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DEVELOPMENT AND EVALUATION OF A ROBUST AND INTELLIGENT DIGITAL CONTROL SYSTEM FOR A ROTARY BLOOD PUMP

DISSERTATION

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University

By

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* * * * *

The Ohio State University

1998

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ABSTRACT

Continuous flow rotary blood pumps have been proposed as effective solutions for ventricular assist devices intended as permanent treatment for end-stage heart failures. Rotary blood pumps have great potentials as implantable ventricular assist systems (VAS) because of their small size, simple structure, and low cost. The motor driver and controller, as "heart of the heart pump", is critical to secure proper operation to meet physiological demands. The motor must be highly efficient and compact, and the driver must be very reliable and compact. Control strategies without sensors are necessary due to the structure requirement. Motor speed and current must be controlled properly to reach optimal hemodynamics. Physiological control of this type of pump is more complicated due to their special characteristics. Flow or pressure information is difficult to identify from the motor speed and current, which makes it difficult to control the pump flow from motor speed and/or current control.

In order to obtain an effective and reliable motor drive system, high performance motor control algorithms without using position encoders are discussed. The permanent magnet (PM) motor is used, and various algorithms such as position perturbation based estimation, direct torque control and back-EMF drive circuit are proposed and evaluated. To accommodate sophisticated motion control and physiological control algorithms, a digital controller using a digital signal processor (DSP) is developed. A
computer simulation model is presented to predict the performance of the cardiovascular system and motor-pump interaction. Various conventional control methods can be evaluated by means of the computer model which gives good understanding of the system performance. An intelligent fuzzy logic flow controller is proposed to achieve pump flow control for proper perfusion requirement while preventing the system from ventricular suction, in which human knowledge, experience, and diagnostic information are incorporated in the fuzzy knowledge base. Sensorless control is achieved by on-line noninvasive measurement of motor variables (speed and current) and flow is estimated based on the pump characteristics and motor variables. By analyzing the motor speed and current waveforms, a fuzzy flow stabilizer is developed to produce a very stable, or nearly constant flow. Effectivenesses of the fuzzy controllers are verified by the computer model. DSP technologies make it possible to reach an implantable device with embedded software containing motion control, physiological control and communication interfaces.
This is dedicated to my parents, my wife, and my son.
ACKNOWLEDGMENTS

I would like to express my first acknowledgment to my advisor, Professor Longya Xu, for his technical guidance, and his serious commitment to my dissertation research. His encouragement has helped me tremendously in completion of my Ph. D. In the past three years, I had learned a lot from his experience. We have coauthored seven papers which have been or will be published in various conferences and journals.

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By the time I submit this dissertation, my father Chunhao passed away due to an accident. Suddenly the world is not, and will never be the same to me as before. Being the greatest father in the world, he and mother devoted everything to their children. God, be your mercy and blessing extended to my father and my family, and let his soul stay in peace!
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Research Publications


**FIELDS OF STUDY**

Major Field: Electrical Engineering
Major Areas of Specialization: Power Electronics, Motor Control and Drives, and DSP/microcontroller Systems
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NOMENCLATURE

\( a_i \)  coefficients of pump characteristic
\( B \)  friction coefficient
\( C \)  capacitance, Farad
\( C \)  vascular compliance (equivalent capacitance), \( ml/mmHg \)
\( E \)  motor back-EMF, \( V \)
\( EW \)  ergonomic workload, \( W \)
\( g_P, g_Q \)  input scaling factors of the fuzzy physiological control model
\( g_I, g_W \)  input scaling factors of the fuzzy flow stabilizer model
\( g_o \)  output scaling factor of fuzzy controllers
\( HR \)  heart rate, \( beats/min \)
\( i \)  current, instantaneous, \( A \)
\( i_a \)  phase A stator current in stationary reference frame, \( A \)
\( i_b \)  phase B stator current in stationary reference frame, \( A \)
\( i_c \)  phase C stator current in stationary reference frame, \( A \)
\( i_x \)  x-axis stator currentvector in stationary reference frame, \( A \)
\( i_y \)  y-axis stator currentvector in stationary reference frame, \( A \)
\( i_q \)  q-axis stator current in synchronous reference frame, \( A \)
\( i_d \)  d-axis stator current in synchronous reference frame, \( A \)
\( i_{f'} \)  q-axis stator current in perturbated synchronous reference frame, \( A \)
\( i_{d^*} \quad \) d-axis stator current in perturbed synchronous reference frame, A

\( I \quad \) motor current, rms, A

\( I^* \quad \) reference (command) motor current, A

\( I_0 \quad \) nominal motor current, A

\( \Delta I \quad \) motor current error, A

\( \delta I \quad \) normalized motor current error

\( \Delta I^* \quad \) change of current command, A

\( \delta I^* \quad \) normalized change of current command

\( J \quad \) inertia of the rotor, \( kg \cdot m^2 \)

\( K_e \quad \) back-EMF coefficient, \( V \cdot s/rad \)

\( K_T \quad \) torque coefficient, \( N \cdot m/A \)

\( K_p \quad \) proportional coefficient of PI controller

\( K_i \quad \) integral coefficient of PI controller

\( K_{R0} \quad \) peripheral resistance constant, \( mmHg \cdot s/ml \)

\( L \quad \) motor winding inductance, H

\( L \quad \) blood inertia (equivalent inductance), \( mmHg \cdot s^2/ml \)

\( L_d \quad \) d-axis inductance, H

\( L_q \quad \) q-axis inductance, H

\( L_{ls} \quad \) stator leakage inductance, H

\( L_s \quad \) stator inductance, H

\( L_{lr} \quad \) rotor leakage inductance, H

\( L_r \quad \) rotor inductance, H

\( L_x \quad \) stator inductance in x-axis, H

\( L_y \quad \) stator inductance in y-axis, H
\( P \) number of poles of the motor
\( P \) blood pressure, \( mmHg \)
\( PAS \) mean arterial blood pressure, \( mmHg \)
\( \Delta P \) differential pressure, \( mmHg \)
\( PQ \) flow pulsation index, \( L/min \)
\( Q \) blood flow, \( L/min \)
\( Q^* \) reference (command) blood flow, \( L/min \)
\( \Delta Q \) blood flow error, \( L/min \)
\( R \) resistance, \( \Omega \)
\( R \) vascular resistance, \( mmHg \cdot s/ml \)
\( R_s \) stator resistance, \( \Omega \)
\( R_r \) rotor resistance, \( \Omega \)
\( t \) instantaneous time, \( s \)
\( T \) sampling time period, \( s \)
\( T_e \) electromagnetic torque, \( N \cdot m \)
\( T_L \) load torque, \( N \cdot m \)
\( \Delta T \) sampling time, \( s \)
\( T_N \) heart rate efferent delay time constant, \( s \)
\( T_R \) peripheral resistance efferent delay time constant, \( s \)
\( T_{O2} \) oxygen response time constant of peripheral resistance, \( s \)
\( T_{O2} \) oxygen response time constant of heart action, \( s \)
\( V \) motor terminal voltage, \( V \)
\( V_d \) d-axis motor terminal voltage in synchronous reference frame, \( V \)
\( V_q \) q-axis motor terminal voltage in synchronous reference frame, \( V \)
\( V_x \)  x-axis motor terminal voltage in stationary reference frame, \( V \)
\( V_y \)  y-axis motor terminal voltage in stationary reference frame, \( V \)
\( V \)  blood volume, \( ml \)
\( \delta \)  power angle between stator and rotor flux linkages, \( rad \)
\( \delta_s \)  angle between stator flux linkage vector and stator current vector, \( rad \)
\( \delta_r \)  angle between rotor flux linkage vector and stator current vector, \( rad \)
\( \Delta \delta \)  angle between reference and actual stator flux linkage vectors, \( rad \)
\( \theta \)  rotor angle, angle of the synchronous reference frame, \( rad \)
\( \theta_s \)  stator flux angle, angle of the stator flux linkage vector, \( rad \)
\( \theta_e \)  estimated rotor angle, \( rad \)
\( \theta_p \)  predicted rotor angle, \( rad \)
\( \Delta \theta \)  error between estimated and predicted rotor angle, \( rad \)
\( \lambda_m \)  rotor permanent magnet flux linkage, \( H \cdot A \)
\( \lambda_q \)  q-axis stator flux linkage in synchronized reference frame, \( H \cdot A \)
\( \lambda_d \)  d-axis stator flux linkage in synchronized reference frame, \( H \cdot A \)
\( \lambda_x \)  x-axis components of estimated stator flux linkage, \( H \cdot A \)
\( \lambda_y \)  y-axis components of estimated stator flux linkage, \( H \cdot A \)
\( \lambda_{q^e} \)  q\textsuperscript{e}-axis components of actual stator flux linkage, \( H \cdot A \)
\( \lambda_{d^e} \)  d\textsuperscript{e}-axis components of actual stator flux linkage, \( H \cdot A \)
\( \lambda_{q^e} \)  q\textsuperscript{e}-axis components of estimated stator flux linkage, \( H \cdot A \)
\( \lambda_{d^e} \)  d\textsuperscript{e}-axis components of estimated stator flux linkage, \( H \cdot A \)
\( \Delta \lambda_{q^e} \)  error flux linkage in q\textsuperscript{e}-axis, \( H \cdot A \)
\( \Delta \lambda_{d^e} \)  error flux linkage in d\textsuperscript{e}-axis, \( H \cdot A \)
\( \lambda_s \)  magnitude of stator flux linkage vector, \( H \cdot A \)
<table>
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<td>(\lambda^*_s)</td>
<td>magnitude of reference (command) flux linkage vector, (H \cdot A)</td>
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<tr>
<td>(\lambda_r)</td>
<td>magnitude of rotor flux linkage vector, (H \cdot A)</td>
</tr>
<tr>
<td>(\lambda_x)</td>
<td>x-axis flux linkage in stationary reference frame, (H \cdot A)</td>
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<td>(\lambda_y)</td>
<td>y-axis flux linkage in stationary reference frame, (H \cdot A)</td>
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<td>(\lambda^*_y)</td>
<td>y-axis reference (command) flux linkage in stationary reference frame, (H \cdot A)</td>
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<tr>
<td>(\mu_{HR})</td>
<td>heart rate index constant</td>
</tr>
<tr>
<td>(\mu_R)</td>
<td>peripheral resistance index constant</td>
</tr>
<tr>
<td>(\omega)</td>
<td>motor speed, (rad/s)</td>
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<td>(\omega^*)</td>
<td>reference (command) motor speed, (rad/s)</td>
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<tr>
<td>(\omega_0)</td>
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<td>(\Delta\omega)</td>
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<tr>
<td>(\delta\omega)</td>
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<td>(P\omega)</td>
<td>speed pulsation index, (rad/s)</td>
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CHAPTER 1

INTRODUCTION

1.1 Rotary Dynamic Blood Pump: A Challenge to Electrical Engineers

Cardiovascular disease is the number one cause of death in the United States and most other western countries. According to the latest statistics, about 400,000 new cases of heart failure are diagnosed each year in the United States. The only currently available therapy for end-stage heart failure is transplantation. Unfortunately, the number of critically ill patients whose lives could be saved by an organ transplant has far exceeded the supply of donor organs, causing approximately 50,000 people a year to die waiting for a transplant\[3\][5][54]. To solve this problem, total artificial heart, and more recently, ventricular assist devices, have been proposed. It has been estimated that anywhere from 35,000 to 165,000 patients a year would be candidates for an artificial heart implant. Additionally, each year 12,000 - 15,000 babies are born with congenital heart defects and might benefit from mechanical cardiac assist to reach surgery or to recover after it\[5\].

Continuous flow, rotary blood pumps have been considered as an effective solution\[6\]-[11]. Research showed that long-term non-pulsatile flow did not produce negative
physiology in animals, although a clear and indisputable indication of physiological long-term adaptation of the circulatory system and its receptor and regulation mechanisms to non-pulsatile perfusion is still under investigation [54][60]. Rotary blood pump has numerous advantages for the next generation of left ventricular assist devices (LVAD): small size, high efficiency, and simplicity of implantation[12]-[14][51][54]. However, these and other advantages are bought at the expense of inherently greater demand for external control[51][54]. Flow and pressure sensors are not wanted, yet pump flow must be adjusted according to physiological demand.

The above issue brings out the challenge in the design of the motor driver and controller. Unlike conventional electrical machines, the motor is not merely the driving horse of the blood pump; it serves as "heart of the heart pump", which not only requires high performance in electrical/mechanical characteristics, but also needs to meet physiological requirements. Reliability and efficiency of the motor operation has to be considered. The controller needs to incorporate motion control and physiological control technologies to achieve optimal hemodynamic performance.

1.2 Digital Control of the Permanent Magnet (PM) Motor

The permanent magnet (PM) motor has been used for the blood pump. The PM motor has the advantage of high efficiency, high torque to current ratio, and low inertia [18]. High performance can be obtained by means of vector control, which requires information of rotor position, and usually a position encoder is used to achieve such a control scheme. Unfortunately, in applications of blood pumps installation of position encoders is unrealistic. Sensorless control has to be employed. Sensorless controls for PM Synchronous Motor (PMSM) and various rotor position
estimation schemes have been reported in literature[30]-[33]. However applications of the reported schemes are still limited since these algorithms are either structure demanding or parameter sensitive, and further incur system complexity and reliability problems. Direct torque control inherently provides an alternative sensorless control approach [20]-[28], yet due to low inductances of the PMSM high torque ripple and noise still exist. New and reliable algorithms are to be developed.

Digital control is necessary to accommodate sophisticated electrical and physiological control algorithms. An advanced digital signal processor (DSP) controller is to be used in such a complex system. The DSP promises high performance for system control, signal processing and diagnosis with its high computational and interfacing capacity. Various operation modes are to be evaluated [15][16][34]. An implantable system can be reached by the embedded DSP software containing all the required control algorithms.

1.3 Computer Modeling and Intelligent Control of Circulatory System and LVAD

To achieve the goal of control, a good understanding of the circulatory system with LVAD and the motor-pump-circulation interaction is necessary. Therefore a computer model for the cardiovascular system and the motor-pump system is of great significance to help investigate the hybrid system. Computer simulation of the circulatory system has been seen in literature for many years[41]-[48]. A general approach is to simulate the cardiovascular system as an electric circuit, since the governing equations of the cardiovascular system are similar to those of an electric circuit, and the cardiovascular parameters can be obtained by solving the circuit equations. Ventricles
can be modeled by time-varying components. Some physical circuits were also used for testing heart assist devices by means of a modular circulatory network. Left ventricular failure can be easily modelled by choosing appropriate time-varying components corresponding to the left ventricle. Effects of heart assist devices can be represented by numerical approaches.

With the computer model, control algorithms can be evaluated and developed before expensive in-vitro and in-vivo tests. Physiological control of rotary blood pump based ventricular system has been still a little-researched area. To maintain the systemic circulation properly, the pump speed or current must be controlled to sustain appropriate outlet flows and perfusion pressure. The characteristic performance of this class of pumps dictates that flow and differential pressure are interdependent. Therefore, it is difficult to control pump flow without flow sensor feedback, or knowledge of afterload or differential pressure. To identify the flow or pressure from motor speed or current is much more difficult. In spectra analysis of the motor current waveform was used and a control method was derived to maintain proper perfusion and avoid ventricular collapse for an axial-flow blood pump. In a prototype algorithm was developed for an axial-flow blood pump to maintain physiologic perfusion to the vital organs while preventing ventricular collapse through the analysis of the electrical current waveform of the motor. presented an in-vitro study of an artificial neural network (ANN) based noninvasive detector for suction and left atrium pressure in the control of rotary blood pumps. However, there is still no systematic algorithm to control these types of pumps in the chronic setting. To maintain normal hemodynamics under the wide range of conditions expected, pump flow needs
to be adjusted rapidly to accommodate physiologic demand and avoid any under-pumping or over-pumping. Reliable flow control algorithms are to be developed, in which involvement of human knowledge and experience is necessary.

1.4 Research Objectives and Organization

The purpose of this research can be summarized as follows.

- Develop and implement a high performance and robust digital controller using digital signal processor (DSP). Motorola's DSP56005 is used. Embedded software, as well as flexible system structure and physiological communication interface capabilities are to be included. Proper structure for future implantation is also to be considered.

- Develop effective, practical, and robust sensorless control algorithms for PM machines. Position perturbation algorithm, direct torque control (DTC) techniques are proposed as PMSM sensorless control approaches, while back-EMF based brushless DC (BLDC) motor drive circuits are also investigated. Various algorithms are to be investigated to obtain a most reliable and efficient controller.

- Develop a computer simulation model for the cardiovascular system with blood pump and motor interactions. An equivalent electric circuit model is considered, and numerical models for the blood pump and motor are also presented.

- Evaluate various operation modes of the motor and investigate the physiological performance with the motor-pump-cardiovascular systém model. An insightful
understanding of performance from computer simulation is an important step to design an effective flow control algorithm to meet physiological demands.

- Develop intelligent fuzzy logic control algorithms for flow control of the blood pump. By means of motor variable measurement, sensorless control without using invasive sensors are developed. Fault-preventive control is introduced, in which ventricle suction is prevented by diagnosing the depulsation of the motor/pump variables. Human knowledge with diagnostic information is incorporated in the fuzzy controller, and effectiveness of proposed algorithms is verified with the computer model.

- Develop fuzzy logic algorithm to stabilize the pump flow. By detecting the motor variables, flow and/or pressure phases are determined and with motor current control the pump output is compensated so that a very stable, nearly constant flow can be obtained. The proposed algorithm is also verified by the computer model.

The dissertation is organized as follows. Chapter 2 proposes a DSP control system for motion control, physiological control and communications. Chapter 3 proposes the position perturbation method for PMSM sensorless vector control and also develops the BLDC drive circuit. Chapter 4 proposes a robust direct torque control algorithm for PMSM control. Chapter 5 develops the computer simulation model for the cardiovascular circulatory system with LVAD. Chapter 6 presents a sensorless and fault-preventive fuzzy logic controller for the pump to produce sufficient output.
that can adapt to physiological demand without ventricular suctions. Chapter 7 proposes a fuzzy flow control algorithm for the stabilization of the pump flow. Finally, chapter 8 discusses conclusions and future work related to this research.
CHAPTER 2

DSP BASED CONTROL AND DRIVE SYSTEM

2.1 Overview

The design of the motor drive circuit and its controller for a rotary blood pump is intended for permanent implant in humans [15][16]. High performance, small size, and very high reliability are essential, and low cost is desirable. The motor controller must control the operation of a permanent magnet (PM) machine, which for size and mechanical simplicity reasons is commutated by a sensorless technique. The driver must adjust its output in accordance with command signals provided by the physiologic controller, and any diagnostic logic built into the system. The motor control circuit must output signals relevant to monitoring pump and motor operation. In principle, the motor control circuitry may have one of two fundamental architecture concepts: analog or digital. With the analog approach, since separate analog components are used, modification and tuning are not flexible. The digital approach is necessary to reach high performance with sophisticated electrical and physiological control algorithms. Motorola’s DSP56005 is used in the digital control system, which offers major advantages with respect to achieving efficient, robust, and responsive motor operation. Also different sensorless control algorithms can be effectively implemented.
and evaluated by using a DSP system[34][64]. Current and speed control schemes are conveniently implemented to maximize motor efficiency and dynamic response. Through a DSP controller, bidirectional communication with the physiologic control system and the diagnostic monitoring is very flexible. Significantly, new generations of software can be designed and implemented quickly and efficiently, when experience indicates the most effective, reliable, and fail-safe system.

2.2 The DSP56005 Based Application System

High performance DSPs are available from various manufacturers such as Motorola, Texas Instruments, Analog Devices, etc. In this application, considering a combined performance for motion control and signal processing, Motorola’s DSP56005 is used.

2.2.1 Overview of the DSP56005

The DSP56005 is a general purpose digital signal processor designed for control and embedded applications. It is the expanded version of the DSP56000 family. Features of the DSP56005 include:

**DSP56000 Family Central Processing Unit (CPU) Features**

- 25 million instructions per second (MIPS) at 50 MHz, or 40 ns instruction cycle
- On-chip Harvard architecture making parallel accesses to program and two data memories
- Single-cycle 24 x 24 bit parallel multiply-accumulator
- Highly parallel instruction set with unique DSP addressing modes
• Fast auto-return interrupts

• Operation with 24-bit data/16-bit address parallel interface to off-chip memory

• STOP and WAIT low-power standby modes

• Low-power CMOS design

**DSP56005 features**

- 4608 x 24-bit program RAM
- Two 256 x 24-bit data RAM
- Two 256 x 24-bit data ROM
- On-chip bootstrap ROM
- Full speed memory expansion port with 16-bit address and 24-bit data buses
- Byte-wide host interface with DMA support
- Synchronous serial interface port and asynchronous serial communication interface port
- Up to 25 general purpose I/O pins
- 24-bit timer/event counter
- Five pulse width modulators
- Watchdog timer
- On-chip emulator port (OnCE) for unobtrusive, full speed debugging
- PLL based clocking with wide input frequency range
2.2.2 The DSP Application System

The block diagram of the DSP56005 based digital motor controller system is shown in Fig. 2.1. The system is composed of the DSP56005 application system, the development system, and the driver circuit. Digital control is realized with a control algorithm that is software programmable. The PM motor can be driven in two basic operating modes: PM synchronous machine (PMSM) mode with indirect position estimation and brushless DC machine (BLDC) mode with back-EMF commutation.

As shown in Fig. 2.1, essential elements of the DSP application system include:

1. The DSP56005.

2. Address Decoder. This element is required for proper operation of the peripherals. The Mach210, an Erasable Programmable Logic Device (EPLD) from Advanced Micro Devices (AMD) is used.

3. A/D Converter. All the analog signals including feedback current, control voltage, etc. need to be converted to digital signals. The Analog Device’s AD7891 is used. It has 8 channels and has a throughput time of 2.2 us.

4. D/A Converter. It will output the diagnostic signals and probably command voltage. The Analog Device’s AD7847 dual converter is used.

5. Bootstrap EPROM. The 27256 is used. During the bootstrap process the program is downloaded and rearranged from the 8-bit EPROM to the 24-bit program RAM of the DSP.
2.2.3 Motor Drive Circuit

The driver circuit is mainly composed of power MOSFETs and drive chips. The power MOSFET has the advantage of being capable of high switching frequency and thus can improve the motor performance. In this implementation a switching frequency of 25 kHz is used. The block diagram of the motor drive circuit is shown in Fig. 2.2.
As for the interfacing signals between the DSP system and the driver circuit, depending on the different algorithm and motor operation mode chosen, it could be a PWM signal with embedded PMSM software for PMSM operation, or a control voltage signal with special driver IC for BLDC operation.

### 2.3 Two Operation Modes of the DSP System

The DSP system can operate in two modes: development mode and standalone mode.

**Development Mode**

In the development mode, the DSP system is interfaced to the host PC through the Advanced Development System (ADS), as shown in Fig. 2.1. Software is developed in the host PC and downloaded into the DSP system through the ADS, and the host PC can also control the execution process of the DSP system.
It can be seen that in the development mode it is very convenient for the system designer to debug both hardware and software, since the software can be easily modified, compiled, and downloaded from the PC, and the execution process can be conveniently controlled. The development mode operation is necessary in the early stage to debug the system and tune the performance.

Stand-alone Mode

In the stand-alone mode the execution process of the system software is no longer controlled by the host PC. The software has been programmed into the external program memory (EPROM) (Fig. 2.1). The DSP56005 has a bootstrap feature. After the system reset, the DSP can automatically execute a bootstrap program that can download the program from the external memory into the internal memory for execution. In this process, although the DSP56005 is a 24-bit processor while most EPROMs are only 8-bit, the bootstrap program can rearrange the 8-bit code into the 24-bit executable code. Such a design can reduce the physical size of the system since only one 8-bit EPROM is needed for the 24-bit processor.

Stand-alone type is used for a finalized system. The process continues execution until a system reset. Software can only be changed by reprogramming the EPROM. It must be noticed that for different types of DSP products the system structure could be different. An example is the TMS320F240 from Texas Instruments, with which an application system is under implementation for motion control purposes. The TMS320F240 has an on-chip flash memory so that no external program memory is needed. Software upgrading is more convenient and physical size of the system is more compact. The TMS320F240 also has encoder fetch unit so that further physical circuit can be saved for many motion control applications. However we choose the DSP56005
since its signal processing capability is more powerful than the TMS320F240. and in
blood pump application extensive signal processing will be needed for physiological
control.

2.4 Discussion

By using the DSP as the central processor, the performance and flexibility are
greatly enhanced. Important features are:

1. Advanced digital control algorithms can be implemented by software approach
through the DSP. Different control modes can be easily programmed and optimized by
means of the powerful arithmetic calculation and data processing capabilities of the
DSP, which is very difficult to implement in a low level microprocessor and unimagi-
nable by analog approach.

2. Advanced interfacing capabilities of the DSP can achieve sophisticated con-
trol and communication for an efficient, reliable and responsive system. Control and
switching mode can be easily adjusted. It can conveniently communicate with physi-
ological and diagnostic equipments.

3. The blood pump motor can operate as a PM synchronous motor (PMSM),
which needs a sinusoidal drive current, or as a Brushless DC motor (BLDC), which
uses a rectangular drive current. By means of the DSP, current and voltage wave-
forms can be conveniently re-shaped mainly through software approach. It has to
be noted that two different sensorless techniques are used for PMSM and BLDC
type of operations. When the blood pump motor operates as a PMSM an indirect
position and speed estimation approach is employed[34]. For BLDC motor the back-EMF measurement technique provides information for motor commutation and speed feedback[64].

4. Performance of the system can be adjusted to best fit the characteristic of the blood pump in specific load conditions. Digital approach makes it easier for software upgrade and fine tuning of the system.
CHAPTER 3

SENSORLESS VECTOR CONTROL OF PM MACHINES

3.1 Overview

Permanent magnet synchronous motors (PMSM) are ideal for advanced motion control systems for their potential of high efficiency, high torque to current ratio, and low inertia. This high performance can be obtained by means of vector control. However, vector control requires information of rotor position, and usually a position encoder is used to achieve such a control scheme, which unfortunately increases the cost and causes inconvenience, and in some occasions is even not permitted. People are increasingly interested in the sensorless controls for PMSM and various rotor position estimation schemes have been reported[30]-[33]. However applications of the reported schemes are still limited since these algorithms are either structure demanding or parameter sensitive.

In this chapter a position sensorless control scheme is proposed. Based on the small position perturbation algorithm, the rotor position is obtained by modifying the initial prediction of the rotor position. The estimated rotor position is used in the vector control algorithm.
Another sensorless technique for PM motors, which employs back-EMF measurement to obtain position information, by using an integrated circuit (IC) driver circuit for BLDC operation, is also discussed and implemented. This provides a practical approach for PM motors operating in BLDC mode [63][64], which mostly applies in small size motors, with the expense that extra hardware is needed.

3.2 Vector Control of PMSM

The model of a PMSM is shown in Fig. 3.1. Different reference frames can be used to analyze the motor, that is, 3-phase frame \((a-b-c)\), stationary frame \((x-y)\), or rotational frame \((d-q)\) [29]. From control point of view, the \(d-q\) reference frame is convenient and most widely used. Note that the \(d\)-axis of the reference frame is locked to that of the permanent magnet.

![Fig 3.1: (a)Different frames of the PMSM. (b)Flux, current and voltage vectors](image)

The voltage and flux equations for a PMSM in the rotational \(d-q\) reference frame can be expressed as:

\[
V_d = R_d i_d + \frac{d\lambda_d}{dt} - \omega \lambda_q
\]  

(3.1)
\[ V_q = R_s i_q + \frac{d\lambda_q}{dt} + \omega \lambda_d \quad (3.2) \]
\[ \lambda_d = L_d i_d + \lambda_m \quad (3.3) \]
\[ \lambda_q = L_q i_q \quad (3.4) \]

where \( V_d, V_q \) and \( i_d, i_q \) are voltages and currents in the \( d-q \) axis, \( R_s \) is the stator winding resistance, \( L_d, L_q \) are inductances in \( d-q \) axis, \( \lambda_d, \lambda_q \) are flux linkages in \( d-q \) axis, \( \lambda_m \) is the main flux linkage of the permanent magnet, and \( \omega \) is the angular frequency of the rotor. The transformation between different reference frames can be achieved by\[29\]

\[
\begin{bmatrix}
    i_d \\
    i_q \\
    0
\end{bmatrix}
= T_{abc-dq}
\begin{bmatrix}
    i_a \\
    i_b \\
    i_c
\end{bmatrix}
\quad (3.5)
\]

\[
\begin{bmatrix}
    i_x \\
    i_y \\
    0
\end{bmatrix}
= T_{abc-xy}
\begin{bmatrix}
    i_a \\
    i_b \\
    i_c
\end{bmatrix}
\quad (3.6)
\]

\[
\begin{bmatrix}
    i_d \\
    i_q
\end{bmatrix}
= T_{xy-dq}
\begin{bmatrix}
    i_x \\
    i_y
\end{bmatrix}
\quad (3.7)
\]

where

\[
T_{abc-dq} = \frac{2}{3}
\begin{bmatrix}
    \cos \theta & \cos(\theta - 2\pi/3) & \cos(\theta + 2\pi/3) \\
    \sin \theta & \sin(\theta - 2\pi/3) & \sin(\theta + 2\pi/3) \\
    1/2 & 1/2 & 1/2
\end{bmatrix}
\]

\[
T_{abc-xy} = \frac{2}{3}
\begin{bmatrix}
    1 & -1/2 & -1/2 \\
    0 & -\sqrt{3}/2 & \sqrt{3}/2 \\
    1/2 & 1/2 & 1/2
\end{bmatrix}
\]

\[
T_{xy-dq} = \begin{bmatrix}
    \cos \theta & \sin \theta \\
    -\sin \theta & \cos \theta
\end{bmatrix}
\]
and

\[
\begin{align*}
T_{dq-abc} &= T_{abc-dq}^{-1}, \\
T_{xy-abc} &= T_{abc-xy}^{-1}, \\
T_{dq-xy} &= T_{xy-dq}^{-1}.
\end{align*}
\]

The torque \( T_e \) can be written as

\[
T_e = \frac{3}{2} P \left[ \lambda_d i_q - \lambda_q i_d \right] = \frac{3}{2} P \left[ \lambda_m i_q - (L_q - L_d) i_d i_q \right] \tag{3.8}
\]

It is apparent that if we can control \( i_d \) to be zero then the torque is directly proportional to \( i_q \). Hence, vector control is achieved by controlling \( i_d \) to be zero and \( i_q \) to produce the required torque. Thus, the PMSM operates in the most efficient state. The vector control scheme is shown in Fig. 3.2.

![Figure 3.2: Vector control of the PMSM](image-url)
It is critical that in this scheme the rotor position must be always known so that proper current vector can be applied.

3.3 Rotor Position Estimation

3.3.1 Position Perturbation Algorithm

Assume that there is a small perturbation, \( \Delta \theta \), from the actual rotor position \( \theta \), as shown in Fig. 3.3. The \( d-q \) axis denotes the reference frame corresponding to the actual rotor position, and \( d^e-q^e \) the perturbed rotor position.

The flux calculated in the \( d^e-q^e \) frame is denoted by \( \lambda^e \). The projection of \( \lambda^e \) onto the \( q^e \) axis is:

\[
\lambda_{q^e} = L_q i_{q^e} \quad (3.9)
\]

The projection of the actual flux vector \( \lambda \) onto the \( q^e \) axis is \( \lambda_{q^e} \),

\[
\lambda_{q^e} = -\lambda \sin(\Delta \theta - \delta)
\]

\[
= -\lambda \sin \Delta \theta \cos \delta + \lambda \cos \Delta \theta \sin \delta \quad (3.10)
\]

where \( \delta \) is the electrical angle between the flux linkage \( \lambda \) and the \( d \) axis.
Because the reluctance of the permanent magnet is high, hence

\[ L_d i_d \ll \lambda_m \quad (3.11) \]
\[ L_q i_q \ll \lambda_m \quad (3.12) \]

Therefore, \( \delta \) is small, and so is \( \Delta \theta \). Hence, we can make the following approximations

\[ \lambda \cos \delta = \lambda_m, \]
\[ \lambda \sin \delta = L_q i_q, \]
\[ \sin \Delta \theta = \Delta \theta, \]
\[ \cos \Delta \theta = 1 \quad (3.13) \]

Then (3.10) can be approximated by

\[ \lambda_{q^*} = -\lambda_m \Delta \theta + L_q i_q \quad (3.14) \]

Due to the position perturbation \( \Delta \theta \), the error flux in the \( q^* \) axis denoted by \( \Delta \lambda_{q^*} \) is

\[ \Delta \lambda_{q^*} = \lambda_{q^*} - \lambda_{q^*} \]
\[ = L_q i_{q^*} - ( -\lambda_m \Delta \theta + L_q i_q ) \]
\[ = \lambda_m \Delta \theta + L_q (i_{q^*} - i_q) \quad (3.15) \]

As \( \delta \) and \( \Delta \theta \) are small, by the approximations in (3.13), (3.15) can be further written as

\[ \Delta \lambda_{q^*} = \lambda_m \Delta \theta \quad (3.16) \]

or, the position error can be expressed in terms of flux error by

\[ \Delta \theta = \frac{\Delta \lambda_{q^*}}{\lambda_m} \quad (3.17) \]
Thus if $\Delta \lambda_{qe}$ is known, $\Delta \theta$ can be computed and the rotor position can be corrected.

### 3.3.2 Procedures of Rotor Position Estimation

The rotor position is estimated based on an initial prediction and the position perturbation algorithm described above. The general torque equation of the motor can be expressed by a second order equation as

$$T_e = J \frac{d^2 \theta}{dt^2} + B \frac{d\theta}{dt} + T_L$$

where $T_e$ is the electromagnetic torque, $J$ the inertia of the rotor, $B$ the friction constant, and $T_L$ the load torque. By solving the discrete difference equation for (3.18), the predicted position $\theta_e$ can be obtained based on the previous rotor positions by\[30\]

$$\theta_e(k) = 3\theta(k - 1) - 3\theta(k - 2) + \theta(k - 3)$$

This predicted position can be used to start a position perturbation process. The estimated flux based on the predicted position for a permanent magnet motor can be represented in the stationary $x - y$ reference frame as:

$$\lambda_x^e(k) = \lambda_m \cos \theta_e(k) + L_x i_x(k)$$

$$\lambda_y^e(k) = \lambda_m \sin \theta_e(k) + L_y i_y(k)$$

The flux of the motor can also be obtained through integration by measuring the phase voltage and current:

$$\lambda = \int (V - R i) dt$$

where $\lambda$ is the flux linkage vector, $V$ the terminal voltage vector, $i$ the current vector, and $R$ the winding resistance. The discrete form of this integration in the stationary
The $x - y$ reference frame is

$$\lambda_x(k) = [V_x(k) - Ri_x(k)]\Delta T + \lambda_x(k - 1) \quad (3.23)$$

$$\lambda_y(k) = [V_y(k) - Ri_y(k)]\Delta T + \lambda_y(k - 1) \quad (3.24)$$

where $\Delta T$ is the sampling period, $\lambda_x, \lambda_y, V_x, V_y$ and $i_x, i_y$ are flux linkages, terminal voltages and phase currents in $x - y$ frame respectively.

The flux error due to the position error in the $x - y$ reference frame is:

$$\Delta \lambda_x(k) = \lambda_x^e(k) - \lambda_x(k) \quad (3.25)$$

$$\Delta \lambda_y(k) = \lambda_y^e(k) - \lambda_y(k) \quad (3.26)$$

By the $xy - dq$ transformation the flux error in the $d^e-q^e$ reference frame can be obtained by

$$\Delta \lambda_{d^e}(k) = -\Delta \lambda_x(k) \sin \theta_e(k) + \Delta \lambda_y(k) \cos \theta_e(k) \quad (3.27)$$

$$\Delta \lambda_{q^e}(k) = \Delta \lambda_x(k) \cos \theta_e(k) + \Delta \lambda_y(k) \sin \theta_e(k) \quad (3.28)$$

With regard to the position perturbation algorithm only the flux error on the $q^e$ axis is of interest.

Using (3.17) the position perturbation can be obtained by (3.29)

$$\Delta \theta(k) = \frac{\Delta \lambda_{d^e}(k)}{\lambda_m} \quad (3.29)$$

Equation (3.29) gives the position error between the actual position and the initially predicted position. By correcting the predicted position with this error, we can obtain an improved position estimation. The corrected position is

$$\theta(k) = \theta_e(k) - \Delta \theta(k) \quad (3.30)$$

The block diagram of this algorithm is shown in Fig. 3.4.
3.4 Sensorless Control of BLDC Machines

As mentioned before, the same PM machine can operate either in PMSM mode, or BLDC mode, depending upon the control signals put onto the driver. For BLDC operation there has been a commercial IC circuit developed using back-EMF commutation technique[63][64]. Various drivers are available from Micro Linear, Motorola, etc. The driver circuit using Micro Linear’s ML4425 can be seen in Fig. 3.5.

The ML4425 provides closed-loop commutation for 3-phase BLDC motors. Back-EMF voltage is sensed from the motor terminals to determine proper commutation.
phase sequence. Start-up timing sequence is accomplished by means of 2 timing capacitors charged by current sources on the device. $C_{RST}$ determines the time the motor stays in align mode and $C_{EN}$ determines the time the motor will ramp before the speed loop closes. Once the speed loop closes the N-channels are in a PWM mode to control the motor speed.

Interfacing from the driver to a digital system can be reached by connecting the $V_{SPEED}$ to a controlled analog signal from the digital system. Thus sophisticated controls can be done in the DSP and the ML4425 acts as a senserless commutation driver and PWM generator. This will partially reduce the computational load of the DSP system, and, to some extent, increases the system reliability in that in
case of a DSP failure the motor can still rotate with a proper preset control voltage $V_{\text{SPEED}}$ [16].

As can be seen in Fig. 3.5, the peripheral capacitors and resistors must be carefully selected to secure proper starting, commutation, and PWM control.

### 3.5 Experimental Results

#### 3.5.1 Experimental Results of a PM Motor Using the Position Perturbation Algorithm

The proposed position perturbation algorithm has been used in testing a PM motor. The motor parameters are listed as follows:

- Number of poles: 8
- Permanent magnet flux linkage: 0.015 Wb
- Inductance $L_q$: 0.00045 H
- Inductance $L_d$: 0.00045 H
- Stator winding resistance: 0.13 Ohm
- Rating voltage: 30 V

Fig. 3.6 shows the estimated rotor position compared to that measured using a rotor position encoder. The motor is under a light load in this test. It can be seen that the estimated rotor position is in good accordance to the actual rotor position.

Using the estimated rotor position and speed the closed loop vector control is achieved. The speed tracking performance is shown in Fig. 3.7. It can be seen that the estimated position is successfully used for the closed loop control and the speed can follow the command very well.
3.5.2 Experimental Results of the Blood Pump Motor

The position perturbation algorithm and the back-EMF commutation algorithm are implemented for the blood pump motor and the test results are shown below.

- Number of poles: 8
- Back-EMF coefficient: 0.0025 V/rpm
- Stator winding resistance: 7 Ohm
- Rating voltage: 15 V
- Rating output power: 3W

Figure 3.8 shows the performance (speed and current) of the blood pump motor in PMSM mode. The system has been tuned to a combined characteristic with a soft speed performance, that is, motor speed changes with the load torque.

![Figure 3.8: Speed and phase current of the blood pump motor in PMSM mode: (1) speed, (2) current](image)

Figure 3.9 shows the speed performance of the BLDC during significant change of load. The speed performance is strong, which means that the motor is in speed regulation and controller gains are large, but can be changed to soft by changing the parameters of the controller.

The phase current in PMSM corresponding to open-loop no-load and close-loop full-load are shown in Figure 3.10. It is apparent from the current waveforms that
Figure 3.9: Speed and phase current of the blood pump motor in BLDC mode: (1) speed (about 3200 rpm), (2) current

after the field orientation close-loop control, the phase current of the blood pump motor is significantly reduced, hence greatly improving the efficiency.

The phase current in BLDC corresponding to no-load and full-load are shown in Figure 3.11. It can be seen that under no-load, or light load, the PWM chopping is relatively significant.

The speed tracking under step command is shown in Figure 3.12. It is seen that the motor speed can respond to a step change very well.

3.6 Discussion

A position perturbation based position and speed estimation algorithm is proposed and experimental results are obtained. The accordance of the estimated rotor
Figure 3.10: Phase current of blood pump motor in PMSM mode: (1) open-loop without load and (2) closed-loop with full load.

position to the actual position indicates that this algorithm is effective and can be used to replace the position encoder. Vector control of the PMSM is realized by using the estimated position and speed. Advanced speed tracking performance and high dynamic response is achieved.

The proposed position estimation and vector control algorithms are implemented in the DSP56005 based digital control system. By using DSP, sophisticated control algorithms can be implemented through software approach, and the control capability of the system is greatly enhanced.
Figure 3.11: Phase current of blood pump motor in BLDC operation: (1) no-load, (2) full load.

It needs to be noted that there is still a common limitation for the flux observation based position estimation: the low speed problem. Performance improvement at low speed can be expected by some other algorithms, such as, direct torque control, as will be described in Chapter 4.
Figure 3.12: Speed tracking of blood pump motor in BLDC operation under full-load: (1) Speed response to step command, (2) Phase current.
CHAPTER 4

DIRECT TORQUE CONTROL

4.1 Overview

Direct torque control (DTC) has been drawing interests in recent years [20]-[28]. It was first proposed by Depenbrock [23] and Takahashi [25] in the 80's, and has been used mainly in induction motor control. The DTC directly controls the stator voltage vector based on the differences between the reference torque and stator flux linkage to their actual values. Current controllers are not needed in DTC systems. The application of the DTC in PMSM has only been seen recently [20][21]. DTC algorithms for PM machines are usually difficult to implement due to their low inductances, and high torque ripple and noise are observed.

In this chapter, a flux based direct torque control algorithm of PMSM without using rotor position encoder is proposed. The actual torque is estimated directly in the stationary reference frame so that transformation to the synchronous reference frame is not necessary. The error between the estimated and command torque directs the next-step stator flux vector to achieve the desired torque. As no reference frame transformation is conducted, no rotor position sensing or estimation is needed. For speed control, the demanded accuracy of the rotor position is much reduced and an
approximated flux based computation suffices. The proposed direct torque control has the advantage of less computation time and fast torque response. Therefore a better sensorless control of PMSM can be expected.

4.2 New Direct Torque Control (DTC) of PMSM

4.2.1 Torque Calculation in Stationary Frame

Fig. 4.1 shows the stator and rotor flux linkage, voltage, and current vectors for a PMSM.

Rewriting (3.8) the torque of the PMSM can also be expressed as

$$ T_e = \frac{3}{2} \frac{P}{2} \frac{\lambda_s}{L_q L_d} \left[ \lambda_r L_q \sin \delta - \frac{1}{2} \lambda_s (L_q - L_d) \sin 2\delta \right] $$

where $\lambda_s$ is the stator flux linkage, and $\delta$ is the angle between stator and rotor flux vectors.

For surface magnet motors $L_d = L_q$, the following torque expression can be obtained:

$$ T_e = \frac{3}{2} \frac{P}{2} \frac{\lambda_s \lambda_r}{L_q} \sin \delta $$
where $\delta_s$ is the angle between the current vector and the stator flux vector, and $\delta_r$ is the angle between the current vector and the rotor flux vector.

From (4.2) (4.3) and (4.4) it can be seen that the torque can be calculated through the cross product between stator and rotor flux linkages, between the stator flux linkage and stator current, or between the rotor flux linkage and stator current. (4.3) is of major interest for DTC since no direct rotor position information is involved.

### 4.2.2 Torque Control Through Stator Flux Linkage

From (4.2) (4.3) and (4.4), it is clear that with certain rotor flux linkage $\lambda_r$ the torque can be controlled by dynamically controlling the stator flux linkage $\lambda_s$.

For PMSM the rotor flux $\lambda_r$ is a rotating vector with a fixed magnitude, while the stator flux $\lambda_s$ is controllable by controlling the motor terminal voltage. Assuming that the stator flux linkage $\lambda_s$ has a small change, hence its magnitude becomes $\lambda_s^*$ and the torque angle has a change of $\Delta\delta$. Then the resultant change of torque is

$$\Delta T_e = \frac{3}{2} \frac{P}{L_q} \lambda_s^* \lambda_r \sin(\delta + \Delta\delta) - \frac{3}{2} \frac{P}{L_q} \lambda_s \lambda_r \sin\delta$$

(4.5)

$$\Delta T_e = \frac{3}{2} \frac{P}{L_q} \Delta\lambda_s \lambda_r \sin\delta + \frac{3}{2} \frac{P}{L_q} \lambda_s \lambda_r \cos\delta \Delta\delta$$

(4.6)

where $\Delta\lambda_s = \lambda_s^* - \lambda_s$.

(4.6) clearly shows that by controlling the angle between stator and rotor flux, and the magnitude of the stator flux, the torque can be controlled accordingly. It is also noticed that the relationship between the change of torque angle $\Delta\delta$ and the change of torque $\Delta T_e$ is rather nonlinear.
4.3 The Direct Torque Control (DTC) Algorithm

From (4.3) the torque of the PMSM can be calculated in terms of the motor current and estimated stator flux linkage. In stationary reference frame the stator flux linkage and current can be expressed as

\[ \lambda_s = \lambda_x + j\lambda_y \]  
\[ i = i_x + j i_y \]

Rewriting (4.3) in terms of \( x - y \) components the following torque expression is obtained:

\[ T_e = \frac{3P}{2}(\lambda_x i_y - \lambda_y i_x) \]

As only the stationary flux and stator current are used, no rotor position is needed at this stage.

If a command torque \( T_e^* \) is required, with the present actual torque \( T_e \), the torque error is

\[ \Delta T_e = T_e^* - T_e \]

From (4.6) it is apparent that for such a torque error, certain adjustment of torque angle \( \Delta \delta \) is required to compensate the torque error. We will discuss later how to obtain \( \Delta \delta \) from \( \Delta T_e \).

Assuming that the magnitude of the stator flux is known (usually a constant flux linkage is used), hence with \( \Delta \delta \) given, the required angle and magnitude of stator flux linkage \( \lambda_s^* \) can be obtained. The difference between \( \lambda_s^* \) and \( \lambda_s \) generates the required
voltage vector according to

$$\int_{\Delta T} (V - R i) dt = \lambda_s^* - \lambda_s \quad (4.11)$$

where $V$ is the voltage vector, $R$ the stator winding resistance, $i$ the stator current, and $\Delta T$ the time duration for $\lambda_s$ to approach $\lambda_s^*$, as shown in Fig. 4.2.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure4_2.png}
\caption{Torque control of PMSM}
\end{figure}

From (4.11), the required voltage vector $V$ can be obtained from the motor stator flux linkage and required flux linkage.

### 4.3.1 Discrete Representation of the Direct Torque Control Scheme

The stator flux linkage of the motor can be obtained through integration by measuring the phase voltage and current

$$\lambda_s = \int (V - R i) dt \quad (4.12)$$

The discrete form of this integration in the stationary $x - y$ reference frame is

$$\lambda_x(k) = [V_x(k) - R_i_x(k)] \Delta T + \lambda_x(k - 1) \quad (4.13)$$

$$\lambda_y(k) = [V_y(k) - R_i_y(k)] \Delta T + \lambda_y(k - 1) \quad (4.14)$$
where $\Delta T$ is the sampling period.

The $x - y$ components of the command flux can be written as:

$$\lambda^*_x(k) = \lambda^*_x(k) \cos(\theta_s(k) + \Delta \delta(k))$$  \hspace{1cm} (4.15)$$

$$\lambda^*_y(k) = \lambda^*_y(k) \sin(\theta_s(k) + \Delta \delta(k))$$  \hspace{1cm} (4.16)$$

where $\theta_s(k)$ is the position of the present stator flux linkage vector.

The voltage vector in the next step, $V(k + 1)$, should be chosen in such a way that the resultant flux linkage in the next step will be

$$\lambda_s(k + 1) = \lambda^*_s(k)$$  \hspace{1cm} (4.17)$$

Therefore, the voltage vector is

$$V_x(k + 1) = (\lambda^*_x(k) - \lambda_x(k))/\Delta T + R_i x(k)$$  \hspace{1cm} (4.18)$$

$$V_y(k + 1) = (\lambda^*_y(k) - \lambda_y(k))/\Delta T + R_i y(k)$$  \hspace{1cm} (4.19)$$

In step $(k + 1)$, the flux linkage should be further modified by

$$\lambda_x(k + 1) = [V_x(k + 1) - R_i x(k + 1)]\Delta T + \lambda_x(k)$$  \hspace{1cm} (4.20)$$

$$\lambda_y(k + 1) = [V_y(k + 1) - R_i y(k + 1)]\Delta T + \lambda_y(k)$$  \hspace{1cm} (4.21)$$

### 4.4 Control of the Torque Angle

As shown in (4.6), the relationship between $\Delta \delta$ and $\Delta T_e$ is rather complicated. Without introducing the rotor position and rotor flux linkage, a PI controller can be used to obtain the required flux angle change $\Delta \delta$ with a given torque error $\Delta T_e$. Fig. 4.3 shows the block diagram of the torque control scheme.
Speed regulation employing direct torque control can be achieved as shown in Fig. 4.4, where the torque control block is the same as that in Fig. 4.3. Compared to a conventional speed regulation scheme using vector control, the new direct torque controller is used to replace the current regulation loop in Fig. 3.2. For direct torque control, the stator flux position and rotor speed are required for proper stator flux vector (magnitude and angle) control and speed regulation. Yet unlike for vector control, in which very accurate position information is needed for current regulation using reference frame transformation, for direct torque control the demand for the position accuracy is much reduced, and angle estimation through stator flux integration suffices and no position encoder is needed.

![Figure 4.3: Block diagram of the direct torque control](image)

4.5 Simulation and Experiment Results

To verify the proposed DTC algorithm, computer simulation and experiments are conducted for the same motor model as investigated in 3.5.1, and results are shown below.

Simulation results are obtained using MATLAB. Fig. 4.5 shows the torque response of the PMSM to a step change of torque command. It can be seen that the torque...
response is very fast. Fig. 4.6 is the speed response of the PMSM under a step change of speed command. The actual motor speed ramps up to the command speed with a large accelerating torque. Relatively high torque ripple can also be seen as a result of small inductances in the PMSM.

The DTC algorithm is implemented using a DSP56005 system and the experimental results are as follows. Fig. 4.7 is the torque response of the PMSM. The result shows that the motor can follow the command torque very well. Relatively high torque ripple is observed for the reason explained earlier. With the direct torque control scheme very wide range speed control is achieved without the position encoder. As shown in Fig. 4.8, the motor speed changes from -3000rpm to 3000rpm without using the position encoder. The DTC algorithm also shows its effectiveness

Figure 4.4: Speed regulation by direct torque control
at low speed, especially in that the motor can self-start and has zero speed crossing performance without the position encoder.

4.6 Discussion

1. A direct torque control method through the stator flux vector control is presented. By controlling the stator flux linkage vector properly, the required torque can be produced with a fast response time.

2. Unlike conventional vector control, which demands an accurate rotor position encoder, the proposed method does not need accurate rotor position information and therefore more robust sensorless control can be achieved.

3. Simulation and experimental results indicate that the proposed scheme is effective in obtaining fast torque response. Moreover, low speed and four quadrature operations are achieved without a position encoder.
Figure 4.6: Speed performance of DTC: (1) Reference speed, (2) Actual speed. (3) Torque

Figure 4.7: Torque response of DTC for PMSM: (1) Command torque, (2) Actual torque.
**Figure 4.8:** Speed performance of DTC: (1) Reference speed, (2) Actual speed.
CHAPTER 5

COMPUTER SIMULATION OF THE CIRCULATORY SYSTEM

5.1 Overview

5.1.1 Human Cardiovascular Circulatory System

The cardiovascular system is the main fluid transport system of a living organism, through which, the blood will be transported to every part driven by the heart. The heart can be regarded in mechanical analogue as an assembly of two pumps, one for left and one for right, and the cardiovascular system can be generally schematized as shown in Fig. 5.1 and Fig. 5.2. Fig. 5.1a shows a general sketch of the cardiovascular circulatory system, and Fig. 5.1b shows the detail of the heart. The four heart chambers are indicated, as well as the four valves, which impose unidirectional flow. The four heart chambers are named left atrium, left ventricle, right atrium, and right ventricle, and the four valves are named mitral-valve (M), aortic-valve (A), tricuspidal-valve (T), and pulmonary-valve (P), as shown in Fig. 5.1b. The two vascular circulation loops, namely the systemic and the pulmonary, are shown in Fig. 5.1a. The part between left ventricle and right atrium which includes the systemic vascular bed is called systemic circulation, and the part between the right ventricle
and the left atrium which includes the pulmonary vascular bed is called the pulmonary circulation (Fig. 5.1a)[41][4]. Fig. 5.2 shows the more detailed circulation system and the percentage of blood volumes in the circulation system.

![Cardiovascular Circulatory System](image)

**Figure 5.1:** The cardiovascular circulatory system: (a) general sketch, (b) detailed schematic of the heart.

From physiological point of view, the task of the cardiovascular system is primarily to supply oxygen, metabolic fuels, nutrients, hormones, and vitamins to the organs and individual cells of the body, and also provide a means of removal of metabolic products from the cells. The circulation also serves to maintain a stable temperature within the body by transporting heat from the inside to the surface of the body.

The overall cardiovascular system needs blood pressure stabilization to insure adequate blood flow to all regions of the body if local changes in blood flow occur. The amount of blood required by different parts of the body can vary greatly under certain circumstances, for example, during heavy physical exercise. To meet this the
Figure 5.2: The circulatory system and blood volumes

The human body has many control mechanisms to ensure adequate functional operation of the circulation. Rapidly occurring pressure changes are sensed by tension-sensitive nerve endings within the wall of the arch of the aorta, near the heart, and in the walls of the two carotid arteries which are located in the neck region. Since all tensions depend on the local blood pressure, these sensors are called pressor- or baroreceptors (Fig. 5.3). Pressure changes sensed by the baroreceptors can influence the properties of the vessels and the heart, leading to changes in resistance and heart activity. It should be noted that such control mechanism with baroreceptors is usually valid for short-term regulation of arterial blood pressure.
5.1.2 Computer Simulation of the Circulatory System

In order to investigate the performance characteristics of the blood pump and its interaction with the pulsating heart, a computer model is necessary to provide a convenient approach to predict the performance before any in-vitro and in-vivo tests. New control algorithms can also be derived based on the computer simulation.

Computer simulations of the circulatory system have been seen in literature for years[41]-[48]. Usually the cardiovascular system can be simulated as an electric circuit, since the governing equations of the cardiovascular system are similar to those of an electric circuit, and the physiological performance can be obtained by solving the
electric circuit equations. The vascular resistance, vascular compliance, and inertia of the blood in the vessels can be replaced by electrical resistance \( R \), capacitance \( C \), and inductance \( L \). The ventricle can be modeled by time-varying parameters, and all the ventricle valves can be modeled by diodes that can only carry unidirectional current. These models generally gave satisfactory results by their reasonable outputs.

Left ventricle failure can be simulated by decreasing the amount of compliance change of the left ventricle\[42\]. Some authors simulated the failing circulation by changing the ventricular elastance or end systolic pressure\[46\], and normal, failing, and assisted failing circulation were simulated.

Very few literature have been seen on simulation of the interaction between the circulatory system and heart assist pumps. In \[42\] the nonpulsatile left ventricular bypass pump was represented by a constant flow source. In \[43\] a centrifugal pump was modeled with second order polynomials, which were adopted by curve-fitting to the pressure-flow data from the pump characteristics.

In this chapter a practical and simplified circuit model is proposed to simulate the cardiovascular system. A regulated system with baroreceptors that can adapt to pressure changes due to various circumstances such as exercise is also discussed. The model will be verified through computer simulation and will be a very useful tool in investigating the circulatory-pump interaction. The motor-pump model is discussed and the interaction with the cardiovascular system is included in the model. As the final control variables are motor speed and current, simulation of such a hybrid model helps to understand and predict the system performance under various motor operation modes and also provides insights to reach a novel noninvasive physiological controller.
5.2 Electrical Model of the Circulatory System

5.2.1 The Equivalent Electrical Circuit of the Circulatory System

The simplified electric circuit model of the circulatory system is shown in Fig. 5.4. In the circuit $R$, $L$ and $C$ represent resistance, inertia, and compliance (capacitance), and $P$ and $Q$ represent blood pressure and flow. The ventricles are modeled with time-varying capacitors combined with resistances. The aorta is modeled with a resistance and an inductance resembling inertia. Atrial elastic characteristics are included in the venous compliances (capacitors). Ideal diodes in series with resistances are used to model the unidirectional resistive behavior of inlet and outlet valves. $R_R$ and $R_L$ represent resistances in right and left ventricles respectively. Systemic and pulmonary circulations are described by systemic and pulmonary peripheral resistances and inductances representing viscous and inertial properties of the blood flow, with capacitances corresponding to the elastic properties of the vessel walls.

![Figure 5.4: Electrical model for the cardiovascular circulation system. 1. left ventricle; 2. aorta; 3. peripheral vessels; 4. systemic vein and right atrium; 5. right ventricle; 6. pulmonary artery; 7. pulmonary vein and left atrium; 8. aorta; 9. systemic peripheral vessels; 10. pulmonary peripheral vessels; 11. tricuspidal valve; 12. pulmonary valve; 13. mitral valve; 14. aortic valve.](image-url)
As stated in [42], ventricular failure can be modeled by decreasing the range of capacitance change of the left ventricle, that is, by increasing the value of diastolic capacity (or, decreasing the elasticity).

The electric circuit model with the blood pump is shown in Fig. 5.5. Since the rotary blood pump is designed to connect from the left ventricle to the aorta, a new branch is added between the left ventricle and the aorta. The blood pump characteristic can be modeled by a polynomial by curve fitting from the pressure-flow test data. $R_{15}$ and $R_{16}$ represent the inlet and outlet cannula resistances, and $C_{15}$ represents the cannula capacitance. $R_{15}$ is a nonlinear resistance to simulate the suction effects, which is normal (0.05) for positive ventricular pressure and is increased (0.25) when ventricular pressure is negative.

![Figure 5.5: Electrical model of the circulatory system with blood pump](image)
The values of parameters in the circuit model can be identified in various methods [41] [44]. The parameters adopted in this simulation are shown in Table 5.1.

<table>
<thead>
<tr>
<th>Component</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C_1 )</td>
<td>12 (systole)-0.3 (diastole)</td>
<td>( ml/mmHg )</td>
</tr>
<tr>
<td>( C_2 )</td>
<td>0.8</td>
<td>( ml/mmHg )</td>
</tr>
<tr>
<td>( C_3 )</td>
<td>1.0</td>
<td>( ml/mmHg )</td>
</tr>
<tr>
<td>( C_4 )</td>
<td>600 (systole)-400 (diastole)</td>
<td>( ml/mmHg )</td>
</tr>
<tr>
<td>( C_5 )</td>
<td>16 (systole)-1.2 (diastole)</td>
<td>( ml/mmHg )</td>
</tr>
<tr>
<td>( C_6 )</td>
<td>3.0</td>
<td>( ml/mmHg )</td>
</tr>
<tr>
<td>( C_7 )</td>
<td>5.0</td>
<td>( ml/mmHg )</td>
</tr>
<tr>
<td>( L_8 )</td>
<td>0.01</td>
<td>( mmHg \cdot s^2/ml )</td>
</tr>
<tr>
<td>( R_8 )</td>
<td>0.5</td>
<td>( mmHg \cdot s/ml )</td>
</tr>
<tr>
<td>( R_9 )</td>
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<td>( mmHg \cdot s/ml )</td>
</tr>
<tr>
<td>( L_{10} )</td>
<td>0.002</td>
<td>( mmHg \cdot s^2/ml )</td>
</tr>
<tr>
<td>( R_{10} )</td>
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<td>( mmHg \cdot s/ml )</td>
</tr>
<tr>
<td>( R_{11} )</td>
<td>0.1</td>
<td>( mmHg \cdot s/ml )</td>
</tr>
<tr>
<td>( R_{12} )</td>
<td>0.01</td>
<td>( mmHg \cdot s/ml )</td>
</tr>
<tr>
<td>( R_{13} )</td>
<td>0.01</td>
<td>( mmHg \cdot s/ml )</td>
</tr>
<tr>
<td>( R_{14} )</td>
<td>0.01</td>
<td>( mmHg \cdot s/ml )</td>
</tr>
<tr>
<td>( R_{15} )</td>
<td>0.05 (( P_{LV} \geq -3 \text{mmHg} ))-0.25 (( P_{LV} &lt; -3 \text{mmHg} ))</td>
<td>( mmHg \cdot s/ml )</td>
</tr>
<tr>
<td>( C_{15} )</td>
<td>0.2</td>
<td>( ml/mmHg )</td>
</tr>
<tr>
<td>( R_{16} )</td>
<td>0.05</td>
<td>( mmHg \cdot s/ml )</td>
</tr>
<tr>
<td>( R_L )</td>
<td>0.0175</td>
<td>( mmHg \cdot s/ml )</td>
</tr>
<tr>
<td>( R_R )</td>
<td>0.0175</td>
<td>( mmHg \cdot s/ml )</td>
</tr>
</tbody>
</table>

Table 5.1: Parameters of the circulation model

5.2.2 Equations for the Circuit Model

From Fig. 5.5 we can obtain the following governing equations.

Equations for the Circulatory System

The volumes can be obtained through the compliances as follows:

\[
V_i = \int Q_i dt \tag{5.1}
\]
\[ V_2 = \int Q_2 dt \] (5.2)
\[ V_3 = \int Q_3 dt \] (5.3)
\[ V_4 = \int Q_4 dt \] (5.4)
\[ V_5 = \int Q_5 dt \] (5.5)
\[ V_6 = \int Q_6 dt \] (5.6)
\[ V_7 = \int Q_7 dt \] (5.7)

Pressure drops across branches 8 through 14 can be written as:

\[ P_1 - P_2 = (R_L + R_{14})Q_{14} \] (5.8)
\[ P_2 - P_3 = L_8 \frac{dQ_8}{dt} + R_8 Q_8 \] (5.9)
\[ P_3 - P_4 = R_9 Q_9 \] (5.10)
\[ P_4 - P_5 = R_{11} Q_{11} \] (5.11)
\[ P_5 - P_6 = (R_R + R_{12})Q_{12} \] (5.12)
\[ P_6 - P_7 = L_{10} \frac{dQ_{10}}{dt} + R_{10} Q_{10} \] (5.13)
\[ P_7 - P_1 = R_{13} Q_{13} \] (5.14)

Flows are balanced by the following node equations

\[ Q_1 = Q_{13} - Q_{14} - Q_{15} \] (5.15)
\[ Q_2 = Q_{14} + Q_{16} - Q_8 \] (5.16)
\[ Q_3 = Q_8 - Q_9 \] (5.17)
\[ Q_4 = Q_9 - Q_{11} \] (5.18)
\[ Q_5 = Q_{11} - Q_{12} \] (5.19)
\[ Q_6 = Q_{12} - Q_{10} \] (5.20)

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\[ Q_7 = Q_{10} - Q_{13} \quad (5.21) \]

The volumes can also be written through compliances and pressures:

\[ V_1 = C_1 P_1 \quad (5.22) \]
\[ V_2 = C_2 P_2 \quad (5.23) \]
\[ V_3 = C_3 P_3 \quad (5.24) \]
\[ V_4 = C_4 P_4 \quad (5.25) \]
\[ V_5 = C_5 P_5 \quad (5.26) \]
\[ V_6 = C_6 P_6 \quad (5.27) \]
\[ V_7 = C_7 P_7 \quad (5.28) \]

**Equations for the Blood Pump**

The pump branch including inlet, outlet and the blood pump can be characterized by

\[ V_{15} = C_{15} P_{15} \quad (5.29) \]
\[ P_1 - P_{15} = Q_{15} R_{15} \quad (5.30) \]
\[ P_{16} - P_2 = Q_{16} R_{16} \quad (5.31) \]
\[ C_{15} \frac{dP_{15}}{dt} = Q_{15} - Q_{16} \quad (5.32) \]

and pump pressure and flow are related to the circulatory variables by

\[ P_{pump} = P_{15} - P_{16} \quad (5.33) \]
\[ Q_{pump} = Q_{16} \quad (5.34) \]
The pump characteristics can generally be obtained through tests. Two groups of characteristic curves can be extracted from a typical pump test, as shown in Fig. 5.6 and Fig. 5.7.

![Figure 5.6: Pump pressure vs flow: (o) 3500rpm, (*) 3000rpm, (+) 2500rpm.](image)

These characteristics can be built in the simulation model as look-up tables. To further simplify the simulation process, mathematical equations can be obtained by curve fitting these curves [62]. The characteristics in Fig. 5.6 can be approximated by

\[ Q^2 = a_1 \omega^2 + a_2 \Delta P + a_3 \]  

(5.35)

where \( \omega \) is the pump speed, \( \Delta P \) the differential flow of the pump outlet to inlet, and \( a_1, a_2 \) and \( a_3 \) are constants. A specific sample is \( a_1 = 3.751 \times 10^{-5}, a_2 = -2.838, a_3 = -12.66 \). The characteristic curves in Fig. 5.7 can be expressed by

\[ Q = a_4 \frac{f}{\omega} + c_5 \]  

(5.36)
where $I$ is the motor current, $a_4$ and $a_5$ are constants. A sample of a pump is $a_4 = 1.76 \times 10^5, a_5 = -13.06$.

5.2.3 Discrete Time Solution for the Model

The discrete time solution for the circuit model can be written as follows. (5.1) to (5.36) can be written as

\begin{align*}
V_1(k+1) &= V_1(k) + (Q_{13}(k) - Q_{14}(k) - Q_{15}(k))\Delta T \\
V_2(k+1) &= V_2(k) + (Q_{14}(k) + Q_{15}(k) - Q_{16}(k))\Delta T \\
V_3(k+1) &= V_3(k) + (Q_8(k) - Q_9(k))\Delta T \\
V_4(k+1) &= V_4(k) + (Q_9(k) - Q_{11}(k))\Delta T \\
V_5(k+1) &= V_5(k) + (Q_{11}(k) - Q_{12}(k))\Delta T \\
V_6(k+1) &= V_6(k) + (Q_{12}(k) - Q_{10}(k))\Delta T \\
V_7(k+1) &= V_7(k) + (Q_{10}(k) - Q_{13}(k))\Delta T
\end{align*}
where $\Delta T$ is the sampling period.

\begin{align*}
P_1(k + 1) &= V_1(k + 1)/C_1(k + 1) \quad (5.44) \\
P_2(k + 1) &= V_2(k + 1)/C_2 \quad (5.45) \\
P_3(k + 1) &= V_3(k + 1)/C_3 \quad (5.46) \\
P_4(k + 1) &= V_4(k + 1)/C_4(k + 1) \quad (5.47) \\
P_5(k + 1) &= V_5(k + 1)/C_5(k + 1) \quad (5.48) \\
P_6(k + 1) &= V_6(k + 1)/C_6 \quad (5.49) \\
P_7(k + 1) &= V_7(k + 1)/C_7 \quad (5.50) \\
Q_8(k + 1) &= (P_2(k + 1) - P_3(k + 1) + \frac{L_9}{\Delta T} Q_8(k))/\left(\frac{L_9}{\Delta T} + R_8\right) \quad (5.51) \\
Q_9(k + 1) &= (P_3(k + 1) - P_4(k + 1))/R_9 \quad (5.52) \\
Q_{10}(k + 1) &= (P_6(k + 1) - P_7(k + 1) + \frac{L_{10}}{\Delta T} Q_{10}(k))/\left(\frac{L_{10}}{\Delta T} + R_{10}\right) \quad (5.53) \\
Q_{11}(k + 1) &= (P_4(k + 1) - P_5(k + 1))/R_{11} \quad (5.54) \\
Q_{12}(k + 1) &= (P_5(k + 1) - P_6(k + 1))/(R_R + R_{12}) \quad (5.55) \\
Q_{13}(k + 1) &= (P_6(k + 1) - P_7(k + 1))/R_{13} \quad (5.56) \\
Q_{14}(k + 1) &= (P_1(k + 1) - P_2(k + 1))/(R_L + R_{14}) \quad (5.57) \\
\end{align*}

The pump branch has

\begin{align*}
V_{15}(k + 1) &= V_{15}(k) + (Q_{15}(k) - Q_{16}(k))\Delta T \quad (5.58) \\
P_{15}(k + 1) &= V_{15}(k + 1)/C_{15} \quad (5.59) \\
P_{16}(k + 1) &= P_2(k + 1) + R_{16} Q_{16}(k) \quad (5.60) \\
Q_{15}(k + 1) &= (P_1(k + 1) - P_{15}(k + 1))/R_{15} \quad (5.61) \\
Q_{16}(k + 1) &= (P_{16}(k + 1) - P_2(k + 1))/R_{16} \quad (5.62)
\end{align*}
\[ P_{\text{pump}}(k + 1) = P_{15}(k + 1) - P_{16}(k + 1) \]  
\[ Q_{\text{pump}}(k + 1) = a_1 \omega^2 (k + 1) + a_2 P_{\text{pump}}(k + 1) + a_3 \]  

The total blood volume keeps constant. To eliminate the round-off error, this can be a further constraint to modify the variables

\[ V(k + 1) = \sum_{i=1}^{7} V_i(k + 1) + V_{15}(k + 1) \]  

and the venous pressures should be modified at each step by

\[ P_i^*(k + 1) = P_i(k + 1) + \frac{V_0 - V(k + 1)}{C_4 + C_7} \]  
\[ P_7^*(k + 1) = P_7(k + 1) + \frac{V_0 - V(k + 1)}{C_4 + C_7} \]  

5.3 The Regulated Cardiovascular System

5.3.1 The Baroreceptor Feedback Control

It is well-known from the literature, that blood pressure is controlled by a multitude of control systems which can be divided into autoregulation, which is due to the hemodynamic properties of the cardiovascular system, and the hormonal and nervous control [41]. The nervous control with the aid of the baroreceptor reflex is the best known mechanism for short-term blood pressure regulation. This reflex is initiated by pressure receptors, so-called baroreceptors, which are located in the aortic arch and in the carotus sinus. An increase of pressure causes the baroreceptors to increase the number of impulses per second from the carotid sinus nerves which are transmitted afferently into the central nervous system, and other signals are in turn sent efferently to the circulation - the arterial system, the venous system, and the heart respectively - to bring arterial pressure back to its normal level. In this section we will restrict to
the heart, the arterial tree, and the vascular bed as the subsystem to be regulated in
the baroreceptor feedback loop.

The baroreceptor activities on heart rate \((HR)\) and peripheral resistance \((R_9)\) are nonlinear functions of the arterial pressure with a negative slope, which corresponds to negative feedback in the closed loop system. Fig. 5.8 and Fig. 5.9 show the baroreceptor feedback loop characteristics of \(HR\) and \(R_9\) over mean arterial pressure \(PAS\).

![Figure 5.8: Baroreceptor feedback loop characteristic: heart rate \(HR\) over mean arterial pressure \(PAS\)](image)

The transition characteristic of the baroreceptor feedback loop has been experimentally derived in literature [41]. The heart rate response can be written as:

\[
HR = HR_o + HR_M(1 - \frac{PASN^{\mu_{HR}}}{1 + PASN^{\mu_{HR}}}) \tag{5.68}
\]

where \(HR_o\) and \(HR_M\) are threshold values of the heart rate, \(PASN\) is the normalized arterial pressure \((PASN = PAS/100)\), and \(\mu_{HR}\) is a constant \((\mu_{HR} = 8)\).
Similarly, the peripheral resistance response can be written as:

\[ R_9 = R_{9o} + R_{9M} \left( 1 - \frac{PASN^{\mu_R}}{1 + PASN^{\mu_R}} \right) \]  \hspace{1cm} (5.69)

where \( R_{9o} \) and \( R_{9M} \) are threshold values of the peripheral resistance, \( PASN \) is the normalized arterial pressure, and \( \mu_R \) is a constant (\( \mu_R = 6 \)).

It is also shown that the heart rate and peripheral resistance responses caused by the pressure changes are delayed by the efferent pathway from the vasomotorical center to the effector cells at the heart muscle. The real time responses of the heart rate and peripheral resistance are expressed as follows [41]:

\[ HR(t) = \int_0^t e^{-\frac{t-\tau}{T_N}} [HR_o + HR_M (1 - \frac{PASN(\tau)^{\mu_R}}{1 + PASN(\tau)^{\mu_R}})] d\tau \]  \hspace{1cm} (5.70)

\[ R_9(t) = \int_0^t e^{-\frac{t-\tau}{T_R}} [R_{9o} + R_{9M} (1 - \frac{PASN(\tau)^{\mu_R}}{1 + PASN(\tau)^{\mu_R}})] d\tau \]  \hspace{1cm} (5.71)

where \( T_N \) and \( T_R \) are delay time-constants for \( HR(t) \) and \( R_9(t) \) respectively.
5.3.2 The Regulated Cardiovascular System

Pressure control with the aid of the baroreceptor reflex is achieved by adjusting the heart rate $HR$ and the peripheral resistance $R_9$ as described above. The block diagram of the physiological regulated closed-loop cardiovascular system is shown in Fig. 5.10.

![Figure 5.10: Block diagram of the regulated closed-loop cardiovascular system](image)

In Fig. 5.10, the baroreceptors sense the blood pressures, and through the feedback regulators, the responses of heart rate $HR(\tau)$ and peripheral resistance $R_9(\tau)$ are obtained. After certain efferent delays, the heart rate $HR(t)$ and peripheral resistance
$R_9(t)$ can be obtained and used in the circulatory model. Any workload (EW) can be treated as disturbance input $d$. The closed-loop regulation will finally stabilize the system after the occurrence of the disturbance.

Fig. 5.11 shows the block diagram of the circulatory system with the blood pump. Given either the physiological parameters ($Q$ or $P$), or the electrical parameters (motor current $I$ or speed $\omega$), the circuit model can be solved.

*Figure 5.11: Block diagram of the circulatory system with the blood pump*
5.3.3 Circulatory Adaptation to Exercise

The workload dependent influence on the cardiac output and hence on the arterial pressure and the peripheral resistance corresponds in the human body to an adequate oxygen supply [41].

The function determining the total peripheral resistance can be written by

\[
R_{9\times}(t) = \frac{R_9(t)}{K_{R0} + R_{9\times}(t)}
\]  

(5.72)

where \( R_9(t) \) is the peripheral resistance under nervous control as described by (5.71), \( K_{R0} \) is a constant, and \( R_{9\times}(t) \) is the time dependent correction factor of the workload affected metabolic stimulation of the peripheral resistance. The relationship between \( R_{9\times}(t) \) and the oxygen amount required to supply the energy for the aerobically workload is given by

\[
\frac{dR_{9\times}(t)}{dt} = -\frac{1}{T_{O2}} R_{9\times}(t) + \frac{K_R}{T_{O2}} EW
\]

(5.73)

where \( T_{O2} \) is the oxygen response time constant under workload, \( K_R \) is the amplification constant, and \( EW \) is the ergometric workload.

The time-behaviour of the heart rate during exercise is given by

\[
HR_4(t) = HR(t) + HR_\times(t)
\]

(5.74)

where \( HR(t) \) represents the nervous control dependent heart rate expressed by (5.70), and \( HR_\times(t) \) is the time dependent correction factor of the workload affected sympathetic and parasympathetic stimulation of the heart frequency and is given by

\[
\frac{dHR_\times(t)}{dt} = -\frac{1}{T_{HR}} HR_\times(t) + \frac{K_{HR}}{T_{HR}} EW
\]

(5.75)
where $T_{HR}$ is the oxygen response time constant of the heart action under workload, $K_{HR}$ is the transfer constant under workload, and $EW$ is the ergometric workload as defined earlier.

The parameters that are used in the circuit model are listed in Table. 5.2.

<table>
<thead>
<tr>
<th>Component</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$HR_o$</td>
<td>50</td>
<td>$1/min$</td>
</tr>
<tr>
<td>$HR_M$</td>
<td>150</td>
<td>$1/min$</td>
</tr>
<tr>
<td>$T_N$</td>
<td>5</td>
<td>$s$</td>
</tr>
<tr>
<td>$\mu_{HR}$</td>
<td>8</td>
<td>$-$</td>
</tr>
<tr>
<td>$T_{HR}$</td>
<td>28</td>
<td>$s$</td>
</tr>
<tr>
<td>$K_{HR}$</td>
<td>0.6</td>
<td>$1/min/W$</td>
</tr>
<tr>
<td>$R_{90}$</td>
<td>0.85</td>
<td>$mmHg \cdot s/ml$</td>
</tr>
<tr>
<td>$R_{9M}$</td>
<td>1.5</td>
<td>$mmHg \cdot s/ml$</td>
</tr>
<tr>
<td>$\mu_R$</td>
<td>6</td>
<td>$-$</td>
</tr>
<tr>
<td>$T_R$</td>
<td>26</td>
<td>$s$</td>
</tr>
<tr>
<td>$K_{RO}$</td>
<td>1.0</td>
<td>$-$</td>
</tr>
<tr>
<td>$T_{O2}$</td>
<td>26</td>
<td>$s$</td>
</tr>
<tr>
<td>$K_{R}$</td>
<td>0.012</td>
<td>$1/W$</td>
</tr>
</tbody>
</table>

Table 5.2: Parameters of the regulated model

5.4 Modeling of the PM motor in Physiological Time Base

The time-varying property of the physiological system is very different from that of the transient electrical system. Usually the time varying period in the physiological system is in the order of seconds\cite{41}\cite{42}\cite{44}, whereas for a PM motor, especially when its size is very small, its electrical and mechanical time constants are in the order of microseconds and milliseconds. Therefore, the transient process of the PM motor can be neglected in investigating the motor-pump-physiology coupling effects. and
steady-state models for the PM motor can be used. The dynamics of the current and speed can be neglected. This can be analyzed in the following section.

5.4.1 Effects of Motor Dynamics on Physiological System

The motor system can be characterized by

\[
J \frac{d\omega}{dt} + B \omega = T_e - T_L \tag{5.76}
\]
\[
E + L \frac{di}{dt} + Ri = V \tag{5.77}
\]

where \( J \) is mechanical inertia, \( B \) the friction coefficient, \( L \) the inductance, \( R \) the resistance, \( T_e \) and \( T_L \) are electromagnetic and load torques respectively, \( E \) the back-EMF, and \( V \) the motor voltage.

The electromagnetic torque and back-EMF can be expressed by

\[
T_e = K_T i \tag{5.78}
\]
\[
E = K_e \omega \tag{5.79}
\]

where \( K_T \) is the torque coefficient, and \( K_e \) the back-EMF coefficient.

Analyzing the above system equations leads to the solutions of the system poles as

\[
s_{1,2} = \frac{1}{2} \left[ \frac{-BL + JR}{JL} \pm \sqrt{\left( \frac{-BL + JR}{JL} \right)^2 - 4\left( \frac{BR}{JL} + \frac{K_e K_T}{J} \right)} \right] \tag{5.80}
\]

For a typical system with parameters \( J = 6.26 \times 10^{-5} \text{in} \cdot \text{lb} \cdot \text{s}^{-2} \), \( B = 0.005 \text{oz} \cdot \text{in} / \text{rpm} \), \( K_T = 3 \text{oz} \cdot \text{in} / \text{A} \), \( K_e = 0.0025 \text{V} / \text{rpm} \), \( R = 7 \Omega \), \( L = 0.0001 \text{H} \), the poles are located at

\[
s_1 = -7 \times 10^4 \tag{5.81}
\]
\[
s_2 = -79.9 \tag{5.82}
\]

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or the time constants are

\[ \tau_1 = \frac{1}{|s_1|} = 1.43 \times 10^{-5} \text{s} \] (5.83)

\[ \tau_2 = \frac{1}{|s_2|} = 0.0125 \text{s} \] (5.84)

From (5.83) and (5.84) it is clearly seen that the motor mechanical and electrical time constants are far much smaller than the physiological response time, which is generally in seconds. Therefore a steady-state motor model can be reasonably used.

### 5.4.2 Steady-state Motor Model

The steady-state voltage equation of the PM motor can be written as (5.85):

\[ V = E + I(R + jX) \] (5.85)

where \( V \) is the motor terminal voltage phasor, \( E \) is the motor back-EMF phasor, \( I \) the motor current phasor, and \( R \) and \( X \) are motor winding resistance and reactance respectively.

\[ E = K_e \omega \] (5.86)

where \( K_e \) is the motor back-EMF coefficient, \( \omega \) the motor speed.

For PM motor usually the inductance is very small, therefore \( X \) can be neglected. Furthermore, by realizing field oriented vector control, the motor current \( I \) is in phase to \( E \), and (5.85) can be written as a scalar equation:

\[ V = K_e \omega + IR \] (5.87)

With closed loop speed and current regulation, as the motor dynamics can be neglected for the physiological cycles, the motor current \( I \) and speed \( \omega \) are assumed to always follow the command current and speed.
Open Loop Operation

In open-loop operation, no feedback control or regulation is involved for the motor variables. The motor operates with a fixed input voltage. By keeping $V = \text{constant}$ in (5.87), the open-loop operation can be evaluated for the hybrid system.

In open-loop operation, the motor speed or current may vary depending on the load conditions.

Speed Mode Operation

Speed mode operation is achieved by controlling motor speed $\omega$ to follow the reference (command) speed. It is noticed that the speed is the most direct motor-pump coupling variable since the pump runs at the same speed as the motor does. The speed mode operation is perhaps the most widely used operation mode yet the performance depends on specific pump characteristics.

Current Mode Operation

Under current mode operation, the motor phase current is controlled to follow the reference (command) current.

The speed mode and current mode are the two essential regulated operation modes. The performance of the pump output depends on the characteristics of specific pumps. Very often it is found that a single speed or current mode operation cannot provide satisfactory output. Dynamic control of pump flow by means of motor speed or current regulation to meet the physiological demand is sophisticated and involves physiological diagnosis and human interferences.
5.5 Result of the Circulatory Model

5.5.1 Non-regulated Circulatory System

Although simple numerical methods are employed to solve the circuit equations for the simplified circulatory system model, as long as the time step is sufficiently small, the result converges.

The non-regulated system can be simulated by a fixed heart rate and peripheral resistance. In the simulation we choose $HR = 80\text{beats/min}$, $R_q = 1.0\text{mmHgs/ml}$, and a time step of 5 ms, and the results converge well. The total blood volume is kept at 4500 ml.

Fig. 5.12 shows the pressure and flow waveforms of a healthy heart. The system reaches systolic aortic pressure 115 mmHg, diastolic aortic pressure 80 mmHg, mean aortic pressure 94 mmHg, and mean system flow 5 L/min.

The detailed ventricular filling and ejection period is shown in Fig. 5.13.

The left ventricular failure is modeled by increasing the diastolic capacitance of the left ventricle. Fig. 5.14 (1) shows the pressure and flow waveforms of a sick heart, which is simulated by taking $C_{ld} = 0.93$, and Fig. 5.14 (2) shows a sick heart by taking $C_{ld} = 1.8$. It is seen that by increasing $C_{ld}$, mean pressure and flow are decreasing and become less pulsatile.

Table. 5.3 shows the aortic pressure and systemic flow for a non-regulated model corresponding to different degree of sickness. It is seen that increasing sickness simulated by increasing $C_{ld}$ causes decreasing of blood pressure and flow, and decreasing of pulsatility (that is, the difference pressure between maximum and minimum pressure becomes lower).
Figure 5.12: Pressure and flow of a healthy heart. $P_{LV}$: Left ventricular pressure; $P_{AO}$: Aorta pressure; $P_{LA}$: Left atrium pressure; $Q_{14}$: Left ventricular output flow; $Q_{13}$: Left ventricular filling flow; $Q_{9}$: System flow.

5.5.2 Regulated Circulatory System

By using the baroreceptor feedback characteristics, the regulated closed-loop circulatory system can be simulated. Fig. 5.15 shows the pressure and flow waveforms of the same model as what was used in Fig. 5.12. The system stabilized to heart rate 73 beats/min, peripheral resistance 1.1 mmHg s/ml, mean aortic pressure 93 mmHg, and mean systemic flow 4.6 L/min.

With the simulation model, the hemodynamics of the circulatory system with the assist of the blood pump can be calculated. Interaction of the pump and the circulatory system can be obtained, and various operation modes of the motor-pump system can be evaluated.
A sick heart with assist when the pump is in speed mode operation is shown in Fig. 5.16. In speed mode operation the pump speed is constant, while due to pulsatile load the motor current is pulsatile, as seen in Fig. 5.16. It is seen that when the pump speed reaches 2750 rpm, it produces an average output flow of $Q=4.73 \text{ L/min}$ and normal hemodynamics is achieved.

Fig. 5.17 shows the simulation results of a pump in current mode operation. In current mode operation, the motor current is kept constant. Due to the cardiac pulsation, the motor speed is pulsatile. For this specific example when the motor
current is 0.27 A, the pump produces an average flow of 5.04 L/min, and thus brings the blood pressure and system flow to normal.

The hemodynamics of the system when the blood pump is in open-loop operation mode is shown in Fig. 5.18. In open-loop operation the motor is applied with a constant voltage. Since we don’t have any speed or current regulation for the system, both motor speed and current are pulsatile as a result of pulsatile load. In this example when the motor voltage $V = 9V$, normal hemodynamics is again reached.

Figure 5.14: Pressure and flow of sick hearts: (1) $C_{ld} = 0.93$, (2) $C_{ld} = 1.8$. 

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Table 5.3: Aortic pressure and systemic flow corresponding to different $C_{td}$

<table>
<thead>
<tr>
<th>$C_{td}(ml/mmHg)$</th>
<th>Aortic Pressure (mmHg)</th>
<th>Systemic Flow (L/min)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>max/min/mean</td>
<td>mean</td>
</tr>
<tr>
<td>0.3</td>
<td>115/80/94</td>
<td>5.0</td>
</tr>
<tr>
<td>0.63</td>
<td>105/80/94</td>
<td>4.4</td>
</tr>
<tr>
<td>0.93</td>
<td>97/63/77</td>
<td>4.0</td>
</tr>
<tr>
<td>1.2</td>
<td>90/58/71</td>
<td>3.7</td>
</tr>
<tr>
<td>1.8</td>
<td>78/48/60</td>
<td>3.1</td>
</tr>
<tr>
<td>2.8</td>
<td>62/37/47</td>
<td>2.4</td>
</tr>
<tr>
<td>4.0</td>
<td>50/30/38</td>
<td>1.8</td>
</tr>
<tr>
<td>6.0</td>
<td>38/22/29</td>
<td>1.3</td>
</tr>
</tbody>
</table>

5.6 Summary

The computer simulation model provides an efficient and convenient approach in analysis of the hemodynamics of the cardiovascular circulatory system and evaluation of effectiveness of heart assist devices and their control strategies. In this chapter an electric circuit model is presented to simulate the circulatory system. Ventricular failures are simulated by changing the system parameters. A self-regulated system is obtained by using the baroreceptor feedback control characteristics. The blood pump is simulated by a mathematic model, which can be obtained from pump designers or from pump test data. The electric motor is represented by its steady-state model, based on the fact that its mechanical and electrical dynamics are negligible compared to physiological dynamics. Various motor operation modes can be simulated and evaluated.

Results through computer simulation indicate that the proposed model gives satisfactory physiological dynamics. Some fundamental control modes (speed, current
and open-loop) of the blood pump are evaluated. For the specific pump these simple control modes may not provide satisfactory performance, however they constitute the basics of more sophisticated and intelligent control algorithms. It will be seen in the following chapters that the simulations model and the fundamental control modes play essential roles in developing new control algorithms to reach a robust and intelligent controller.

Figure 5.15: Pressure and flow of a healthy heart with the regulated model.
Figure 5.16: Physiological and electrical parameters under speed mode operation. \( \omega = 2750 \text{ rpm} \).
Figure 5.17: Physiological and electrical parameters under current mode operation. $I=0.27$ A.
Figure 5.18: Physiological and electrical parameters under open loop (constant voltage) operation, $V = 9\, V$. 
CHAPTER 6

SENSORLESS AND FAULT-PREVENTIVE CONTROL
FOR THE ROTARY BLOOD PUMP

6.1 Overview

6.1.1 Demand for a High Performance Physiological Controller

Physiological control of rotary blood pump based ventricular system has been still a little-researched area. To maintain the systemic circulation properly, pump flow must be adjusted rapidly to accommodate physiologic demand. To avoid using invasive sensors, motor speed and current are the only observable parameters to reach flow control. The pump speed or current must be controlled to sustain appropriate outlet flows and perfusion pressure. The characteristic performance of this class of pumps indicates that flow and differential pressure are interrelated and the pump output is highly dependent on the cardiac cycle. Therefore, it is difficult to control pump flow without flow sensor feedback, or knowledge of afterload or differential pressure. Reliable flow control algorithms are to be developed, in which involvement of human knowledge and experience is necessary.

These issues have gained increasing attentions in literature recently. In [51] spectra analysis of the motor current waveform was used for an axial-flow blood pump and
a control method was derived to maintain proper perfusion and avoid ventricular collapse. In [54] the authors proposed an algorithm for an axial-flow blood pump which regulates the pump speed by comparing the motor current waveform with reference waveforms using a matched filter to maintain physiologic perfusion to the vital organs while preventing ventricular collapse. [61] presented an in-vitro study of an artificial neural network (ANN) based noninvasive detector for suction and left atrium pressure in the control of rotary blood pumps. However, there is still no systematic algorithm to control these types of pumps.

The motor-pump system may operate in simple speed or current mode. However, depending on the type of pump, it is often found that single speed or current operation generally gives unsatisfactory performance. Wild variation of flow can be observed for a certain speed with the pulsatile pressure differences. Serious reverse flow could occur. On the other hand, ventricular collapse or suction could happen when pump output is too high.

### 6.1.2 Fuzzy Logic Control

Imprecisely defined classes play an important role in human thinking. Fuzzy logic theory derives from the fact that almost all nature classes and concepts are fuzzy rather than crisp in nature. Humans work from approximate data, extract meaningful information from massive data, and find crisp solutions. Fuzzy logic provides a suitable basis for the ability to summarize information and to extricate from the collections of masses of data impinging upon the human brain those and only those facts that are relevant to performance of the task at hand.
The biomedical system is considered to be a large-scale, complex, stochastic, and non-linear system that includes many multi-level feedback loops and time varying unknown parameters. Hence, it is quite difficult to establish a well-approximated and unified global model using traditional mathematical methods. On the other hand, inside the brain of the medical specialist there must exist a knowledge-base that contains empirical knowledge of control and monitoring or logical rules for decision making accumulated from practical experiences. However the human knowledge-base is not well organized and may include inconsistent information. Fuzzy logic is good at expressing such uncertain linguistic knowledge in a computer language. Therefore, it has great potential in biomedical applications.

Fuzzy logic control has found various applications in many areas in the past decade [2]. This is largely because fuzzy logic control has the capability to control non-linear, uncertain systems even in the case where no mathematical model is available for the controlled system. Moreover, it provides a systematic way to incorporate human experience in the controller. Recent literature has paid much attention to its great potential in the application to motion control and drives [35]-[40]. These results did show better system performances.

Applications of fuzzy logic in the area of biomedical engineering have also gained interests recently. M. Yoshizawa, et al. [57], developed an expert system realized by means of fuzzy logic algorithms for monitoring and malfunction diagnosis of the left ventricular assist device (LVAD). An electrical circuit model was adopted to calculate the cardiovascular dynamics from the direct measurements. Abnormality detection was realized by applying fuzzy logic to the beat-by-beat data obtained from the system. A set of empirical linguistic rules constituted the knowledge-base that was
given by the medical specialist. *In vivo* experiments using an adult goat were carried out. The experiments confirmed that the system worked successfully in the case of hardware malfunction. However, the transient responses of the estimated variables of the cardiovascular dynamics were too complicated to distinguish clearly the origin of physiological abnormalities. A more refined algorithm is needed, in which the thresholds are automatically set if the patient or the clinical conditions change.

In [58], K. Becker, *et al.*, provides approaches of the fuzzy logic applications to biomedical engineering problems, including intelligent alarms and decision support in cardioanaesthesia, focusing on the knowledge acquisition task, the inference engine, and the human-computer interface. A fuzzy knowledge base for the intelligent alarm system had been determined in co-operation with an experienced cardioanaethetist. Further, the knowledge-base was modified by a group of experienced cardioanaesthesitists. All the input information for the real time evaluation of the patient’s hemodynamic state variables was automatically collected on-line. The system was evaluated in the laboratory using a patient model for the circulation. The system’s judgement on the model’s hemodynamic state variables was reproducible and yielded a good representation of the patient’s hemodynamic state.

In [59], R. Kaufmann, *et al.*, presented a fuzzy control scheme for a total artificial heart (TAH). The primary task of the control system was the automatic adaptation of pump rate and consequently of pump output to organ perfusion demand. The secondary task was the prevention of damage to arteries by hyperpressures. There were two linguistic input variables, the actual “pump-rate”, and the “filling”. The output was the actual “rate-change”. *In-vitro* investigations using TAH-lab type and appropriate mock-loop circulation systems proved the effectiveness of the control
method. During experiments the adaptation of the controller to a preload change was reproducible. Further development is needed so that more input parameters can be handled to control the pump rate. Furthermore, the left-right pump output balancing is also very important. Such a system will be very complex and strongly non-linear, and an optimum intelligent controller is desired.

In [60], R. Kaufmann, et al., presented an implantable fuzzy controlled pulsatile LVAD. The control method was based on processing the DC motor phase current curve obtained from the driver. The fuzzy control system worked without any preload and afterload detection sensors. The current signal after preprocessing provided information on preload and afterload. Input parameters to the fuzzy controller were current and actual speed, and the output was the change of speed. Experimental results obtained in a circulatory mock loop show a sensitive and reproducible pump flow adaptation to simulated preload, which indirectly represent the organ perfusion demand. An appropriate pump rate adjustment was achieved for a wide range of pump output. The interaction between LVAD, heart and circulatory system is complex and non-linear. The results shown in this paper further demonstrate the advantages of the use of fuzzy control in terms of better understandability, easier controller development and on-line optimization, transparent function facilitation of interdisciplinary discussion, potential of processing sensor signals of poorly defined physiological conditions. Refinements of the controller is necessary. Some fault protection should be included to prevent the stop of the motor.

Research in this area has shown that fuzzy logic approach has great potential in biomedical engineering, where the difficulty of highly nonlinear and complicated dynamic properties are dramatic, which is the case of the rotary blood pump control.
The task of this chapter is to develop and evaluate a robust controller that can adapt to physiological demand and prevent the occurrence of fault conditions by using fuzzy logic. Sensorless control of flow is achieved by noninvasive measurement of motor speed and current. The flow pulsation index is used as a controller input to diagnose the ventricular suction. Computer simulation results are presented to evaluate the proposed scheme, based on the simulation model described in the previous chapters.

6.2 Closed-loop Sensorless Control of the Blood Pump in the Circulatory System

6.2.1 Closed-loop Control of the Blood Pump

Literature shows that required systemic flow has certain relationship with the heart rate[41] [62]. Therefore the required pump flow is also related to the heart rate. For the circulatory model under investigation the following relationship can be used

\[ Q^* = K_Q HR + Q_0 \]  \hspace{1cm} (6.1)

where \( K_Q \) and \( Q_0 \) are constants. With such a relationship, the closed-loop pump controller can be achieved as shown in Fig. 6.1.

As shown in Fig. 6.1, the reference flow \( Q^* \) is obtained from the heart rate. By comparing the reference flow \( Q^* \) with the actual flow \( Q \), the controller produces a reference current \( I^* \) (if in current mode) or reference speed \( \omega^* \) (if in speed mode) for the motor. The motor will drive the pump to produce required flow.

6.2.2 Sensorless Control

In the closed-loop control model as shown in Fig. 6.1, the feedback flow is required for the controller to produce the required current (or speed). However, in the blood
pump applications, flow (or pressure) sensors are not wanted for their long-term reliability limitations. Therefore noninvasive sensing and control of the pump flow (or pressure) is needed.

The most conveniently available variables in the pump system are motor current and speed (or frequency). Therefore the primary intention is to measure and control the pump flow from the motor electrical variables.

Rewrite (5.35) and (5.36)

\[ Q = a_4 \frac{I}{\omega} + a_5 \]  
\[ \Delta P = \frac{1}{a_2} \left( Q^2 - a_1 \omega^2 - a_3 \right) \]
It is easy to see that given motor current $I$ and speed $\omega$, the pump flow $Q$ and pressure $\Delta P$ can be readily solved from (6.2) and (6.3).

The strategy of monitoring and control of the pump flow from only the motor variables is shown in Fig. 6.2.

As shown in Fig. 6.2, the actual flow $Q$ is obtained from the motor speed $\omega$ and current $I$ measurement by looking up the pump characteristic data. By comparing this indirectly obtained flow with the reference flow $Q^*$, the error flow $\Delta Q$ is fed to the controller which produces a reference speed $\omega^*$ (in speed mode) or reference current $I^*$ (in current mode). The motor controller drives the motor and the blood pump to required state. As seen in Fig. 6.2, no flow sensor is needed. Also in such a controller sufficient electrical data can be acquired so that certain physiological information can be diagnosed by analyzing the electrical data.
6.3 Fuzzy Fault-preventive Physiological Controller

6.3.1 Fault Conditions of the Rotary Dynamic Blood Pump

As mentioned before, the dynamic blood pump is a passive working horse in that it drains according to the motor current or speed no matter how the physiology responses. In certain extreme conditions very low or even negative inlet pressure can be developed and this may lead to cannula collapse or suction. This may cause muscle damage to the ventricle and must be avoided.

Fig. 6.3 shows the situation of suction due to excessive draining. It is seen that excessively increasing the pump speed finally cause the ventricular suction. When suction occurs, pump flow will be very pulsating.

It is worthy to investigate the pre-suction condition. From Fig. 6.3 it is seen that over pumping generally causes depulsatile in the flow. Further increasing the pump speed after the depulsation will again produce pulsatile flow and ventricular collapse occurs. Therefore, as a preventive approach, it is necessary to reduce the pump output when depulsation is observed.

It may be very difficult to use conventional approach to write mathematical equations for such a controller. Fuzzy logic provides an ideal approach to deal with such a nonlinear, multi-input controller.

6.3.2 Principles of Fuzzy Logic Systems

In this section a brief description of a fuzzy logic system is given, and a simple example is illustrated. Detailed information can be found in literature, such as in [2].

- **Linguistic Variables**: If a variable can take words in natural languages (for example, “small”, “large”, “slow”, “fast”, etc.) as its values, this variable is
Figure 6.3: Ventricular suction due to excessive pumping

defined as a linguistic variable. These words are usually labels of fuzzy membership functions. A linguistic variable can take either words or numbers as its values. The value of the linguistic variable is called linguistic value.

- **Fuzzy Membership Functions:** The fuzzy membership function describes the “certainty” of a linguistic variable to a linguistic value. For example, Fig. 6.4 shows the certainty of linguistic variable $I$ (motor current) to linguistic value, “positive low”. As shown in Fig. 6.4 (a), when the current is 0.4 A, the certainty of the current being “positive low” is 1, and when the current is 0.2 A, the certainty of the current being “positive low” is 0.5. We can put a scaling factor
for the current (as gain), as seen in Fig. 6.4 (b), so that the 0.4 A is scaled to 1. In this way the membership functions for different variables can be very generic.

![Membership function for linguistic value "positive low"](image)

**Figure 6.4**: Membership function for linguistic value "positive low"

Fuzzy logic system is a system which has a direct relationship with fuzzy concepts (such as fuzzy membership functions, linguistic variables, etc.) and fuzzy logic. Fig. 6.5 shows the block diagram of a fuzzy logic system. In the system $x_1, x_2, ..., x_n$ are inputs to the system, and $y$ is the output of the system. The fuzzy logic system is composed of fuzzification interface, fuzzy rule-base, fuzzy inference engine, and defuzzification interface.

- **Fuzzification**: The fuzzification interface converts crisp inputs to fuzzy sets which the inference mechanism can easily use to apply rules. The fuzzification interface performs the following two functions:

  - Determine which linguistic values the input variables belong to;
Figure 6.5: Block diagram of a fuzzy controller

- Determine the certainties of the input variables to the activated linguistic values.

- **Fuzzy Rule-base:** The fuzzy rule-base comprises fuzzy rules describing how the fuzzy system performs. It is the heart of the whole system in the sense that the other three components are used to interpret and combine these rules to form the final system. The fuzzy rule-base consists of a collection of fuzzy \( IF - THEN \) rules in the following form:

\[
IF \ x_1 \ is \ F_1^i, \ \cdots, \ and \ x_n \ is \ F_n^i, \ THEN \ y \ is \ G^i.
\]

where \( F_i^i \ (i = 1, 2, \ldots, n) \) and \( G^i \) are fuzzy sets, and \( x_i \ (i = 1, 2, \ldots, n) \) and \( y \) are input and output linguistic values.

Generally there are two ways to obtain fuzzy \( IF - THEN \) rules: (1) asking human experts; or (2) using training algorithms based on experimental data. The first approach is the most straightforward method of obtaining rules. However, in many cases human experts may not be able to provide sufficient rule-bases. Then, training algorithms are necessary to generate the rules.
• **Fuzzy Inference Engine:** The fuzzy inference engine uses techniques in approximate reasoning to combine the fuzzy *IF – THEN* rules in the fuzzy rule-base into a mapping from the fuzzy sets of the inputs to the fuzzy sets of the output.

• **Defuzzification:** The defuzzication interface converts the output fuzzy sets to crisp output. The most commonly used defuzzification method is Center of Gravity (COG) described by

\[ u = \frac{\sum_{j=1}^{m} y_j \mu_V(y_j)}{\sum_{j=1}^{m} \mu_V(y_j)} \]  

(6.4)

where \( y_j \) is the center of the \( j \)th output fuzzy set, \( \mu_V(y_j) \) is the linguistic value for \( y_j \) \((j = 1, 2, \ldots, m)\), and \( m \) the number of output fuzzy sets.

Fig. 6.6 shows an example of the process of implementation of this type of fuzzy controller. The fuzzy system shown in this example has two inputs and one output. Five triangle type membership functions are used to map each crisp input into input fuzzy set and to map the output fuzzy set into the crisp output. The rule-base of the fuzzy controller is expressed by a 5 x 5 table, where \( nl, ns, z, ps, pl \) express negative large, negative small, zero, positive small, and positive large. In this example when the input \( e_1 = 0.75, e_2 = 1.4 \), the output of the fuzzy system is \( u = -1.3 \).

### 6.3.3 Fault-preventive Control

As seen in Fig. 6.3, the controller needs to identify the pre-suction condition, which in this system is the depulsion. A new input variable, the flow pusatile index \( PQ \), reflecting the degree of flow pulsation, is defined by

\[ PQ = Q_{max} - Q_{min} \]  

(6.5)
where \( Q_{\text{max}} \) and \( Q_{\text{min}} \) are maximum and minimum flow respectively.

With the pulsatile index, the occurrence of depulsation can be diagnosed. As a pre-suction condition, when flow depulsation is diagnosed, the controller must take certain action to reduce the pump output to prevent suction. The principle of such a preventive controller is shown in Fig. 6.7.

The fuzzy controller is a nonlinear controller that adjusts the output according to the flow error and flow pulsation. Fig. 6.8 shows the structure of the fuzzy controller. Triangular membership functions can be used. The input membership functions are

\[
\begin{align*}
\text{Rule} & \quad \text{Base} & \quad E_1 \\
-2 & \quad -1 & \quad 0 & \quad 1 & \quad 2 \\
-2 & \quad 2 & \quad 1 & \quad 1 & \quad 0 \\
-1 & \quad 2 & \quad 1 & \quad 1 & \quad 0 \\
0 & \quad 1 & \quad 1 & \quad 0 & \quad -1 \\
1 & \quad 1 & \quad 0 & \quad -1 & \quad -1 \\
2 & \quad 1 & \quad 0 & \quad -1 & \quad -1 \\
\end{align*}
\]

\[
u = -0.45 \cdot(-1)+0.30\cdot(-2)+0.15\cdot(-1)+1.0\cdot(-1)
\]

\[
= -1.3
\]
Figure 6.7: A fault-preventive controller to prevent the ventricular suction shown in Fig. 6.9 and the output membership functions are shown in Fig. 6.10. Table 6.1 illustrates the rule-base of the physiological controller.

Figure 6.8: Block diagram of the fuzzy fault-preventive controller

In the fuzzy controller, the inputs are flow error $\Delta Q$ and flow pulsation index $PQ$. The fuzzy controller produces a change of current command $\Delta I^*$ so that the actual
flow could follow the reference flow. The reference current is given by

$$I^* = I + \Delta I^*$$  \hspace{1cm} (6.6) 

where $I$ is the actual current.

From the rule-base illustrated in Table 6.1, it is seen that when the pulsatile index $PQ$ is high, the change of current $\Delta I^*$ is almost in linear relation with the flow error $\Delta Q$. However, when $PQ$ becomes lower, we should be very careful in increasing the current. This is reflected in the fuzzy rule-base in that increasing or decreasing the current is in non-linear relation with the flow error. This may, sometimes, cause slower flow tracking, or in extreme cases actual flow may not be able to reach the reference flow. However, more importantly overpumping is prevented and ventricular suction is avoided.
Table 6.1: Fuzzy rule-base of the fault-preventive controller

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The complete block diagram of the closed-loop sensorless and fault-preventive physiological controller is shown in Fig. 6.11. The block in the dotted lines is the self-regulated cardiovascular circulatory system model, as described in Fig. 5.10 in Chapter 5.

In Fig. 6.11, the motor-pump and circulatory system interaction effect is considered. The pump operation will cause physiological reactions on blood pressure, flow, heart rate, and peripheral resistance. The required pump flow $Q^*$ is obtained from the heart rate as defined in (6.1). The actual pump flow $Q$ and pulsation index $PQ$ are indirectly obtained from motor speed $\omega$ and current $I$. The fuzzy physiological fault-preventive controller takes the error flow $\Delta Q$ and pulsation index $PQ$ as inputs and produces the command current $I^*$ (in current mode operation) or command speed $\omega^*$ (in speed mode operation) to the motor driver. Special control mechanisms are included in the fuzzy controller to prevent ventricular suction while producing sufficient output flow.
Figure 6.11: Block diagram of the circulatory system with the closed-loop blood pump control

6.4 Simulation Results of the Physiological Controller

To evaluate the effectiveness of the proposed control algorithm, computer simulation is conducted with the circulatory system model.

Fig. 6.12 illustrates the result of a patient with heart assist at rest. The command flow is obtained from the heart rate requirement produced by the self-regulatory circulatory model. With the blood pump providing blood flow $Q = 4.7 L/min$, normal hemolysis is reached by the observation of normal system flow and pressures. The result of same sickness without heart assist was shown in Fig. 5.14(1) in Chapter 5.
Simulation results can be obtained for the blood pump when the patient is under certain exercise, and comparisons are made between a conventional PI controller and a fuzzy logic controller. Fig. 6.13 shows the result of a sick heart for a certain exercise using a conventional PI controller. At the time of $t = 10s$ an ergometric workload of $50 \, \text{W}$ is applied and is later released at $t = 50s$. With the self-regulated circulatory system an increase of flow is demanded, and the pump does produce an increased flow. Since there is no preventive procedures as to monitor and prevent the flow depulsation, with the ever-increasing flow demand, the pump output increases too much, and negative inlet pressure is developed, leading to the very dangerous
situs of ventricular suction. Fig. 6.14 shows the same situation but using a fuzzy logic controller. It is seen that the pump output flow can follow the command flow well and provide sufficient perfusion to the physiological system. With further higher output demand, the flow pulsation is decreased, yet with the fuzzy algorithm certain pulsation is still maintained to secure a safe operation.

Figure 6.13: Sick heart under assist, at load, using PI controller
Figure 6.14: Sick heart under assist, at load, using fuzzy fault-preventive controller

6.5 Discussion

Fuzzy logic control has the advantage of being able to deal with highly non-linear systems, interpret and organize human experience and knowledge in practical systems. The biomedical system is a highly complex and non-linear system, and medical specialist's knowledge and decision are needed in a real system. Therefore fuzzy logic has promising prospectives in the biomedical engineering area.

A fuzzy logic sensorless control system for the rotary blood pump is proposed in this chapter. The purpose of the controller is to produce sufficient flow to meet the perfusion demand, while prevent the occurrence of ventricular suction, without using
flow and/or pressure sensors. Motor speed and current are measured to estimate the pump flow using pump characteristic data. By the diagnosis of the flow pulsation index as an indication of pre-suction condition, motor output is adjusted to prevent ventricular suction. The application of fuzzy logic in this system demonstrates the unique advantage of the fuzzy representation in that, in human definition the "degree of pulsation" is usually a vague expression, and it is hard to find a mathematical equation to represent and coordinate the diverse demand to prevent suction while meeting the organ perfusion requirement. The fuzzy logic system, however, can represent such expressions. Sensorless control is achieved by measurement of motor speed and current and pump flow is estimated by using pump characteristic data.

Computer simulation using the proposed algorithm has been implemented and the simulation result indicates that the fault-preventive physiological controller is superior to conventional PI approaches and is very effective. The implementation of the fuzzy knowledge base is very straight-forward in general human sense, and tuning of the controller is simple. More experimental data of the pump will be necessary to refine the knowledge base and improve the performance.
CHAPTER 7

DYNAMIC FUZZY FLOW STABILIZER

7.1 Overview

The purpose of the blood pump system is to produce a physiologically sufficient output. Unlike traditional displacement pumps, which can automatically adapt to the filling phase, the output flow of rotary dynamic pump is solely dependent on the differential pressure and motor input. The differential pressure over the pump can be highly pulsatile due to changes in preload and/or afterload, and cardiac activities. This results in a highly pulsatile pump flow with fixed motor input, no matter whether the motor is in speed mode or current mode operation. Such flow pulsations sometimes cause negative impacts, such as reverse flow, and certain biochemical implications are still not clear yet.

The purpose of this chapter is to develop a control algorithm to produce a stable, or more preferably, a constant flow. To do this, diagnosis of the cardiac phase is the first step. Then, certain action must be taken by the motor controller to reduce or increase the motor input based on the diagnostic information. Since no flow or pressure sensors are available, the diagnosis needs to be done based on the motor current and speed.
waveforms. Fuzzy logic is used together with the given pump characteristics to achieve the control goal, and simulation results will also be presented.

7.2 Diagnose the System Demand from Motor Speed and Current Operation Modes

The test data for the pump under investigation are shown in Fig. 7.1 and Fig. 7.2. Fig. 7.1 shows the pressure and flow relationship at different speeds. Fig. 7.2 shows the flow and motor current relationship at different speeds.

![Figure 7.1: Pump pressure vs flow: (o) 3500rpm, (*) 3000rpm, (+) 2500rpm.](image)

From Fig. 7.1 it can be seen that the rotary blood pump under investigation has constant pressure type characteristic, that is, under certain speed, pump flow will change radically with the change of pressure. The pump is to be connected from the left ventricle to the aorta. The differential pressure over the pump is highly pulsatile, from a maximum of as high as around 100 mmHg (aorta pressure) to a minimum of
Figure 7.2: Pump flow vs motor current: (o) 3500rpm, (*) 3000rpm, (+) 2500rpm.

For pressure type pumps the control is complicated, since simple speed control gives unsatisfactory performance. The simulation model provides a means to understand and investigate the pump-circulatory system interactions to secure a stable flow. For sufficient perfusion, ideally a constant flow is desired. Since the pump pressure is pulsatile, the pump speed/current must be adjusted accordingly.

Speed mode and current mode operations have been investigated in the previous chapters. To control a stable, or more preferrably, a constant flow, neither speed nor current mode operation can provide satisfactory performance. Highly pulsatile flow is observed in either case. A constant flow requires the speed and current varying accordingly. However, as no pressure or flow sensor can be used, it is impossible to control the motor speed or current in the dynamic flow/pressure environment. As
Figure 7.3: Differential pump pressure of a failing heart, Cls=0.93

illustrated in Fig. 7.4, speed variation and current variation are needed to secure an ideal constant flow.

The current task is obvious. Since conventional controller can not reach both speed and current control, a highly intelligent controller is desired. As neither pressure nor flow sensor is available, the dynamic physiological information must be identified from the speed and current signals and then be used to further control the speed and current.

Careful consideration must be made to choose either the speed or the current mode as the base mode. For the motor-pump model under investigation, the current mode is used. The reason for that is, as shown in Fig. 7.5 and Fig. 7.6, the pure current mode gives less pulsatile flow due to the pump property.
7.2.1 Information from Speed Mode

The pump pressure, flow, and motor current waveforms are shown in Fig. 7.5 for speed mode operation. When speed is constant, it can be found that a drop (or rise) of the pump differential pressure causes a rise of the motor current and a rise of the pump flow. This information is very important to construct the intelligent knowledge base in the controller. However to find an analytical relationship between the flow or pressure and the motor current is difficult as a result of high nonlinearity. The fuzzy description however is a good means to represent such relationships.

The implication from Fig. 7.5 is important. For a given speed the occurrence of a current rise (or drop) indicates a flow rise (or drop). If a human being is involved,
he or she may want to decrease (or increase) the motor current to keep the flow unchanged. This information will be brought to the fuzzy rule-base for the fuzzy inference engine, namely:

*Under certain speed, the occurrence of a current rise (or drop) indicates a flow rise (or drop), and the action should be to decrease (or increase) the current.*

![Figure 7.5: Failing heart with assist, speed mode, 2650rpm, Q\text{mean}=4.76L/min.](image)

**7.2.2 Information from Current Mode**

All the relevant signal waveforms under current mode operation are shown in Fig. 7.6. It is apparent that under constant current, a decrease of pump differential pressure causes a speed drop (or rise) and a flow rise (or drop). One may want to, if
available, adjust the current to decrease (or increase) when diagnosing a speed drop (or rise) to obtain a constant flow.

\[ \text{Figure 7.6: Failing heart with assist, current mode, } I=0.27\text{A, } Q_{\text{mean}}=5.04\text{L/min} \]

Therefore the information which will be brought to the fuzzy rule-base is: **under certain current, the occurrence of a speed rise (or drop) means a flow drop (or rise), and the action should be to increase (or decrease) the current.**

### 7.3 Fuzzy Dynamic Flow Stabilizer

From the speed and current mode operation data, a logic inference action has been built as described in the previous section. Such logic relationships are hard to describe in analytical relations but can be described by fuzzy logic.
7.3.1 Construction of the Fuzzy Rule-Base

The rule-base is the core of the fuzzy controller which interprets human intelligent knowledge that is difficult to describe in mathematical equations. The following logics has been established in the previous sections:

1. *Under certain speed, a positive (or negative) current error indicates a flow rise (or drop), and the action should be to decrease (or increase) the motor current.*

2. *Under certain current, a positive (or negative) speed error indicates a flow drop (or rise), and the action should be to increase (or decrease) the motor current.*

Based on these logics and by further investigating the waveforms of speed and current mode operations, the fuzzy rule-base can be obtained as in Table 7.1.

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Table 7.1: Fuzzy rule-base of the flow stabilizer

7.3.2 Fuzzy Flow Stabilizer

The proposed fuzzy flow stabilization controller (stabilizer) is shown in Fig. 7.7. The inputs to the fuzzy logic controller are current error and speed error. The fuzzy
controller contains intelligent human knowledge from the diagnosis information described above.

With the proposed fuzzy flow stabilization controller, the base operation mode of the motor is the current mode. However, the command current to the motor controller is not fixed. Instead this command current is varying according to the system dynamics. The fuzzy flow controller shown in Fig. 7.7 provides such a command current based on the diagnosis information from motor speed and current to produce a stable flow. Introducing such a fuzzy controller eliminates instantaneous flow and pressure sensors to reach the flow control. Furthermore, with the extensive knowledge base no explicit calculation of flow is needed either, which can greatly reduce the computation load for frequent table look-up operations.

It can be seen from Fig. 7.7 and Table 7.1 that under certain output flow requirement, the fuzzy algorithm produces a current modification vector to control the motor current according to the dynamics in motor speed and current reflecting the flow dynamics. This matches to our specific requirement that in order to control an optimal flow, we do not want a constant speed nor a constant current. As we use the current

\[ \text{Figure 7.7: Fuzzy flow stabilization controller for blood pump} \]
mode as the motor operation mode, the command current also needs to be adjusted based on the diagnostic information obtained from speed error and current error. Therefore, the fuzzy controller and the rule-base already includes diagnose-and-react functions.

The system block diagram is shown in Fig. 7.8. Given a desired flow $Q^*$, from the pump data the nominal current $I_0$ and speed $\omega_0$ can be obtained. With $I_0$ and $\omega_0$, by comparing to the feedback current $I$ and speed $\omega$, the fuzzy flow controller produces a command current $I^*$ to the motor current controller. The current controller produces the control voltage to the motor driver by feedback current regulation.

![Figure 7.8: System diagram of fuzzy flow stabilizer](image)

The computer simulation result of an open-loop fuzzy flow controller is shown in Fig. 7.9. The circulatory system has fixed parameters, and the pump is given a fixed flow. It can be seen that the flow is much smoother than that in speed or current mode operation, as shown in Fig. 7.5 and Fig. 7.6 above.
7.4 Overall System Structure

The overall system block diagram is shown in Fig. 7.10. The system is composed of the fuzzy flow stabilizer described earlier in this chapter, the fuzzy sensorless physiological controller described in Chapter 6, and the cardiovascular circulatory system and baroreceptor control described in Chapter 5.

It is noticed that for the fuzzy physiological controller, the input variable for the pre-suction identification is changed from $PQ$ to $P\omega$. This is because we are now trying to reach a stable, or more preferably, a constant flow, whose pulsation will be very low, therefore it is no longer reasonable to use $PQ$ as the pre-suction sign. However, the motor speed and current still have such pulsatile properties as shown in

Figure 7.9: Failing heart under assist, with flow stabilizer, $Q_{\text{mean}}=4.92\text{L/min}$.
Fig. 7.9, and the pre-suction condition also causes the depulsation of the speed and current signal, depending on the operation mode. Since the current mode is used as the base mode, here the speed pulsation index, $P_\omega$, is used. $P_\omega$ is defined by

$$P_\omega = \omega_{\text{max}} - \omega_{\text{min}}$$  \hspace{1cm} (7.1)

where $\omega_{\text{max}}$ and $\omega_{\text{min}}$ are maximum and minimum speed in certain period respectively.

### 7.5 Simulation Results

Computer simulation based on the model developed in previous chapters are conducted to evaluate the proposed fuzzy algorithm.
Simulation results of the controller performance without and with the fuzzy flow stabilizer are shown in Fig. 7.11 and Fig. 7.12 respectively. It can be seen in Fig. 7.11 that with the fuzzy physiological controller, the pump can produce average flow of $Q_{mean} = 4.7L/min$ and normal hemodynamics can be reached by the observation of normal blood pressures and system flow. The pump flow is still very pulsatile due to pulsatile cardiac cycle. In Fig. 7.12, the fuzzy stabilizer is added. It is seen that with the same amount of average pump output, the pump flow is nearly constant. This will reduce the stress on the pump and avoid possible negative impacts due to pulsatile flow.

Figure 7.11: Sick heart under assist, without fuzzy flow stabilizer
Fig. 7.12: Sick heart under assist, with fuzzy flow stabilizer

Fig. 7.13 shows the result of a sick heart with assist device under certain exercise. At $t = 15\, \text{s}$, an ergometric workload of 50 W is added and is released at $t = 55\, \text{s}$. It can be seen that the pump output can meet the required flow, and the pump flow is very stable (non-pulsatile). The result for the same heart and device with a conventional PI controller was shown in Fig. 6.13, which lead to dangerous negative inlet pressure, and with a fuzzy fault-preventive controller but without flow stabilization, the flow was pulsatile as shown in Fig. 6.14.
7.5.1 Discussion

The fuzzy stabilizer utilizes the information of flow performance under speed and current control modes to control the pump to produce a stable, nearly constant flow. The fuzzy logic knowledge-base is largely based on these information. By means of on-line measurement of motor speed and current, specific cardiac phase can be determined and control actions can be taken to change the motor reference current accordingly. Computer simulation results are obtained on the sample model. These
results show that the fuzzy algorithm reaches very stable flow in various cardiac and load activities.

The overall system model, with a self-regulated circulatory model, a fault-preventive physiological controller, and a dynamic flow stabilizer, simulates the real system and evaluates the performance of the proposed intelligent control algorithms. Simulation results indicate that the controller can produce a stable flow to meet the physiological demand, and prevent the system from ventricular suction.
8.1 Conclusions

1. To secure a reliable and efficient operation of a rotary blood pump, a DSP control system has been developed. Extensive tests have shown that the DSP system is very effective and robust. High flexibility of the DSP system has also been proved in various tests which require only software modifications.

2. The sensorless control for the PM motor with a back-EMF commutation drive circuit has been effectively used, while other sensorless vector control algorithms such as position perturbation based estimation and direct torque control techniques also provide alternative approaches to reaching high performance motion control.

3. Computer simulation provides approaches to predicting the physiological performance and evaluating control algorithms without expensive tests, and also gives good understandings of the motor-pump-cardiovascular system interactions. A circuit model has been proposed and its effectiveness is verified by its physiological outputs. Pump data and motor models have also been included in the simulation model.
4. A fuzzy logic fault-preventive controller has been proposed for the blood pump system to control the pump flow to meet physiological demands while secure safe operation. To avoid invasive flow or pressure measurement, a sensorless flow control scheme, based on the measurement of motor variables (speed and current) has been developed. Simulation results indicate that the proposed controller can provide sufficient flow without the occurrence of ventricular suction.

5. Wildly pulsatile flow due to changes in differential pressures has negative impact and may result in some deposition. To obtain a stable, nearly constant flow, a fuzzy logic flow stabilizer has been presented. Based on the on-line measurement of motor speed and current, the fuzzy logic system diagnoses the system from the motor speed and current waveforms, and further controls the motor output (by controlling the motor reference current) to produce a stable flow. Computer simulation for this algorithm has shown that the pump flow is not pulsatile in the pulsatile environment.

8.2 Future Work

1. The control for a rotary blood pump is complicated without direct flow or pressure measurements because of pump characteristics. A system controller is highly desirable for the rotary blood pump to reach its practical application. To obtain a more practical and effective controller, the fuzzy logic algorithm can be further refined. By investigating more detailed pump test data, the fuzzy knowledge base can be further tuned to fit to specific pumps.

2. Performance of various operation modes are to be carefully examined to improve the knowledge base. Current mode has been used in the simulation, but further
effort should be made to evaluate both current and speed mode operations as the base mode. Effects to the physiological system need to be found for these two modes.

3. In the modeling and simulation, the steady-state pump characteristic has been used. The real pump characteristic is much more complicated. Effects of its transient process and hysteresis need to be evaluated. In the modeling of the electric motor, since the motor time constants are much smaller than the physiological time constants, the steady-state motor model has been used in simulation. Further efforts might be put on the transient modeling and more accurate performance can be expected.

4. Finally, experimental verification of proposed algorithms is also expected in the future. Extensive mock-loop tests are necessary to gather sufficient information to refine the fuzzy knowledge base and the control algorithm. On-line training of the fuzzy system will be a practical approach for a real system by reviewing some typical operation modes. The artificial neural network (ANN) technology provides an effective approach for system self-training, learning and diagnosis to reach desired performance, and the advanced neuro-fuzzy technique is potentially an attractive approach for such a sophisticated system. All these issues are the prospective topics to achieve a systematic controller for practical implantation.
BIBLIOGRAPHY


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