% \( b_{21}\_Fp1 = 0.33; \ b_{20}\_Fp1 = -0.3; \)
% \( b_{31}\_Fp1 = 0.77; \ b_{30}\_Fp1 = -0.73; \)

% Define minimum values of estimated process parameters range.
% \( a_{3}\_Fp1\_min = -0.53; \ a_{2}\_Fp1\_min = -0.22; \)
% \( a_{1}\_Fp1\_min = -0.39; \ a_{0}\_Fp1\_min = 0.27; \)
% \( b_{11}\_Fp1\_min = 0.71; \ b_{10}\_Fp1\_min = -0.7; \)
% \( b_{21}\_Fp1\_min = 0.33; \ b_{20}\_Fp1\_min = -0.3; \)
% \( b_{31}\_Fp1\_min = 0.77; \ b_{30}\_Fp1\_min = -0.73; \)

% Define variation (or \( k\)-break point*delta) for process parameters.
% \( \text{del}_a_{3}\_Fp1 = 0.04; \ \text{del}_a_{2}\_Fp1 = 0.02; \)
% \( \text{del}_a_{1}\_Fp1 = 0.02; \ \text{del}_a_{0}\_Fp1 = 0.02; \)
% \( \text{del}_b_{11}\_Fp1 = 0.1; \ \text{del}_b_{10}\_Fp1 = 0.1; \)
% \( \text{del}_b_{21}\_Fp1 = 0.1; \ \text{del}_b_{20}\_Fp1 = 0.1; \)
% \( \text{del}_b_{31}\_Fp1 = 0.1; \ \text{del}_b_{30}\_Fp1 = 0.1; \)

% Number of discredited steps (or break points of parameters)
% \( k = 2; \)
% \( K_{p1}\_Fp1 = \text{zeros}(k,k,k,k,k,k,k,k,k); \)
% \( K_{i1}\_Fp1 = \text{zeros}(k,k,k,k,k,k,k,k,k,k); \)
% \( K_{p2}\_Fp1 = \text{zeros}(k,k,k,k,k,k,k,k,k,k); \)
% \( K_{i2}\_Fp1 = \text{zeros}(k,k,k,k,k,k,k,k,k,k,k); \)
% \( K_{p3}\_Fp1 = \text{zeros}(k,k,k,k,k,k,k,k,k,k,k); \)
% \( K_{i3}\_Fp1 = \text{zeros}(k,k,k,k,k,k,k,k,k,k,k,k); \)

% fminsearch: optimization function in Matlab. See Table C.1.2.
% \( \text{x=fminsearch(@(x) lookup}\_Fp1(x),[0.21 -0.14 0.21 -0.14 0.21 -0.14]); \)
% \( \text{x=fminsearch: optimization function in Matlab. See Table C.1.2.}; \)
% \( \text{[0.21 -0.14 0.21 -0.14 0.21 -0.14]: initial values of gains.} \)
Table C.1.1: The look-up table generation code via optimization for $F_p^1$ corner: Similar code is required for each of the other punch force corners.
% Control Method: Look-Up table-based indirect self-tuning regulator
% MISO 4th order model + SIMO PI control + Pre-compensator
% September 15, 2009
% Lim, Yongseob (PhD candidate)
% Mechanical Engineering @ University of Michigan, Ann Arbor.

function [f1 f2 f3] = lookup_Fp1(x)

% define process parameters as global variables
global a3_Fp1 a2_Fp1 a1_Fp1 a0_Fp1 b11_Fp1 b10_Fp1 b21_Fp1 b20_Fp1
b31_Fp1 b30_Fp1

% Five desired pole locations
p1 = 0.62+0.2i; p2 = 0.62-0.2i; % Two dominant poles
p3 = 0.05; p4 = 0.1; p5 = 0.12; % Three fast (or non-dominant) poles

z3 = p1*(p2+p3+p4+p5)+p2*(p3+p4+p5)+p3*(p4+p5)+p4*p5;
z1 = p1*p2*(p3*p4+p3*p5+p4*p5)+p2*p3*p4*p5+p1*p3*p4*p5;

% Equations for error norm.
f1 = (b11_Fp1*x(1)+b21_Fp1*x(3)+b31_Fp1*x(5)+a2_Fp1-a3_Fp1-z3)^2;
f2 = (b11_Fp1*x(2)+b10_Fp1*x(1)+b21_Fp1*x(4)+b20_Fp1*x(3)+b31_Fp1*x(6)+b30_Fp1*x(5)+a1_Fp1-a2_Fp1-z2)^2;
f3 = (b10_Fp1*x(2)+b20_Fp1*x(4)+b30_Fp1*x(6)+a0_Fp1-a1_Fp1-z1)^2;

return

Table C.1.2: Sub-program for the code in Table C.1.1: Similar code is required for each of the other punch force corners.
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