

NON LINEAR CONTROL OF SMA AS A LINEAR ACTUATOR

by

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ACADEMIC ETHICS AND INTEGRITY STATEMENT

I, Ahmet Atasoy, hereby certify that I am aware of the Academic Ethics and Integrity Policy issued by the Council of Higher Education (YÖK) and I fully acknowledge all the consequences due to its violation by plagiarism or any other way.

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ABSTRACT

NON LINEAR CONTROL OF SMA AS A LINEAR ACTUATOR

Precise force control is critical for various actuator applications. Shape Memory Alloys (SMAs) are attractive candidates due to their high power-to-weight ratio and ability to generate substantial force. However, inherent complexities in SMA behavior, including non-linear relationships, hysteresis, and temperature dependence, hinder precise force control. Most existing studies primarily focus on characterizing SMA behavior and offering control methods in laboratory environments. The properties of the SMA used in real-world applications may differ from those observed in the laboratory due to changing test and operating conditions and material properties. This gap necessitates a more practical approach for reliable SMA actuator performance. This study proposes a novel approach utilizing Recurrent Neural Networks (RNNs) and real-time measurements to achieve precise force control in SMAs. A compact testbed equipped with sensors acquires voltage, current, and generated force data. RNNs are well-suited for learning complex temporal relationships, making them ideal for modeling the dynamic behavior of SMAs. Trained forward and Inverse RNN models predicts force output or adjusts input voltage for a desired force, respectively, in real-time. This approach significantly improves force control accuracy, achieving a desired force trajectory at the actuator output with a high degree of success (e.g., 99%). This paves the way for more reliable SMA actuator operation in diverse real-world scenarios.

Keywords: Layer-Recurrent Neural Network (LRNN), Non-Linear Force Control, Prosthetic Finger, Prosthetics, Real-Time Measurement, Recurrent Neural Network (RNN), Resistance Measurement, Shape Memory Alloy (SMA), Shape Memory Alloy Spring Actuator, Upper Limb Prosthetics.

ÖZET

DOĞRUSAL AKTÜATÖR OLARAK SMA'NIN DOĞRUSAL OLMAYAN KONTROLÜ

Hassas kuvvet kontrolü çeşitli aktüatör uygulamaları için kritik öneme sahiptir. Şekil Hafızalı Alaşımlar (SMA'lar), yüksek güç-ağırlık oranları ve önemli kuvvet üretme kabiliyetleri nedeniyle ilgi çekici adaylardır. Ancak, doğrusal olmayan ilişkiler, histerezis ve sıcaklık bağımlılığı gibi SMA davranışındaki içsel karmaşıklıklar, hassas kuvvet kontrolünü zorlaştırır. Mevcut çalışmaların çoğu öncelikle SMA davranışını karakterize etmeye ve kontrollü laboratuvar ortamlarında kontrol yöntemleri sunmaya odaklanır. Gerçek dünya uygulamalarında kullanılan SMA'nın özellikleri, değişen test ve çalışma koşulları ve malzeme özellikleri nedeniyle laboratuvarda gözlemlenenlerden farklı olabilir. Bu boşluk, sahada güvenilir SMA aktüatör performansı için daha pratik bir yaklaşım gerektirir. Bu çalışma, SMA'larda hassas kuvvet kontrolü elde etmek için Tekrarlayan Sinir Ağları (RNN'ler) ve gerçek zamanlı ölçümler kullanan yeni bir yaklaşım önermektedir. Sensörlerle donatılmış kompakt bir test yatağı voltaj, akım ve üretilen kuvvet verilerini alır. RNN'ler, verilerdeki karmaşık zamansal ilişkileri öğrenmek için oldukça uygundur ve bu da onları SMA'ların dinamik davranışını modellemek için ideal hale getirir. Bu veriler üzerinde eğitilen İleri ve Ters RNN modelleri, kuvvet çıktısını tahmin eder ve giriş sinyallerini gerçek zamanlı olarak ayarlar. Bu yaklaşım, kuvvet kontrol doğruluğunda önemli bir iyileştirme gösterir ve aktüatör çıkışında istenen kuvvet yörüngesini yüksek bir başarı oranıyla (örneğin, %99) elde eder. Bu, çeşitli gerçek dünya senaryolarında daha güvenilir SMA aktüatör çalışmasının önünü açar.

Anahtar Sözcükler: Katmanlı-Yinelemeli Sinir Ağı (LRNN), Doğrusal Olmayan Kuvvet Kontrolü, Parmak Protezi, Protez, Tekrarlayan Sinir Ağı , Gerçek Zamanlı Ölçüm, Direnç Ölçümü, Şekil Hafızalı Alaşım (SHA), Şekil Hafızalı Alaşım Yay Eyleyici, Üst Ekstremité Protezleri.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BAP	Bogaziçi Research Projects
BLDC	Brushless DC Motor
CAD	Computer Aided Design
DARPA	Defense Advanced Research Projects Agency
DIP	Distal Interphalangeal
DNN	Dynamic Neural Network
DOF	Degrees of Freedom
EAP	Electro Active Polymers
ED	Extensor Digitorum
EEG	Electroencephalography
EMG	Electromyography
ENG	Electroneurography
FDP	Flexor Digitorum Profundus
FDS	Flexor Digitorum Superficialis
HRNN	Hysteretic Recurrent Neural Network
IEAP	Ionic Electro Active Polymers
IPMC	Ionic Polymer-Metal Composite
LRNN	Layer Recurrent Neural Network
LSTM	Long Short-Term Memory
MCP	Metacarpophalangeal
MEMS	Microelectromechanical Systems
MPC	Model Predictive Control
MPL	Modular Prosthetic Limb
NARX	Nonlinear AutoRegressive with External Input
NN	Neural Network
Ni-Ti	Nickel-Titanium
NTC	Negative Temperature Coefficient

PID	Proportional Integral Derivative
PIP	Proximal Interphalangeal
PL	Palmaris Longus
PTC	Positive Temperature Coefficient
PWM	Pulse Width Modulation
RAPHaEL	Robotic Air Powered Hand with Elastic Ligaments
RNN	Recurrent Neural Network
RTD	Resistance Temperature Detectors
SMA	Shape Memory Alloy
SME	Shape Memory Effect

1. INTRODUCTION

Shape Memory Alloy (SMA) is a class of materials that exhibit unique temperature-dependent properties. At low temperatures, it exists in a deformable "martensite phase." When heated, it undergoes a phase transformation to the "austenite phase" and returns to its pre-defined shape. This ability to recover the original shape produces force and makes it valuable for actuator applications. It is this force generation capability of SMA, resembling muscle-like contraction, that makes it interesting as an actuator. SMA wires and springs are common forms, offering a high power-to-weight ratio and the ability to generate substantial force [17–19]. While SMA springs provide greater displacement changes compared to SMA wires, precise control of the generated force remains a challenge for all types of SMA.

1.1 Motivation

This thesis began with the assumption that Shape Memory Alloys (SMAs) could be used as actuators in prosthetic hand designs. The human hand, with its intricate motor control and dexterity, poses significant challenges when attempting to replicate its movements in prosthetics. Despite advancements in prosthetic technology that offer functional and user-friendly solutions, mimicking the natural movements of the human hand remains a complex task. The goal of this work was to develop a solution capable of addressing this challenge. At the start of the research, SMAs were considered as part of a hybrid system alongside BLDC motors, where SMAs would function similarly to muscles in a prosthetic hand. The original idea was to use BLDC motors for movements requiring greater force, while SMAs would handle more delicate, precise movements, such as those of the fingers or palm. SMAs are particularly attractive for such applications due to their compactness and ability to return to their original shape when electrically activated.

During this phase, alternative actuation technologies were also explored, including Electro Active Polymers (EAP), which exhibit muscle-like behavior. However, EAPs were found to be less suitable for practical applications due to their high voltage requirements, insufficient force generation, and challenges in chemical processing. After considering these limitations, the focus shifted back to SMAs as the primary actuator technology.

As the prosthetic hand design progressed, technical challenges gradually narrowed the scope of the research. The initial goal of designing an entire hand capable of movement was refined to focus on a single finger and, eventually, to the design of an SMA spring actuator. Each step of this process contributed to a deeper understanding of the potential and limitations of SMAs as actuators, as well as the significant challenges posed by controlling these materials.

SMAs, while promising for prosthetic applications due to their unique properties, also present significant challenges in terms of control due to their nonlinear behavior. The complex relationship between temperature, resistance changes, and force production requires more advanced control methods. Traditional control techniques proved insufficient, which led to the exploration of neural network-based approaches. To control the SMA springs effectively, Recurrent Neural Networks (RNN) and other advanced models were introduced.

Although the focus of the thesis gradually shifted from a broad goal of designing a fully functioning prosthetic hand to the more specific challenge of controlling an SMA spring actuator, each stage of the research provided valuable insights. Initially, the aim was to develop a complex prosthetic system, but the challenges encountered along the way highlighted areas where more specialized and focused research was needed. As a result, this thesis investigates how the nonlinear behavior of SMA spring actuators can be effectively controlled and how these control methods can contribute to practical applications, such as prosthetics.

In conclusion, while the thesis began with ambitious goals, it evolved into a more focused but deeper investigation. Each step provided valuable contributions to the understanding of how SMAs can be used and controlled in prosthetic technology, ultimately offering important advancements in this field.

1.2 Research Objectives

This thesis identifies two primary research objectives, each evolving through a series of key milestones. Initially, the focus was on the broader application of Shape Memory Alloys (SMAs) in prosthetic hand design. However, as the research progressed, technical complexities and the unique characteristics of SMAs necessitated a more focused investigation into their precise control. This evolution led to a refined second objective centered on advanced modeling and control strategies for SMA actuators.

1.2.1 Objective 1: Initial Vision and Evolution - From Prosthetic Hand to Single Actuator

This section details the initial ambitious scope of the research, beginning with the design of a hybrid prosthetic hand utilizing SMA actuators. It outlines the anatomical considerations, the exploration of various actuation technologies, and the subsequent narrowing of the focus from a full hand to a single finger, and ultimately, to the fundamental control of the SMA spring actuator itself. The challenges encountered during this phase, particularly the complexities of a multi-actuator hybrid system and the nonlinear behavior of SMAs, directly led to the re-evaluation and refinement of the primary research problem. More detailed explanations of this evolution can be found in the Motivation (Section 1.1).

1.2.2 Objective 2: Refining the Focus - Precision Control of SMA Through Advanced Modeling

Building upon the challenges identified in Objective 1, this section describes the refined primary objective: achieving precise force control in SMA actuators using advanced modeling techniques. The narrative details the transition from initial empirical modeling attempts to the adoption of Recurrent Neural Networks (RNNs) for overcoming the inherent nonlinearities of SMAs. It highlights the development of robust data collection systems, noise reduction strategies, and the exploration of various neural network architectures, culminating in the implementation of forward and inverse RNN models for real-time force prediction and control. This evolution was driven by the necessity for more sophisticated solutions to leverage SMA's potential effectively in practical applications like prosthetics.

1.2.3 Summary of Objectives and Achieved Milestones

- (i) **Objective 1-** The initial aim of this research was to design an anthropomorphic dexterity prosthesis operated with Shape Memory Alloys (SMA) actuators, which later evolved into a focused study on the fundamental control challenges of SMA.
 - **Milestone 1** - The studies started with a detailed examination of the anatomy of the hand and examples in the literature, and it was decided that it would be more efficient to work with a hybrid structure instead of creating all the actuators that would provide the movements of the hand with SMA. It was planned to have BLDC motors and SMA actuators in the hand. After a good start with the support of the TÜBİTAK 1001 "Cognitive Controlled Myoelectric Hybrid Prosthetic Hand" project, it turned out that the structure was quite difficult to control.
 - **Milestone 2**— As a result of the experiments and studies conducted, it was concluded that it would be more meaningful to continue the studies on a single finger. SMA actuators are placed on two sides of the metacarpals of a finger, like in real human fingers.

- **Milestone 3** - Voltage, current, and force values are taken in real-time, and resistance is calculated from the voltage and current data. The data is used for polynomial fitting, linear, and nonlinear regression to find the relationship between these variables. However, a generalized equation or model cannot be created due to the noisy data from inactive parts and on-off switching. The problem has evolved from the finger driven by the SMA to the actuator itself.
 - **Milestone 4** - These challenges highlight the need for advanced control methods such as neural network algorithms to model and control the behavior of the SMA springs effectively.
- (ii) **Objective 2** – To achieve precise force control in SMA actuators, this study revised its main objective to focus on developing a new approach using Recurrent Neural Networks (RNNs) and real-time measurements, addressing the inherent nonlinear behavior of SMAs for enhanced control precision in practical applications like prosthetic devices.
- **Milestone 1-** Establishment and Improvement of Data Collection System: Various electronic circuits were designed to control and measure the voltage and current applied to the SMA actuator. The INA260 voltage and current sensor was selected to monitor changes in SMA resistance, and the data acquisition system was implemented with several improvements.
 - **Milestone 2-** Data Analysis and Noise Reduction: Numerous experiments were conducted using the INA260 sensor to collect data. MATLAB's linear and nonlinear regression methods were applied to capture the relationship between inputs and outputs. Although partial polynomial equations were developed for each phase, generalization was not achieved due to inconsistent test results. Noise reduction techniques, such as filtering and signal shifting, were applied to improve data quality.
 - **Milestone 3-** Enhancements to Data Collection Circuit: Modifications were made to the electronic circuit to increase the sampling rate, yielding cleaner and more comprehensible data. The system was enhanced to read 77-79

samples per second for voltage, current, and force measurements.

- **Milestone 4-** Modeling with Neural Networks: Neural network models, including MATLAB's fitting app and NARX models, were used to explore the complex relationships between inputs and outputs. Different neural network structures were tested to improve performance.
- **Milestone 5-** Exploration of RNN Models: Recurrent Neural Networks (RNNs) were employed for both forward and inverse modeling. Improved results were achieved by shifting the input and output data, creating time-shifted versions for better modeling accuracy.
- **Milestone 6-** Evaluation of Results and Feedback Loops: The RNN models were optimized in both directions, and their performance was evaluated. These models were tested in real-time systems and refined based on feedback from experimental results.

1.3 Research Strategy and Methodological Process

Traditional control methods often struggle due to the inherent complexities of SMA behavior, including non-linear relationships between applied voltage/current and force, hysteresis effects, and sensitivity to temperature variations [2, 20, 21]. Additionally, precise real-time measurement of small amounts of change in voltage, current, and force remains a challenge, particularly at low voltages and under varying environmental conditions [22].

Most existing studies primarily focus on characterizing SMA behavior and offering methods in controlled laboratory environments [21–25]. These systems typically involve measuring various parameters and establishing relationships under specific conditions. Furthermore, they often need complex setups with numerous devices and components to maintain these controlled environments and gather data [21, 23]. Since temperature is the primary control factor for SMAs as thermal actuators, existing systems typically allow for gradual temperature increases or decreases to characterize the

material. The speed of the data acquisition in these systems is not fast enough due to slow temperature response, therefore limiting real-time utilization. A more practical approach is required that does not depend on temperature measurement but measures voltage, current, or resistance that affect the temperature change.

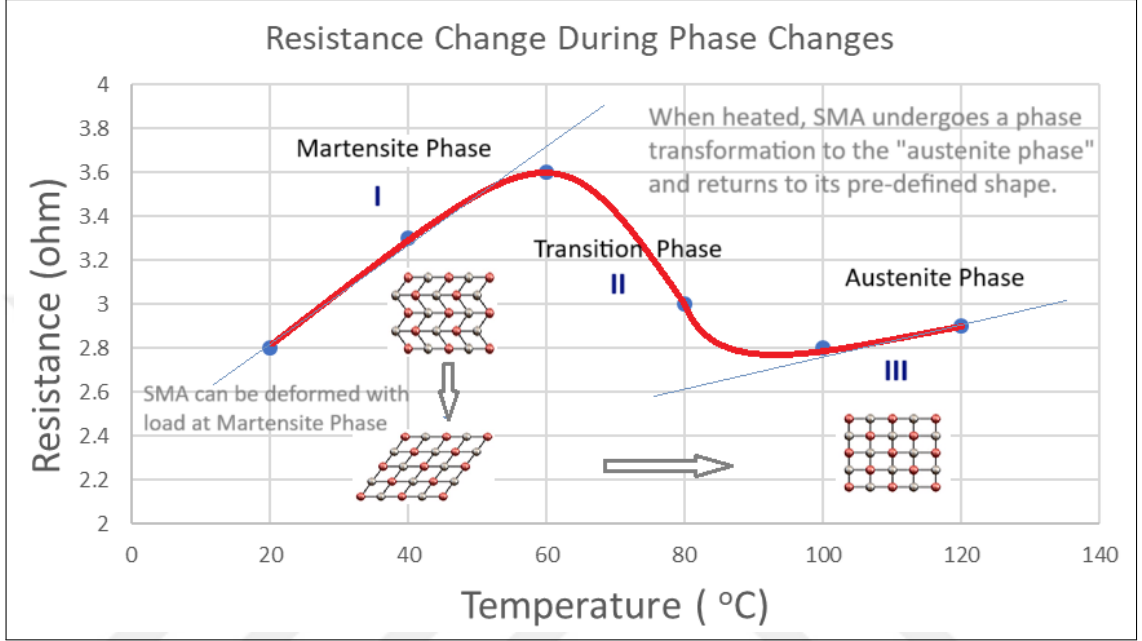


Figure 1.1 Resistance change during martensite to austenite phases. SMA resistance changes due to temperature with different behavior for each phase; martensite (I), transition (II), and austenite (III) phases [1,2].

SMA's undergo phase changes driven by temperature and stress changes. Furthermore, stress shifts the phase transition points; however, temperature is the primary cause of these phase changes. These phase changes, caused by shifts in material structure, also lead to changes in electrical resistance. By monitoring the resistance and temperature precisely, it is possible to determine which phase the SMA is in and to estimate how long it has been stimulated for a given voltage (Figure 1.1). Therefore, theoretically, a relation between the resulting resistance, temperature, and force could be established [1, 2, 21, 22, 24, 25]. A more detailed explanation of SMA behavior as an actuator is presented in the Background (Chapter 2). This makes the real-time measurement of SMA parameters, particularly temperature and resistance, crucial for an effective control. However, traditional temperature sensors frequently lack the necessary speed and accuracy to meet these demands. In addition, precise measurement of continuously changing resistance is not possible with a practical setup, especially at

low signal levels. To overcome these difficulties, we propose an indirect approach for estimating force from applied voltage and resulting current. This is possible because temperature is the result of the power consumed as a result of the applied voltage on the SMA resistance, and the resistance is related to the applied voltage and resulting current. However, this is a complex relation. Hysteresis effects, temperature dependence, and environmental factors contribute to non-linearities that make it difficult to model the relationship between input parameters (voltage, current) and desired output (force). Furthermore, material fatigue can cause changes in the SMA's behavior over time, necessitating adaptive strategies. Advanced control methods based on Neural Networks (NNs) offer a promising approach to address these challenges. Recurrent Neural Networks (RNNs) is particularly well-suited for this application due to its ability to capture temporal dependencies. This study aims to identify a control scheme by employing inverse and forward RNN models to predict the force-voltage relations of an SMA actuator. A practical data collection setup is designed as explained in Methods.

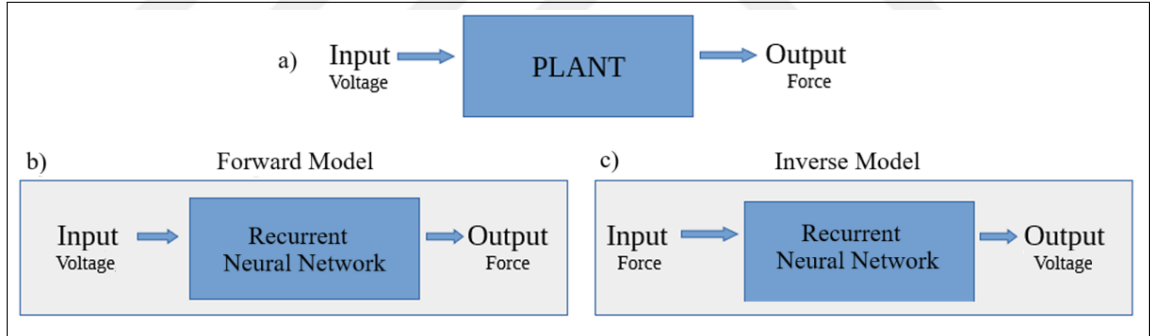


Figure 1.2 This figure illustrates the plant (set-up) (a), forward model (b), and inverse model (c) using LRNNs for force control of SMA. An LRNN is trained as the forward model to predict the generated force for a given voltage input to the system. For inverse control, another LRNN is trained as the inverse model by reversing the input and output to predict the voltage required to achieve a desired force from the system.

In this paper, the properties and applications of SMAs are discussed in the Background (Chapter 2), along with a review of previous studies in the literature. In the Method (Chapter 3), the preliminary studies and exploratory approaches undertaken to identify a suitable methodology are first discussed. This is followed by a more detailed description of the data acquisition scheme. The RNN structures for forward and inverse models are explained. A number of test scenarios are prepared for the

assessment of force control accuracy. After achieving satisfactory levels of accuracy, repeatability, we could illustrate that RNNs are capable of learning the relation between voltage and the force, as discussed in the Results (Chapter 4). The proposed approach is presented as a viable solution to utilize SMA as an actuator where precise control is required.

1.3.1 Overview of Research and Method Steps

- Literature Review and State-of-the-Art Analysis: A thorough review of existing research on SMA actuators, alternative technologies, and control methods.
- SMA Material Selection and Design Considerations: Ni-Ti-based SMA springs were selected for their specific properties.
- Experimental Setup and Real-Time Data Acquisition: A real-time data acquisition system was developed to gather the necessary data for modeling SMA actuators.
- Neural Network Modeling and Control Strategy: Layer Recurrent Neural Networks (LRNNs) were used for forward and inverse modeling to predict and control actuator behavior.
- Simulation and Validation: MATLAB simulations validated the control models and their application to SMA actuators.
- Integration with Real-World Applications: The system was designed for seamless integration into biomedical devices, particularly prosthetic hands.

1.4 Summary

The mechanical design of the finger and hand in this study was crafted with close attention to anatomical features. Each phalanx was optimized with tunnels and connection points for tendons to enhance efficient motion capabilities. The prototypes,

produced using 3D printing with ABS plastic, were tested in a mechanical simulation environment to validate their effectiveness.

During the design process, extensive experiments with Shape Memory Alloy (SMA) actuators were conducted to refine control methods. Techniques like Pulse Width Modulation (PWM) were utilized to reduce energy consumption and enhance the performance of the actuators. A variety of test scenarios were implemented, and data related to the actuator's performance were gathered. In particular, the changes in electrical resistance, when evaluated together with the applied voltage, provided insight into the force generated by the SMA actuators. However, noise and unwanted signals in the data initially made it difficult to establish a clear relationship between resistance and force. To address this, indirect measurement methods were adopted to improve accuracy.

The study presents a practical and efficient approach to model and control SMA spring actuators, relying heavily on monitoring electrical resistance as a key indicator of the material's phase transitions. The dynamic behavior of SMA, driven by temperature changes, was captured by monitoring these resistance shifts, which corresponded to phase transitions between martensite and austenite. Ni-Ti-based SMA springs were selected due to their well-documented shape memory properties and controllable transition temperature (45°C). This monitoring allowed for the precise characterization of the SMA's operational range, preventing overheating and preserving the actuator's longevity.

The simplicity of the electronic circuit used for driving the SMA actuator was a crucial aspect of this method, ensuring that the system could be practically applied in real-time environments. The design relied on a current sense amplifier to measure voltage and current, combined with a force sensor to measure the force generated by the actuator. All components were controlled by a CC3200 microcontroller, which interfaced with a mobile application for real-time data acquisition and visualization.

Data collected from the system, including voltage, current, and force measurements, were processed and analyzed using MATLAB to establish a detailed model of the SMA actuator's behavior. This model was critical for training two-layer recurrent Neural Networks (LRNNs), which were used to predict the relationship between input (voltage and current) and output (generated force). The LRNN structure was selected because of its ability to handle time-dependent, non-linear data, a characteristic inherent to SMA actuators.

Two models were developed:

- (i) **Forward Model:** Predicts the force output based on the applied voltage and current.
- (ii) **Inverse Model:** Determines the required voltage to generate a specific force.

The combination of these models allowed for precise control of the SMA actuator in real time, overcoming the challenges posed by the hysteresis and nonlinear behavior of SMA materials. By applying this method, the study successfully achieved accurate force control using SMA actuators, showcasing its potential for practical applications, including biomedical devices such as prosthetics.

To support the thesis approach, a comprehensive experimental and methodological framework was developed, focusing on both theoretical and practical aspects of controlling Shape Memory Alloy (SMA) actuators. This framework is divided into three key areas: **Background**, **Method**, and **Results and Conclusion**.

The **Background** chapter lays the foundation by exploring the anatomy of the human hand, the current state of prosthetic devices, and various actuator technologies, with an emphasis on SMAs. A Literature Review and State-of-the-Art Analysis were conducted to identify gaps in the field. The review examined alternative technologies like pneumatic actuators, motors, and electroactive polymers, highlighting their limitations in biomedical applications. It was concluded that SMAs offer unique advantages,

such as a high force-to-weight ratio and compactness, which make them particularly suited for prosthetic hands. However, the challenges of controlling SMAs due to non-linearity, hysteresis, and phase transitions were also noted, setting the stage for the work presented in this thesis.

The **Method** chapter details the experimental design and approach, starting with hand and finger design, the integration of actuators, and the system's electronic and mechatronic design. It also explains data collection techniques, preprocessing methods, and the control algorithms developed for SMA actuators. This chapter explains how the neural networks and control strategies were developed and tested.

This section details the experimental design, starting with the selection of SMA Material. Ni-Ti-based SMA springs were chosen for their favorable phase transition temperature (45°C), allowing efficient, real-time actuator control near ambient conditions. This choice aligned to create a practical, energy-efficient actuator system.

An Experimental Setup and Real-Time Data Acquisition system were developed, integrating voltage, current, and force sensors to capture high-resolution data during the actuator's operation. The integration of actuators and the system's electronic and mechatronic design. It also explains data collection techniques, preprocessing methods, and the control algorithms developed for SMA actuators. These measurements were crucial for modeling SMA behavior and creating control strategies.

Neural Network Modeling and Control Strategy: Layer Recurrent Neural Networks (LRNNs) were employed for both forward and inverse modeling to predict and control actuator behavior.

The Forward Model, which predicts the force output based on the input voltage, **The Inverse Model**, which calculates the necessary voltage to produce a specific force. Both models were extensively trained and tested to enhance force prediction and control. MATLAB was chosen as the development environment for these simulations.

In the Inverse Model - Forward Model Connection, simulations were conducted in MATLAB Simulink, where LRNN models created a system allowing for desired force inputs. The inverse model calculates the estimated voltage and current necessary to achieve the desired force. These values are then fed into the forward model to produce an estimated force. Comparing the desired force ($F_{desired}$) with the estimated force ($F_{estimated}$) allows for an evaluation of the accuracy and performance of the control strategy.

This simulation approach provides a robust method for testing and refining control strategies before physical implementation on the SMA actuator system, ensuring reliable and accurate force output.

The **Results** section presents the outcomes of the methodology, particularly the success in Force Prediction and Control Optimization. Continuous monitoring of real-time voltage, current, force, and resistance changes allowed for precise control, preventing issues such as overheating and material fatigue. The LRNN models proved effective in predicting the voltage required for the desired force output, optimizing control precision.

Through Simulation and Validation in MATLAB, the control models were thoroughly tested, confirming the validity of the approach. The simulations demonstrated that the control strategies could be successfully applied in real-world applications, such as prosthetic devices.

Finally, the Integration with Real-World Applications section highlights how the system was designed for practical use. The simplicity of the circuit design and mobile app interface facilitates easy implementation in biomedical devices such as prosthetic hands, reinforcing the thesis's contribution to advancing SMA actuator control for prosthetic applications.

2. BACKGROUND

2.1 Inspiration: Hand Anatomy

This section delves into the detailed anatomy of the human hand, exploring its intricate structure, muscle functions, and range of motion. Replicating the natural dexterity of the human hand in a prosthesis is a significant challenge due to its complex system of multiple degrees of freedom (DOF), which enables precise and diverse movements. The difficulty in designing a prosthetic hand that mimics such versatility stems from the need to accurately reproduce the coordinated movements of bones, muscles, tendons, and joints. To achieve the closest possible dexterous capabilities in a prosthesis, it is essential to imitate the structure of a real hand, including all its joints, muscles, and tendon connections. The human hand comprises bones, muscles, tendons, ligaments, and their interconnected joints, alongside tactile sensory systems, nerves, and blood vessels. Among these, the bones, muscles, tendons, ligaments, and joints form the primary mechanical framework responsible for motion and function.

To better understand the anatomy of the hand, one must first examine how grip tasks and movements are performed. The hand comprises 27 distinct bones (Figure 2.1) the phalanges (finger bones), metacarpals (palm bones), and carpals (wrist bones). Eight small carpal bones, collectively called the carpus, articulate with the ulna and radius at the wrist on their proximal end, and with the five metacarpal bones on their distal surface [13, 26]. These metacarpal bones extend from the carpus to each digit of the hand. The distal heads of the metacarpals are rounded, forming condyloid joints with the phalanges. There are 14 phalanges making up the fingers: each finger has three phalanges (proximal, middle, and distal), while the thumb has two. These phalanges are long and form hinge joints with each other. The Metacarpophalangeal (MCP) joints connect the fingers to the palm, while the Proximal Interphalangeal (PIP) joints and Distal Interphalangeal (DIP) joints are the main finger joints. Ligaments connect bones, keeping them together, constraining their movements, and also forming

tunnel-like arrangements to hold tendons in place on the bones.

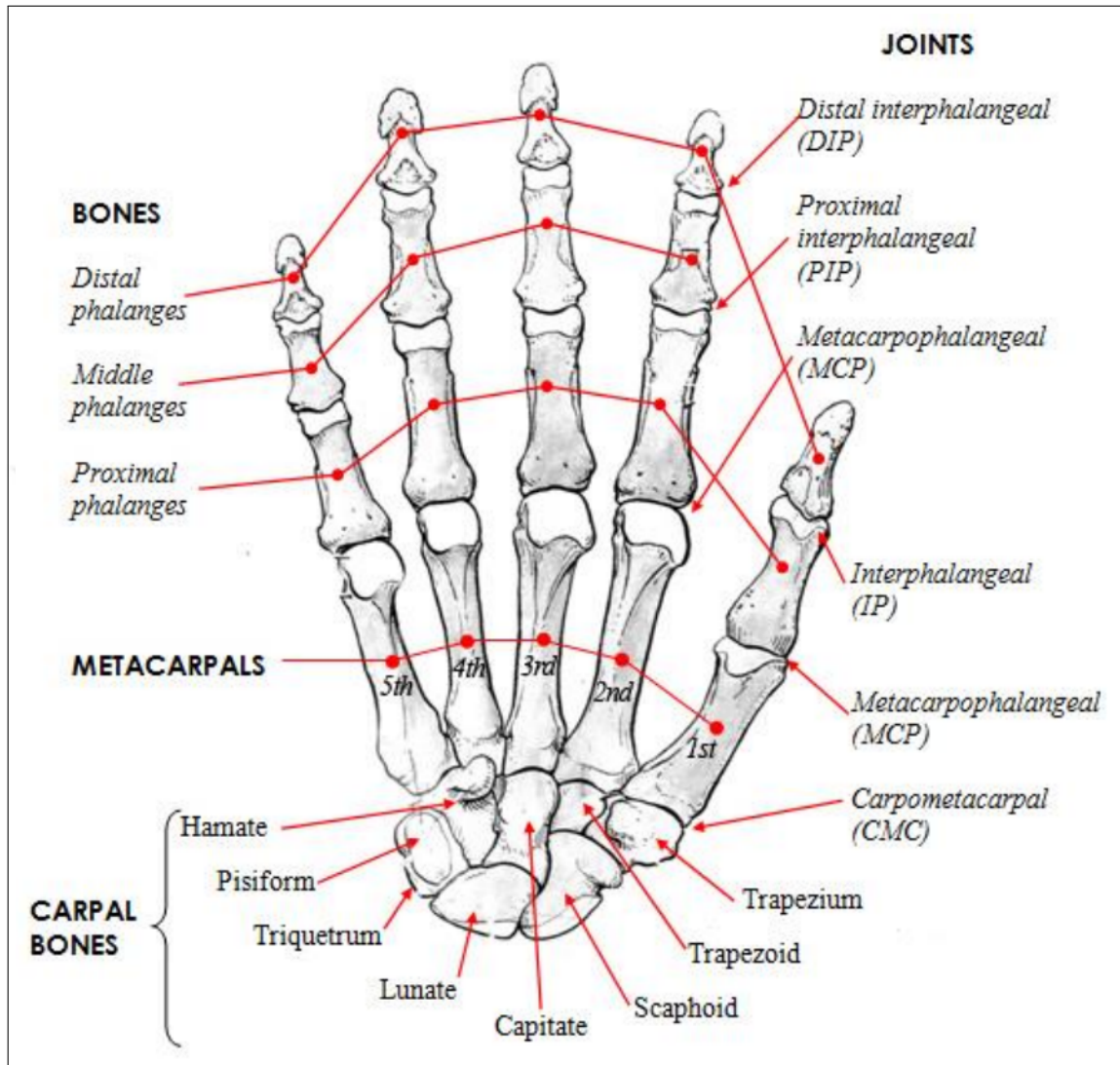


Figure 2.1 Bones and Joints of a Human Hand [3].

Muscles are the actuators that generate active movement at the joints in the hand and, consequently, the fingers. Motion in a finger joint arises from the contractions of antagonistic muscle pairs—the flexor and extensor muscles. These muscles are connected to the bones via tendons, which transmit force to the solid segments. The tendon system incorporates pulleys and a synovial sheath that forms a tunnel-like structure [13, 14, 26]. This structure serves multiple crucial functions: i) holding the tendon close to the joints and phalanges, ii) protecting the tendon from friction, iii) preventing bow-stringing, and iv) providing a biomechanically efficient fulcrum for flexion and extension of the finger [5] (Figure 3.15). A finger joint's motion is thus a result of coordinated flexor and extensor muscle contractions; when flexors contract,

extensors relax, and vice versa. This antagonistic pairing controls motion, enables slowing it down, fine-tuning it, and returning the joint to its initial position.

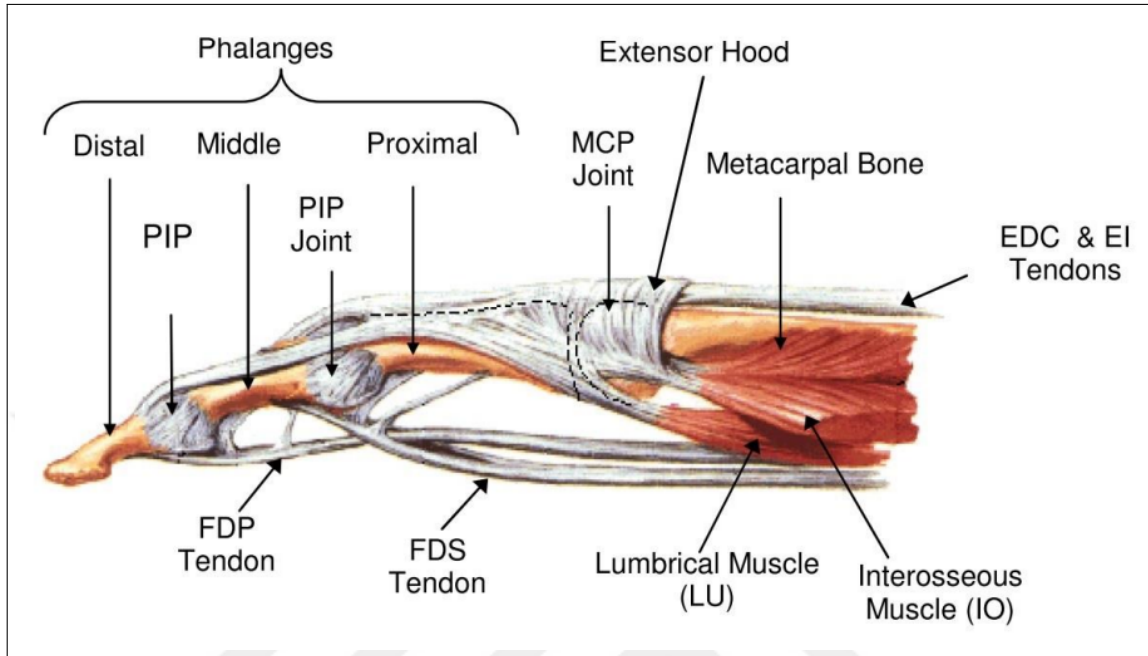


Figure 2.2 Anatomy of Human Index Finger [4].

Tendons, as fibrous cords at the end of muscles, attach muscles to the radius, ulna, carpals, metacarpals, and phalanges. These precise connection points (Figure 2.4) are vital for generating efficient force at the desired level with optimum articulations. Human finger movements can be broadly classified into four directions: flexion (bending), extension (straightening), abduction (moving sideways away from the body's midline), and adduction (moving sideways towards the body's midline). The PIP and DIP joints are one Degree of Freedom (DOF) revolute joints, primarily capable of extension and flexion. In contrast, the MCP joint possesses two DOFs, allowing for movement in all four directions.

For powerful actions like heavy lifting, the movement of the phalanges of the index finger is primarily controlled by extrinsic muscles, which are located in the forearm (Figure 2.5). Their long tendons extend into the hand and fingers, acting on the phalanges to enable gripping or lifting. These muscles are mainly responsible for gross motor skills like flexion and extension. Examples include the Flexor Digitorum Superficialis (FDS), which flexes the MCP and PIP joints; the Flexor Digitorum Pro-

fundus (FDP), involved in flexing the MCP, PIP, and DIP joints; the Palmaris Longus (PL), assisting in wrist flexion and grip strength; and the Extensor Digitorum (ED), primarily extending the MCP and PIP joints.

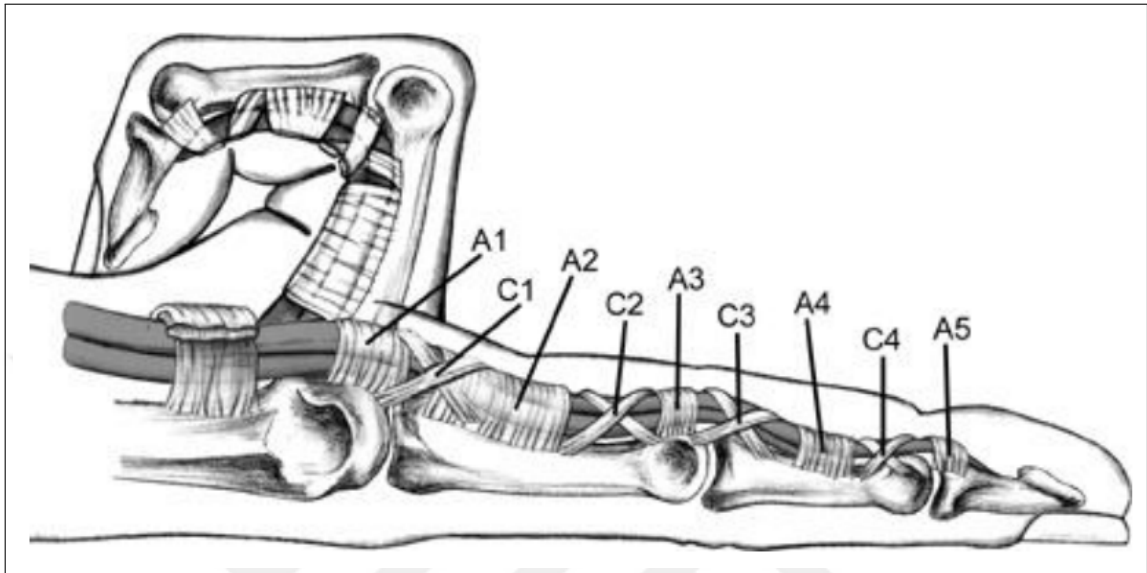


Figure 2.3 Pulleys of a Finger [5].

Conversely, intrinsic muscles are located entirely within the hand, mainly in the palm region (Figure 2.5). They play a crucial role in fine motor control, enabling precise movements such as pinching, holding small objects, and coordinating intricate finger motions. These muscles facilitate finer adjustments of finger positions, including abduction, adduction, and other complex manipulations. Examples include the Palmar Interossei, responsible for adducting the fingers; the Adductor Pollicis, which helps adduct the thumb; the Dorsal Interossei, which abduct the fingers; and the Lumbricals, which flex the MCP joints while extending the PIP and DIP joints [5,27].

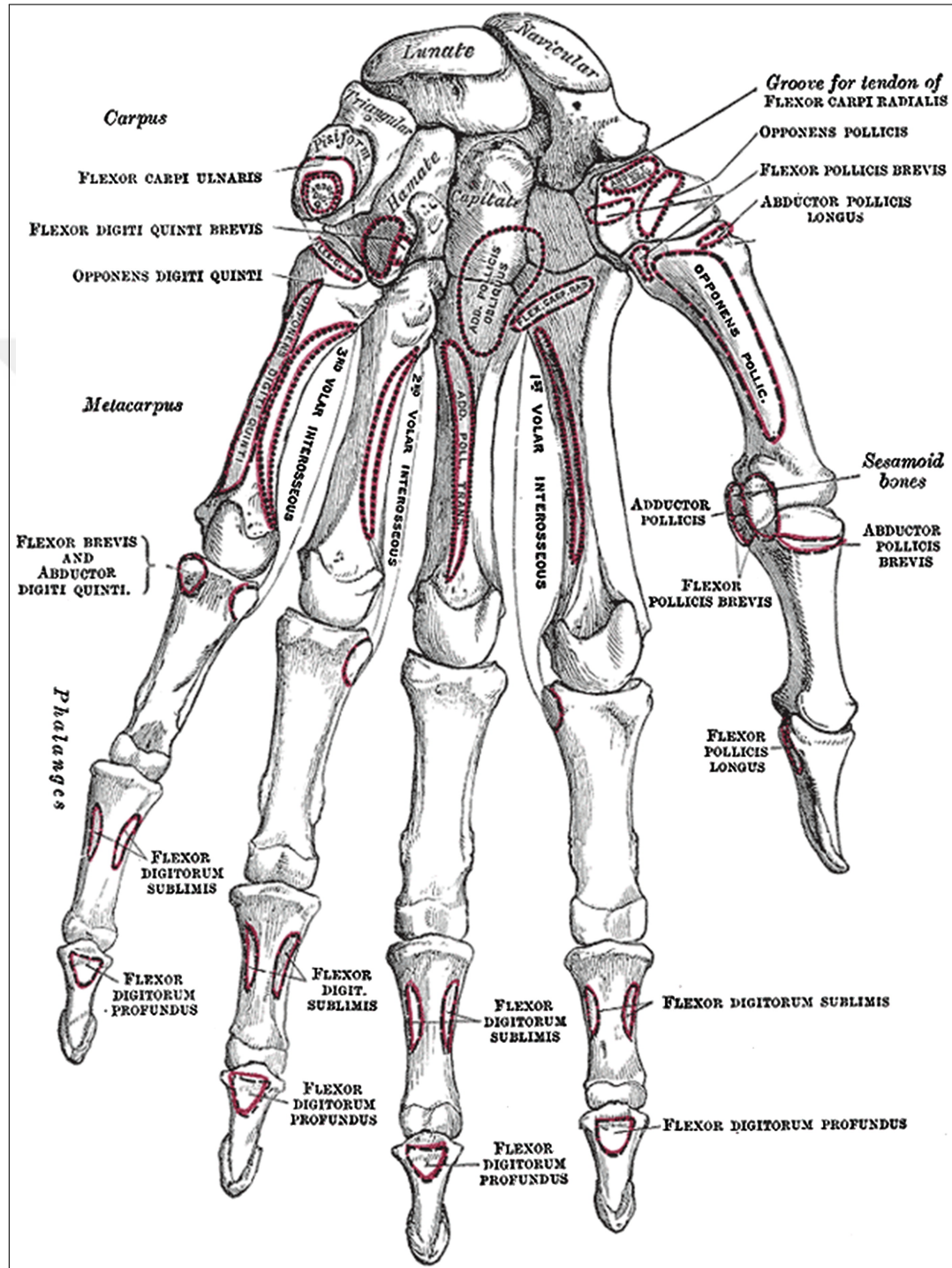


Figure 2.4 Tendon Attachment Points [6].

The intricate interplay of these muscles allows for the diverse functionality of the hand. The FDS and FDP muscles are critical for finger flexion: FDP spans all three main finger joints (MCP, PIP, and DIP), enabling flexion at each, while FDS primarily controls flexion at the MCP and PIP joints. Extensor muscles like the Extensor Digitorum predominantly generate extension at the MCP and PIP joints. However, full extension of the DIP joint is largely facilitated by the intrinsic muscles, particularly the lumbricals and interossei. It is important to note that while extrinsic muscles handle extension at the MCP joints and flexion of the IP joints, achieving isolated movement (e.g., flexing the DIP while leaving the PIP extended) is challenging due to the interconnected nature of the joints and ligaments. When the DIP joint flexes, it exerts a pulling effect on these ligaments, often resulting in the flexion of the PIP joint.

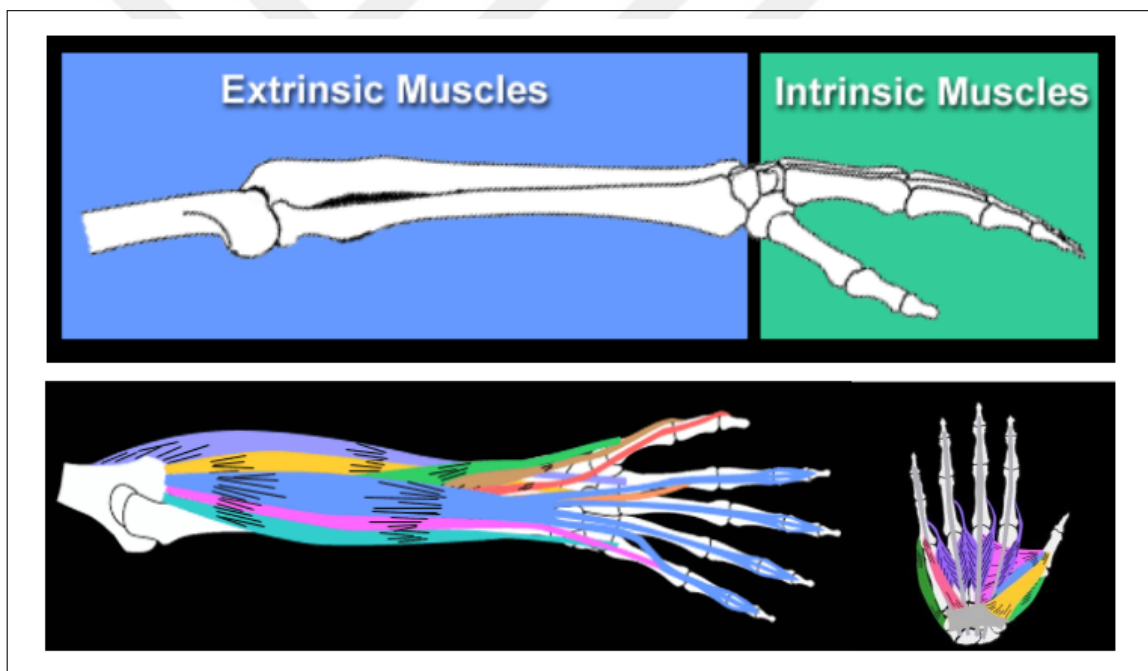


Figure 2.5 Extrinsic and intrinsic muscles are responsible for finger motion [7].

Muscle Structure and Contraction Types:

Muscles are soft tissues capable of contraction or relaxation to move an organ or a part of the body. Muscle cells contain protein filaments of actin and myosin that slide past one another, creating a contraction that changes the cell's length and shape. Muscles function to produce force and motion. A muscle fiber generates tension when properly stimulated by the nervous system or electrical impulses, a physiological

process known as muscle contraction. While under tension, the muscle may lengthen, shorten, or remain the same length, leading to different types of contractions. These include;

- Concentric Contraction, where the muscle develops sufficient tension to overcome resistance and shorten (e.g., the brachialis bringing a glass to the mouth),
- Eccentric Contraction, where the muscle develops tension less than the opposing force, causing it to lengthen (e.g., lowering a weight); and
- Isometric contraction, where the muscle develops tension equal to the opposing force, with no change in length or body part movement (e.g., holding a weight steady).

Figure 2.6 illustrates the sarcomere, the basic contractile unit of muscle cells, which consists of repeating sections of thin (actin) and thick (myosin) filaments that slide past each other during contraction and relaxation. Myofibrils, long chains of sarcomeres, make up muscle cells.

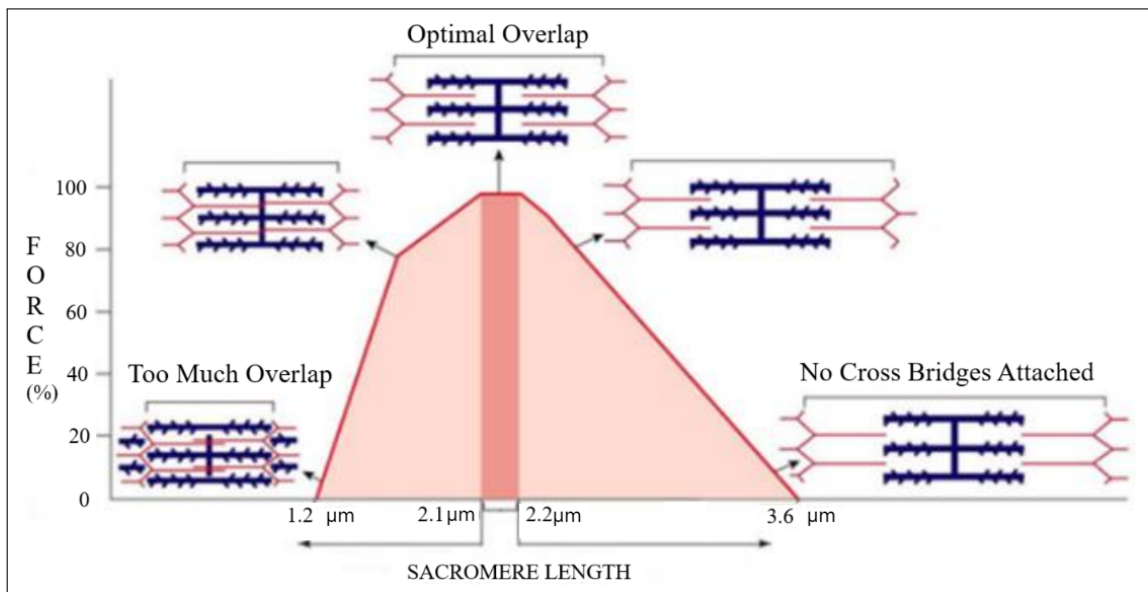


Figure 2.6 Sarcomere and Its Length-Tension Relationship [8].

Studying the anatomy of the hand, including muscle types, contraction mechanisms, and motor units, is crucial for designing biomimetic actuators capable of per-

forming desired functions. Classifying muscles as either extrinsic or intrinsic allows for strategic placement of actuators based on their functional requirements, such as force generation or fine motor control. While Shape Memory Alloy (SMA) wires contract by up to 8%, their use in spring form enables them to shorten to their full length, effectively mimicking human muscle behavior. This insight aids in designing actuators in series or parallel configurations to replicate the necessary force or precision required by different muscles. Additionally, understanding muscle contraction types helps inform control strategies for tasks such as holding an object in place or executing complex movements, allowing actuators to simulate both static and dynamic hand functions.



Figure 2.7 Flexor Muscles of fingers (Flexor digitorum superficialis, flexor digitorum profundus) [7].

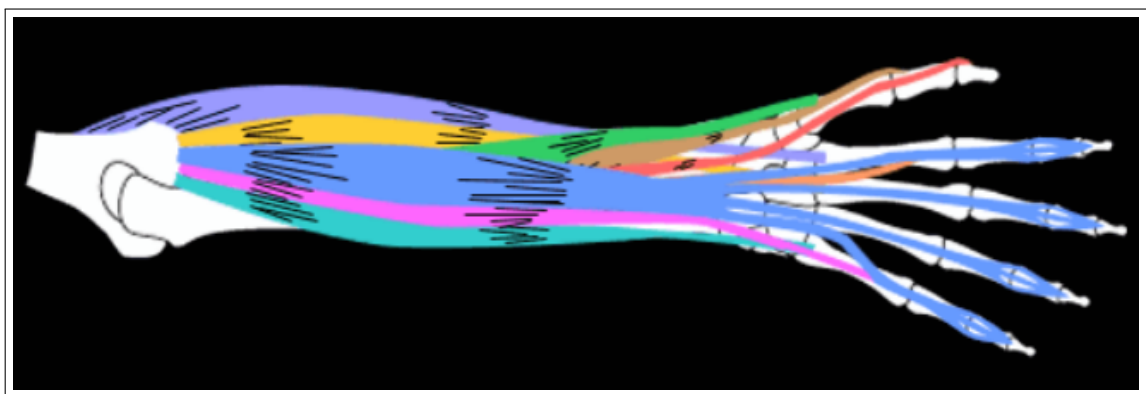


Figure 2.8 Extensor Muscles of fingers (Extensor indicis, extensor digiti minimi, extensor digitorum communis, extensor pollicis brevis, extensor pollicis longus) [7].

In any hand action, the agonist muscle group causes movement through its contraction, providing the primary force. In contrast, the antagonist muscle of this pair opposes the agonist group. Antagonistic pairs are named dynamically with the direc-

tion of movement. If the muscle causes a motion in the same direction of contraction, it is named the agonist; if the muscle opposes this agonist muscle, it controls the motion and is named the antagonist. The human finger movements can be classified in four directions: flexion, extension, abduction (moving sideways away from the body), and adduction (moving sideways towards the body). The primary muscles involved in these movements are broadly categorized as flexors (e.g., Flexor carpi radialis, Palmaris longus, Flexor digitorum superficialis, Flexor digitorum profundus, Lumbricals), extensors (e.g., Abductor pollicis longus, Extensor carpi radialis longus, Extensor digiti minimi, Extensor digitorum communis), abductors (e.g., Flexor carpi radialis for wrist abduction, Abductor digiti minimi, Dorsal interossei, Abductor pollicis longus, Abductor pollicis brevis), and adductors (e.g., Flexor carpi ulnaris for wrist adduction, Palmar interossei, Adductor pollicis). These muscle groups work in concert to provide the hand's remarkable dexterity.

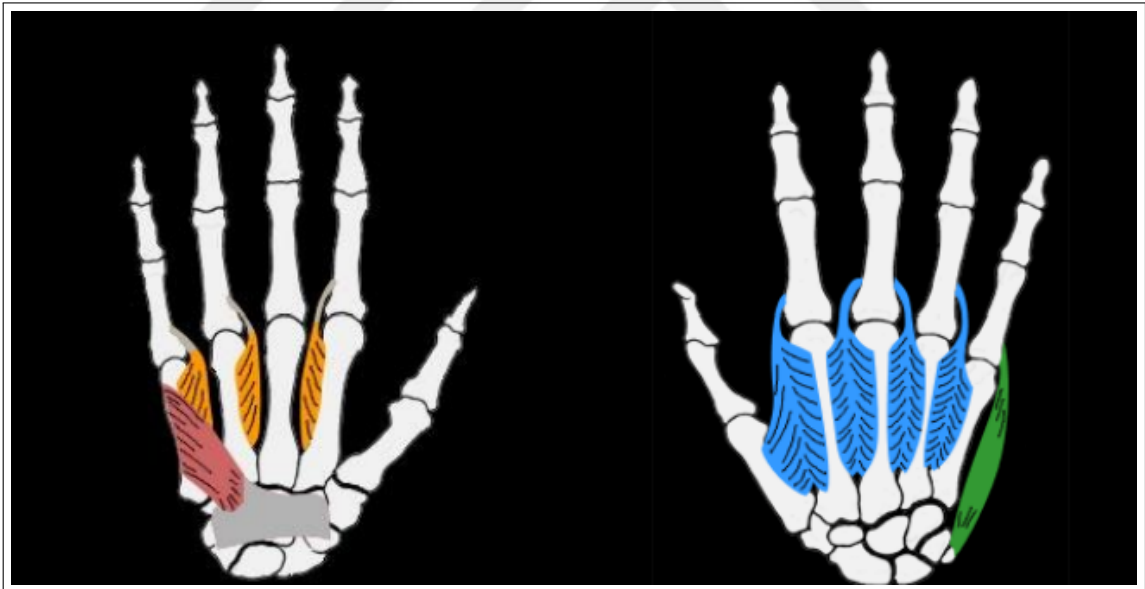


Figure 2.9 Adductors (Palmar interossei, Adductor pollicis) and Abductors of fingers (dorsal interossei, abductor digiti minimi) [7].

The flexor and extensor muscles responsible for finger motion are divided into two main groups:

- Extrinsic Muscles:
 - Flexor Digitorum Superficialis (FDS): Responsible for flexing the MCP (Metacar-

pophalangeal) and PIP (Proximal Interphalangeal) joints.

- Flexor Digitorum Profundus (FDP): Involved in flexing the MCP, PIP, and DIP (Distal Interphalangeal) joints.
- Palmaris Longus (PL): Assists in wrist flexion and supports grip strength.
- Extensor Digitorum (ED): Primarily extends the MCP and PIP joints.

- Intrinsic Muscles:

- Palmar Interossei: Responsible for adducting the fingers (bringing them towards the middle finger).
- Adductor Pollicis: Helps adduct the thumb.
- Dorsal Interossei: Abduct the fingers (move them away from the middle finger).
- Lumbricals: Flex the MCP joints and extend the PIP and DIP joints.

The Flexor Digitorum Superficialis (FDS) and Flexor Digitorum Profundus (FDP) muscles play a central role in finger flexion. While the FDP spans the metacarpophalangeal (MCP), proximal interphalangeal (PIP), and distal interphalangeal (DIP) joints, thereby enabling flexion at all three levels, the FDS is limited to the MCP and PIP joints, providing flexion specifically at these segments. In contrast, extensor muscles such as the Extensor Digitorum are primarily responsible for extension at the MCP and PIP joints. Full extension of the DIP joint, however, is not achieved by the extrinsic extensors alone; rather, it is facilitated by intrinsic muscles, particularly the lumbricals and interossei. Although extrinsic muscles manage extension at the MCP and flexion of the interphalangeal (IP) joints, achieving isolated joint movement remains challenging due to the interconnected anatomical structure of joints and ligaments. For example, attempting to flex the DIP joint in isolation typically results in a pulling effect on the associated ligaments, which in turn induces flexion in the PIP joint as well.

Table 2.1
Flexor, extensor, abductor, and adductor muscles of a hand.

Flexors of the hand	Extensors of the hand	Abductors of the hand	Adductors of the hand
Flexor carpi radialis	Abductor pollicis longus	Flexor carpi radialis (Abductor of wrist)	Flexor carpi ulnaris (Adductor of the wrist)
Palmaris longus	Extensor carpi radialis longus	Extensor carpi radialis longus (Abductor of the wrist)	Extensor carpi ulnaris (Adductor of the wrist)
Flexor carpi ulnaris	Extensor pollicis longus	Extensor carpi radialis brevis (Abductor of the wrist)	Palmar interossei:
Flexor digitorum superficialis	Extensor indicis	Abductor digiti minimi	Adductor pollicis:
Flexor digitorum profundus	Extensor digiti minimi	Dorsal interossei	
Flexor pollicis longus	Extensor carpi ulnaris	Abductor pollicis longus	
Lumbricals	Extensor pollicis brevis	Abductor pollicis brevis	
	Extensor carpi radialis brevis		
	Extensor digitorum communis		

2.2 Upper Limb Prosthetics

An overview of upper limb prosthetics is provided in this section, focusing on the evolution of prosthetic devices, the variety of designs available, and the common mechanisms used to replicate hand function. A prosthesis is a device designed to restore, as much as possible, the function or appearance of a missing limb or body part. Worldwide, many individuals are born without arms, hands, or legs due to congenital defects, while others lose their extremities in traffic accidents, terrorist attacks, or industrial accidents.

2.2.1 History and Evolution of Prosthetics

The development of prosthetics has spanned centuries, with one of the earliest known artificial limbs—a bronze and iron leg with a wooden core—being discovered in Capua, Italy, around 300 B.C. This prosthesis, designed for a below-knee amputee, marked an early step in the history of limb replacement. During the Dark Ages (476-1000 AD), prosthetic advancements were minimal, primarily focusing on concealing deformities rather than restoring functionality. However, the Renaissance (1400s-1800s) brought about significant progress in art, medicine, and engineering, leading to the construction of prosthetic limbs made from materials like iron, steel, copper, and wood.

The 19th century, particularly during the American Civil War (1861–1865), saw prosthetics gain greater prominence, as over 30,000 amputations were performed on the Union side alone. Prosthetic limbs, often made with wooden sockets, still closely resembled earlier designs. This remained the case until World War II (1939–1945), when significant advancements were made with the introduction of lighter materials such as plastics and aluminum. These new materials, coupled with improved mechanical joints, resulted in prosthetics that were both more comfortable and functional. Mechanical arms with hook mechanisms were also developed, allowing amputees to open and close the hook through shoulder movement.

During the Vietnam War in the 1960s and 1970s, a new wave of amputees spurred further innovation. By this time, electronic control systems for prosthetic limbs had been introduced. The field continued to progress with the development of control systems using Electroencephalography (EEG), Electromyography (EMG), and Electroneurography (ENG) signals. Postwar research, significantly supported by the U.S. Veteran's Administration, furthered these advancements. In 2008, the Defense Advanced Research Projects Agency (DARPA) launched the "Revolutionizing Prosthetics Program," which focused on creating prosthetic devices that closely mimicked upper-extremity functionality [28, 29]. This initiative led to the development of cutting-edge devices such as the LUKE Arm by DEKA and the Modular Prosthetic Limb (MPL) by Johns Hopkins University, both of which incorporated motor and sensory neuron

control for more intuitive, natural movement [30].

Despite these advancements, many prosthetic users still express dissatisfaction with their devices. Common issues include excessive weight, unnatural movements during tasks like gripping, and noise during operation. Surveys reveal that about 71.43% of users cite functional limitations, while 23% are dissatisfied with the weight of their prosthetics. Moreover, 30-50% of upper extremity amputees ultimately opt not to use prosthetics, underscoring the need for continued innovation.

Recent advances in materials science are helping address some of these challenges. Composite materials, such as carbon fiber-reinforced plastics, are increasingly used in prosthetic design for their strength, durability, and lighter weight compared to traditional materials. Silicon-based compounds have also improved prosthetic comfort and made them more realistic in appearance. Modern prosthetics can now be custom-molded to closely resemble the user's remaining limb and be adjusted over time as their body changes. The ultimate goal of modern prosthetic design is to create devices that actively mimic the functionality of human muscles. This objective has driven research towards integrating prosthetics with control signals such as EEG, EMG, and ENG, allowing for more natural movement using artificial muscles.

2.2.2 State-of-the-Art and Popular Examples

Throughout history, various solutions have been sought to address the need for prostheses, with different designs developed according to the available technology of the time. Over the years, as technology has advanced, prostheses have evolved into more complex structures with enhanced capabilities. Early mechanical solutions were developed using different materials to either restore the appearance and functionality of a lost limb or serve purely cosmetic purposes. As technology progressed, mechanical-electronic systems brought superior capabilities compared to earlier prostheses.

The human arm has seven degrees of freedom (DOF) from the shoulder to the

wrist, while the human hand has 21 DOF (24 DOF with wrist), allowing for intricate finger movements. Designing a prosthetic hand with such complex functionality is a significant goal for those who have lost their limbs.

Advanced prosthetic hands, designed to mimic human anatomy closely, are currently the focus of many technological endeavors. The most sophisticated hands are often developed in academic settings under special conditions, demonstrating advanced functionality. However, controlling these complex structures requires equally complex control systems, making them expensive solutions and not yet economically viable for widespread commercial use.

Among commercially available products, there are advanced prosthetic hands designed to replicate natural hand functions and more affordable, accessible myoelectric prosthetic hands. While offering sophisticated control and a range of grip patterns, devices like the Otto Bock Michelangelo or Touch Bionics iLimb come with significant drawbacks, including high cost, frequent maintenance, limited battery life, and considerable weight. More affordable myoelectric prosthetics, while simpler, still face challenges with unreliable muscle signal control, regular battery charging, and potential delays or inaccuracies in movement.

Despite these functional advantages, many individuals still opt for simpler passive or cosmetic prostheses due to minimal maintenance, absence of battery management, and reduced weight for comfort. Furthermore, the actuators used in these popular prosthetic examples—whether electric motors or pneumatic systems—are fundamentally different from the way our muscles work. These mechanical actuators, while capable of mimicking some basic functions, are far from replicating the fluid, natural movement of human muscles. This leads to a limitation in the naturalness of movement, reducing the overall dexterity and range of motion. This disparity highlights the ongoing need for alternative actuation solutions.

2.2.3 Types of Upper Limb Prostheses

Prostheses range from mostly passive or cosmetic types on one end to primarily functional types on the other, with the purpose of most prostheses falling somewhere in the middle. Cosmetic prostheses can look extremely natural, but they often are more difficult to keep clean, can be expensive, and usually sacrifice some function for increased cosmetic appearance.

Prostheses can be divided into several types: passive/cosmetic prosthesis, body-powered prosthesis, electrically powered prosthesis, and hybrid prosthesis. A body-powered prosthesis is powered and controlled by gross body movements. These movements, usually of the shoulder, upper arm, or chest are captured by a harness system and used to pull a cable that is connected to a TD (hook or hand). For some levels of amputation or deficiency, an elbow system can be added to provide additional motion [31,32] For a patient to control a body-powered prosthesis, the individual must be capable of producing at least one or more gross body movement.

Electrically powered prostheses use electric motors that provide more proximal function and greater grip strength, along with improved cosmetics, but they can be heavy and expensive. Patient-controlled batteries and motors are used to operate these prostheses. Currently, available designs generally have less sensory feedback and require more maintenance than body-powered prostheses. The two types of commonly available control systems are myoelectric and switch control [33,34].

These devices are controlled by the amputee through myo-electric interfaces or neuro interfaces. The human-driven signals are collected by the electrodes. For Myo-electric signals, electrodes are placed on the muscle surfaces, and for neuro-electric signals, electrodes are placed directly into the peripheral nervous system or central nervous system. Collected Signals are interpreted through microcontrollers for driving the actuators of the prosthetic devices. As a result, a number of leading research institutes have been investigating the utilization of EEG, EMG, and neural interfaces [35–42].

Table 2.2: Overview of Different Prosthesis Types, Their Descriptions, Advantages, and Disadvantages.

Prosthesis Type	Description	Advantages	Disadvantages
Passive/Cosmetic Restoration	Primarily for aesthetic purposes with limited or no movement. Often very natural-looking but sacrifices some function for appearance.	Lightweight, durable, affordable, easy to maintain, provides a natural look.	Non-functional, minimal movement, often expensive for advanced cosmetic appearance, harder to keep clean.
Body-Powered Prosthesis	Controlled by gross body movements (shoulder, chest, upper arm) through a harness and cable system. Offers basic functionality with terminal devices like hooks or hands.	Durable, relatively affordable, and provides good proprioceptive feedback through body control.	Limited range of motion, requires physical effort, can be uncomfortable or cumbersome due to the harness system.
Electrically Powered Prosthesis (Myoelectric)	Powered by motors that detect muscle signals (myoelectric) or switch controls, offering greater grip strength and movement through motors in hand, wrist, and elbow.	Functional, natural-looking movements, can perform complex actions, no cables or harnesses, proportional control allows varied movement.	Heavy, expensive, requires regular maintenance, limited battery life, fragile parts, less sensory feedback than body-powered prostheses, and requires precise muscle control.

Overview of Different Prosthesis Types (<i>Continued</i>)			
Prosthesis Type	Description	Advantages	Disadvantages
Hybrid Prosthesis	Combines body-powered and electrically powered elements to balance control and functionality. Typically used for specific combinations like a body-powered elbow with a myoelectric hand.	Combines benefits of body-powered and electrically powered prostheses, better versatility and functionality, balances weight and control.	Complex to operate, expensive, still relatively heavy, requires more advanced maintenance.
Task-Specific Prosthesis	Designed for specialized tasks such as running or swimming, optimized for specific activities but not suitable for general, everyday use.	Highly functional for specific activities, often lightweight, durable for the task.	Limited versatility, not suitable for everyday tasks, may require additional prosthesis for general use.

Switch-controlled, externally powered prostheses utilize small switches, rather than muscle signals, to operate the electric motors. Typically, these switches are enclosed inside the socket or incorporated into the suspension harness of the prosthesis [43]. This can be a good option to provide control for external power when myoelectric control sites are not available or when the patient cannot master myoelectric control.

Examples such as the Stanford/JPL Hand, the NTU Hand, the Utah/MIT Hand, the DLR I & II Hands, the NASA-designed Robonaut Hand, the Belgrade/USC Hand, and the Southampton-Remedi Hand all actuated via DC motors. Other groups experimented with pneumatic solutions, such as the Shadow Hand, the Blackfingers Hand, and RAPHaEL (Robotic Air Powered Hand with Elastic Ligaments). Their

drawback is their reliance on a compressed air supply.

Commercially available prosthetic robot arms offer a wide variety of solutions by manufacturers such as Otto Bock Michelangelo, Bebionics, and Touch Bionics iLimb. These devices are controlled by the amputee through myoelectric interfaces. Prosthetic hands have several sensors and feedback mechanisms to maintain their functions, almost likely natural hands.

In most current systems DC motors are used as the actuator of intelligent upper limb prosthesis. However, the weight and dimensions of DC motors are not always compatible with the geometric restrictions of a prosthetic hand. Inevitably degrees of freedom reduce, and the prosthesis becomes uncomfortable for the end-user because of these geometric restrictions and dimensions of DC motors. As a result, the search is ongoing to find a more appropriate actuation solution that is lightweight, noiseless, strong, and cheap. Shape memory alloy (SMA) actuators offer the potential to meet these requirements. To date, no commercially viable upper limb prosthesis using SMA actuators has been developed [44].

In February 2008, the Defense Advanced Research Projects Agency (DARPA) announced a program titled “Revolutionizing Prosthetics Program,” aimed at replicating the abilities of an upper extremity using prosthetic devices. This initiative spurred several scientific projects, including two prominent ones: the LUKE Arm by DEKA and the Modular Prosthetic Limb (MPL) by Johns Hopkins University. The LUKE Arm had an 18 million USD budget and incorporated 18 degrees of freedom (DOF), leveraging existing motor neurons. Johns Hopkins’ Advanced Physics Laboratory, leading a group of institutions with a budget of up to 30 million USD, pursued similar ambitions, aiming to utilize both motor and sensory neurons in their bionic hand. This collaboration emphasized algorithm development and motor cortex signal decoding for finger movements.

The most significant difference between these advanced prosthetics and commercially available prosthetic hands lies in the method of control—using direct neuro-

electric signals. These projects are currently in clinical testing phases. Similarly, the European Commission funded a project called SmartHand, focusing on neuro-electric and myoelectric control of prosthetic hands, examining biocompatibility, bio-mechatronics, nerve recordings, stimulation, and bio-signal recognition.

Many commercial prosthetic hands, such as the Bebionic, Touch Bionics iLimb, and Otto Bock's Michelangelo, use DC motors to actuate movement. However, DC motors are often heavy and bulky, limiting the degrees of freedom and making the prostheses uncomfortable for users.

These devices are controlled by the amputee through myoelectric interfaces. The human-driven signals, collected by the electrodes placed on the muscle surfaces, are interpreted through microcontrollers driving the actuators of the prosthetic devices. Surface electrodes are noise-prone and irritating. The gathered data provides less information for agile tasks. As a result, several leading research institutes have been investigating the utilization of EEG and neural interfaces. DARPA supported the Modular Prosthetic Limb (MPL) project, headed by Johns Hopkins Applied Physics Laboratory, in Phase III, which is human subject testing. The project is a 22-degree-of-freedom prosthetic arm controlled by the brain. The motor cortex action potentials are recorded by implanted microarray electrodes [44, 45].

Another 18 Million USD, DARPA-funded project, LUKE Arm, headed by DEKA Research Labs, has 18 DOF and exploits a technique called "targeted muscle reinnervation," aiming at the usage of existing motor neurons². Different from the commercial bionic hands and arms the state-of-the-art research is focusing on direct neuronal interface for more reliable command reception and agile control. Among the several architectures that have been developed and tested, prostheses are aimed at substituting lost parts of the body; and exoskeletons are intended to augment or restore reduced human capabilities. This has led researchers to explore alternative actuators, such as shape memory alloys (SMA), which offer lightweight, noiseless, and strong actuation. To date, however, no commercially viable upper limb prosthesis using SMA actuators has been developed.

2.2.4 Most Popular Examples

This section will classify prosthetic devices based on the number of degrees of freedom (DOF) they offer, the types of actuators they use, and their overall design objectives. Key topics include an examination of the most widely used prosthetic hands in the market, providing an overview of products and whether they use SMAs or other types of actuators, alongside an examination of relevant academic research that has contributed to advancements in prosthetic hand design, with a focus on actuator technologies.

- **Commercial and Most Popular Examples:** Examining the most widely used prosthetic hands in the market. Overview of products and whether they use SMAs or other types of actuators.
- **Academic Studies:** An examination of relevant research that has contributed to advancements in prosthetic hand design, with a focus on actuator technologies.

In prosthetic hands, both commercial products and academic studies have made significant strides. Commercially, devices like the **Otto Bock Michelangelo Hand** and the **Touch Bionics iLimb** stand out for their refined design and versatility. These prosthetics incorporate myoelectric control and offer multiple grip patterns to enable a more natural hand movement. However, these advanced features come with high costs, frequent maintenance requirements, and issues such as battery life and complex control systems.

Other commercial options, such as the **Bebionic Hand** and **Steeper's Myoelectric Prosthesis**, offer similar functionality with individually powered fingers and customizable grips. These devices aim to enhance user control and provide responsiveness. Still, users often report challenges, including the devices being heavy and difficult to operate continuously without frequent recharging.

In academic circles, research-driven prosthetics like the **LUKE Arm (DEKA)** and **Modular Prosthetic Limb (MPL)** aim to push boundaries with designs that integrate neuro-electric control and sensory feedback. These devices promise high degrees of freedom (DOF) and the ability to mimic human movements. However, their complexity and cost limit their commercial availability, keeping them primarily within research environments.

Projects such as the **SmartHand** from the EU, the **Stanford/JPL Hand**, and **DLR Hand I & II** from the German Aerospace Center offer novel approaches with pneumatic and motor-based actuation systems. Though promising in terms of precision and fluid movements, these designs remain limited in terms of affordability and practicality for everyday users. The **Shadow Hand**, similarly, focuses on research with a pneumatically actuated system but is not yet suitable for commercial use due to its specialized control mechanisms.

Despite these advancements, many of these prosthetic systems struggle to replicate the natural fluidity and intuitive movements of human muscles. Their actuator mechanisms, whether motorized or myoelectric, still fall short of the organic motion control found in biological systems.

Commercial and Most Popular Examples

- **Otto Bock Michelangelo Hand:** Offers multiple grip patterns with a refined design and advanced myoelectric control.
- **Touch Bionics iLimb:** Features independently powered fingers and customizable grip configurations.
- **Bebionic Hand:** Known for its sleek design, multiple grip modes, and lightweight construction.
- **Steeper's Myoelectric Prosthesis:** Utilizes powerful electric motors with responsive EMG-based control.

- **Esper Hand (Esper Bionics):** Uses cloud-based learning and artificial intelligence to personalize grip behavior over time.
- **Naked Prosthetics:** Provides robust, mechanical finger prostheses tailored for partial hand amputees.
- **Vincent Hand Evolution:** A compact and highly functional prosthesis compatible with standard myoelectric systems.
- **Open Bionics Hero Arm:** Lightweight and customizable, designed for younger users with accessible pricing and modularity.

Academic and Research-Based Developments

- **LUKE Arm (DEKA):** DARPA-funded arm with up to 18 DOF, enabling near-natural arm and hand movement.
- **Modular Prosthetic Limb (MPL):** Developed at Johns Hopkins, with fine motor control and bidirectional neural feedback.
- **SmartHand (EU Project):** Combines biomaterials, myoelectric control, and sensory feedback through a multi-national collaboration.
- **Stanford/JPL Hand:** DC motor-actuated robotic hand designed for dexterity and adaptability in research contexts.
- **DLR Hand I & II:** Complex robotic hands from the German Aerospace Center, offering multi-fingered, articulated motion.
- **Shadow Hand:** A pneumatically actuated robotic hand designed for precision and biomimetic movement in lab studies.
- **SoftHand Pro (IIT, Pisa):** A soft-robotic hand with a single actuator and underactuated design for adaptive grasping.
- **MIT HANDEXT Project:** Integrates EMG control with an exoskeleton system for hybrid active assistance.

The commercial market for upper limb prosthetics offers a spectrum of solutions, from highly advanced devices mimicking natural hand functions to more accessible myoelectric hands. Advanced prosthetic hands, such as the Otto Bock Michelangelo or Touch Bionics iLimb, offer sophisticated control with a range of grip patterns, precision movements, and even sensory feedback. However, these devices come with significant drawbacks. They are often very expensive, making them inaccessible for many users, and require frequent maintenance due to their complex mechanical and electronic systems. Battery life is another major issue, as these prosthetics typically need to be recharged often, which can be inconvenient in daily life. Furthermore, the weight of these devices, due to the motors and electronics inside, can cause discomfort over time, especially for prolonged wear. In contrast, more affordable myoelectric prosthetic hands provide basic functionality but come with their own limitations. While less expensive, they still rely on muscle signals for control, which can be unreliable, especially in users with limited muscle activity. These devices, although simpler in design, also require regular battery charging and can be prone to control issues, such as delayed or inaccurate movements, particularly during complex tasks. For some users, mastering the control of these myoelectric devices can be challenging, requiring extensive training and adjustment.

Despite the advantages of improved control and functionality in these prosthetics, many individuals still opt for simpler passive or cosmetic prostheses. These are preferred due to the minimal maintenance required, the absence of battery management, and the reduced weight, which makes them more comfortable to wear. While passive prostheses offer little to no functionality, they are often favored for their aesthetic appeal and ease of use, particularly for users who prioritize appearance over function. Furthermore, the actuators used in these popular prosthetic examples, whether electric motors or pneumatic systems, are fundamentally different from the way our muscles work. These mechanical actuators, while capable of mimicking some basic functions, are far from replicating the fluid, natural movement of human muscles. This leads to a limitation in the naturalness of movement, reducing the overall dexterity and range of motion.

Table 2.3: Summary of Leading Companies, Their Products, and the Associated Advantages and Disadvantages in Upper Limb Prosthetics.

Company	Products	Advantages	Disadvantages
Össur	i-Limb Quantum, i-Digits Quantum, i-Limb Skin Natural, i-Limb Wrist, Touch Bionics Silicone Solutions	Offers world-leading upper extremity prosthetic technologies and support services, including realistic passive silicone prostheses. Provides training and clinical support.	High cost and complexity of electronic systems; requires frequent maintenance.
Ottobock	DynamicArm, ErgoArm, AxonHook, Myo Plus control system, SensorHand Speed	Global leader in prosthetic technology with over 100 years of history and innovation. Offers durable, reliable, and functional upper extremity prosthetics.	Some users report difficulty with fine motor control and wrist flexibility in certain models.
Touch Bionics	i-Limb Ultra, i-Digits Quantum, i-Limb Skin Natural, i-Limb Wrist	Pioneers in developing advanced upper extremity prosthetics that mimic natural hand movements and sensations. Offers versatile, high-skill, feedback-enabled myoelectric prosthetics.	High power consumption requires regular charging; can be heavy for extended use.
Fillauer	Motion Control Utah Arm 3+, Motion Control Utah Arm 4+, Motion Control ETD2 Electric Terminal Device	Over 100 years of experience offering upper extremity prostheses with powerful performance, precise control, and user-friendly design.	Mechanical systems may lack the finesse of electronic alternatives; significant training required for optimal use.

Summary of Leading Companies in Upper Limb Prosthetics *(Continued)*.

Company	Products	Advantages	Disadvantages
Naked Prosthetics	MCPDriver™, PIPDriver™, ThumbDriver™	Provides functional finger prosthetics designed for partial hand loss. Prosthetics work with the body to mimic natural finger movements. Durable, protective, and aesthetically pleasing.	Limited to partial hand prosthetics, with users finding adaptability to specific tasks challenging.
Vincent Systems GmbH	Vincent Partial Hand, Vincent Evolution, Vincent Young	An innovative, award-winning company offering myoelectric prosthetic hands and fingers with water resistance, light weight, and customization.	Some models have limited grip strength compared to other high-end prosthetics.
Steeper	Bebionic Hand, Bebionic Small Hand, Bebionic Wrist Rotator, Bebalance Arm System	Over 90 years of experience in upper extremity prosthetics. Offers advanced myoelectric hands and wrists that provide strength, speed, precision, and natural movements.	High customization needed, increasing production times; advanced control systems may not be intuitive for all users.
Liberating Technologies Inc.	Boston Digital Arm System, Boston Elbow System, VariGrip III Myoelectric Hand System, VariPlus Speed Myoelectric Hand System	Leader in upper extremity prosthetics offering powerful externally powered prosthetic arms, elbows, and hands. Provides high performance, reliability, and ease of use.	Devices can be bulky, limiting comfort and use for smaller users with smaller fit needs.

Table 2.4: Overview of Notable Academic Studies in Upper Limb Prosthetics.

Project	Advantages	Disadvantages
LUKE Arm (DEKA)	Up to 18 DOF, mimics human movement, advanced neuro-electric design.	Highly experimental, high cost, not yet commercially available.
Modular Prosthetic Limb (MPL)	Neuro-electric signal control, integrated sensory feedback.	Complex, costly, limited to research use.
SmartHand (EU Project)	Combines myoelectric and neuro-electric control with biomaterials.	Remains experimental, far from commercialization.
Stanford/JPL Hand	Highly dexterous, DC motor-actuated, precise movements.	Primarily for research, lacks affordability for wider application.
DLR Hand I & II	Robust mechanical design, intricate features, high functionality.	Complex system, not suitable for commercial use.
Shadow Hand	Precise, fluid pneumatic actuation, suited for research.	Specialized control systems, not practical for everyday usage.

2.3 Alternative Solutions

Body-powered prostheses

Body-powered prostheses, sometimes referred to as conventional or cable-driven prostheses, are powered and controlled by gross body movements. These movements, usually of the shoulder, upper arm, or chest, are captured by a harness system and used to pull a cable connected to a terminal device (TD), such as a hook or hand. For certain levels of amputation or deficiency, an elbow system can be added to provide additional motion [46, 47]. For a patient to control a body-powered prosthesis, the individual must be capable of producing at least one or more of the following gross body movements: glenohumeral flexion, scapular abduction or adduction, shoulder depression and elevation, chest expansion, and elbow flexion.

Externally powered prostheses Externally powered prostheses are driven by electric motors, offering more proximal function and greater grip strength, along with improved cosmesis. However, they can be heavy and expensive. Patient-controlled batteries and motors operate these prostheses. Currently, available designs generally have less sensory feedback and require more maintenance than body-powered prostheses. Externally powered prostheses require a control system, with the two most common types being myoelectric and switch control [36,48].

This category of prosthesis uses small electric motors in the terminal device (TD) (hand or hook), wrist, and elbow to provide movement, powered by a rechargeable battery system. Myoelectric control, the most common method, involves deriving signals from the contraction of voluntary muscles in the residual limb. These signals are recorded by surface electrodes implanted in the prosthetic socket, which must maintain contact with the specific muscles generating the control signals. The recorded myoelectric signal is first amplified and then processed into a control signal that governs the electric motors. The magnitude of the processed signal is roughly proportional to the isometric force exerted by the muscle, allowing the microprocessor to calculate actions based on the signal's strength. Proportional control enables the patient to control the speed and force of the TD, wrist, and elbow movements by varying the strength of muscular contraction/signal input. For instance, a larger myoelectric signal results in greater grip force or speed of opening and closing, providing a more natural response with less effort than the traditional on/off action of a purely digital control system [37].

These devices are controlled by the amputee through myoelectric or neuro interfaces. Human-driven signals are collected by electrodes; for myoelectric signals, electrodes are placed on muscle surfaces, while for neuro-electric signals, electrodes are placed directly into the peripheral or central nervous system. The collected signals are interpreted by microcontrollers to drive the prosthetic device's actuators. As a result, several leading research institutes have been investigating the utilization of EEG, EMG, and neural interfaces for control [36–42,44,45,48–52].

Switch-controlled, externally powered prostheses use small switches, rather than muscle signals, to operate the electric motors. These switches are typically enclosed inside the socket or integrated into the prosthesis's suspension harness. A switch can be activated by the movement of a remnant digit, a bony prominence against the switch, or a pull on a suspension harness (similar to movements made when operating a body-powered prosthesis). This offers a viable control option when myoelectric control sites are unavailable or when the patient cannot master myoelectric control.

In most current systems, DC motors are used as actuators for intelligent upper limb prostheses. However, the weight and dimensions of DC motors are often incompatible with the geometric restrictions of a prosthetic hand. This inevitably reduces degrees of freedom and makes the prosthesis uncomfortable for the end-user. As a result, the search is ongoing for more appropriate actuation solutions that are lightweight, noiseless, strong, and affordable. Shape Memory Alloy (SMA) actuators offer the potential to meet these requirements. To date, however, no commercially viable upper limb prosthesis using SMA actuators has been developed [44].

2.3.1 Electric Motors

Traditional DC and servo motors are widely employed in prosthetics due to their precision and reliability. They provide well-controlled movements, but their bulky size, weight, and complex gearing systems can limit degrees of freedom and reduce overall comfort. These issues have spurred interest in alternative, more compact actuation methods for prosthetics.

2.3.2 Pneumatic Actuators

Pneumatic actuators use compressed air to generate movement, offering strong force output with relatively low weight. While capable of producing effective and rapid actuation, the need for an external air supply and the complexity of maintaining air pressure systems make them less practical for daily use in prosthetics.

2.3.3 Electroactive Polymers

EAPs are flexible materials that change shape or size when electrically stimulated, providing a lightweight and adaptable alternative to conventional actuators. They offer smoother and more natural movements, making them ideal for mimicking human-like flexibility. However, EAPs face limitations in force output, energy efficiency, and long-term durability, which restrict their widespread adoption in prosthetic devices.

2.3.4 Shape Memory Alloy

SMA s are metals that can revert to their original shape when heated, making them attractive due to their high force-to-weight ratio, mechanical simplicity, and low noise levels. These characteristics make SMA s well-suited for prosthetics. However, challenges like slow response times, limited fatigue life, and significant hysteresis during heating and cooling cycles hinder their full potential in dynamic applications.

Here's a table comparing the advantages and disadvantages of different actuator technologies, including Electroactive Polymers (EAP), Shape Memory Alloys (SMA), Motors, and Pneumatic actuators:

Table 2.5: Overview of Actuator Types, Their Advantages and Disadvantages.

Actuator Type	Advantages	Disadvantages
Electroactive Polymers (EAP)	- Lightweight and flexible - Capable of mimicking muscle-like movements - Silent operation - Low voltage requirements (especially IEAP)	- Low force generation - Limited durability over time - Requires careful chemical processing - Complex control mechanisms
Shape Memory Alloys (SMA)	- High force-to-weight ratio - Simple, compact design - Can achieve large deformation - Long operational lifespan	- Slow response time due to heating/cooling cycle - Limited control precision - Requires high energy input for phase changes
Motors (DC/BLDC)	- High precision control - Fast response time - Readily available, with mature technology - High torque and efficiency	- Relatively heavy and bulky - Requires complex mechanical systems (gears, pulleys) - Noisy operation
Pneumatic Actuators	- Capable of producing high force - Simple construction - Fast actuation and responsive in dynamic environments	- Requires external air compressor - Bulky system components - Leakage issues can cause loss of efficiency

2.4 Detailed Study of Electroactive Polymers

This study aimed to design and develop a lightweight prosthetic hand with superior performance compared to state-of-the-art devices, capable of mimicking human-like movements. The focus is reviewing alternative actuator technologies, particularly Electroactive Polymers (EAP), their capabilities, and limitations when used in prosthetic hands. This section also covers examples of actuators based on EAPs and other cutting-edge technologies, comparing them to Shape Memory Alloys (SMA).

In our TÜBİTAK-supported project, the initial plan involved a hybrid prosthetic hand system incorporating DC motors and SMAs. However, based on an extensive literature review, we identified the potential of EAP actuators, specifically Ionic Electroactive Polymers (IEAP), for simulating muscle movements. IEAPs stood out for their ability to be controlled with low voltage levels, typically between 5 to 10 volts, and for their muscle-like properties such as noiseless operation, strong performance, and lightweight design. This led to design adaptations aimed at replacing the SMA actuators with EAPs, intending to develop an anthropomorphic structure that aligns with human functionality. The new design focused on enabling basic gripping functions and defining joint and phalanx configurations compatible with EAP actuators.

To explore the potential of IEAPs further, a research project funded by BAP was undertaken. The required materials and techniques for IEAP production were determined, and initial trials for manufacturing the actuators were conducted. Adjustments to the system design were made to facilitate the integration of IEAP actuators into the prosthetic hand system. Despite promising characteristics, several limitations emerged during testing, including challenges related to chemical processing, insufficient force generation, and long-term stability issues. While IEAPs operated at low voltages, the force produced was inadequate for the precise and reliable actuation needed in prosthetic hands.

As a result, although various EAP materials and control mechanisms were tested, the limitations led to a shift back to SMA as the primary actuator technology, offering a more reliable and practical solution for achieving human-like movement in prosthetic hands. This section details the research conducted on IEAP actuators, covering both the production methodologies and the outcomes of the trials.

Considering smart materials other than SMAs, Electroactive Polymers (EAP) also have the potential to be used as a muscle with lightweight, noiseless, strong, and long-life properties. Ionic Electroactive Polymers (IEAP) can be controlled with low voltage levels (5-10 Volts) and have the potential to mimic human muscles.

There are several ways to produce IEAPs. We decided to follow two different production methods:

IPMC Encapsulation (Parylene coating) and Photoinduced polymerization of polypyrrole-silver electrodes on an ionomeric membrane. We applied for and received the Boğaziçi Research Projects (BAP) Grant. It is assumed that IEAP can be used like SMA actuators on fingers for abduction, adduction, flexion, and extension.

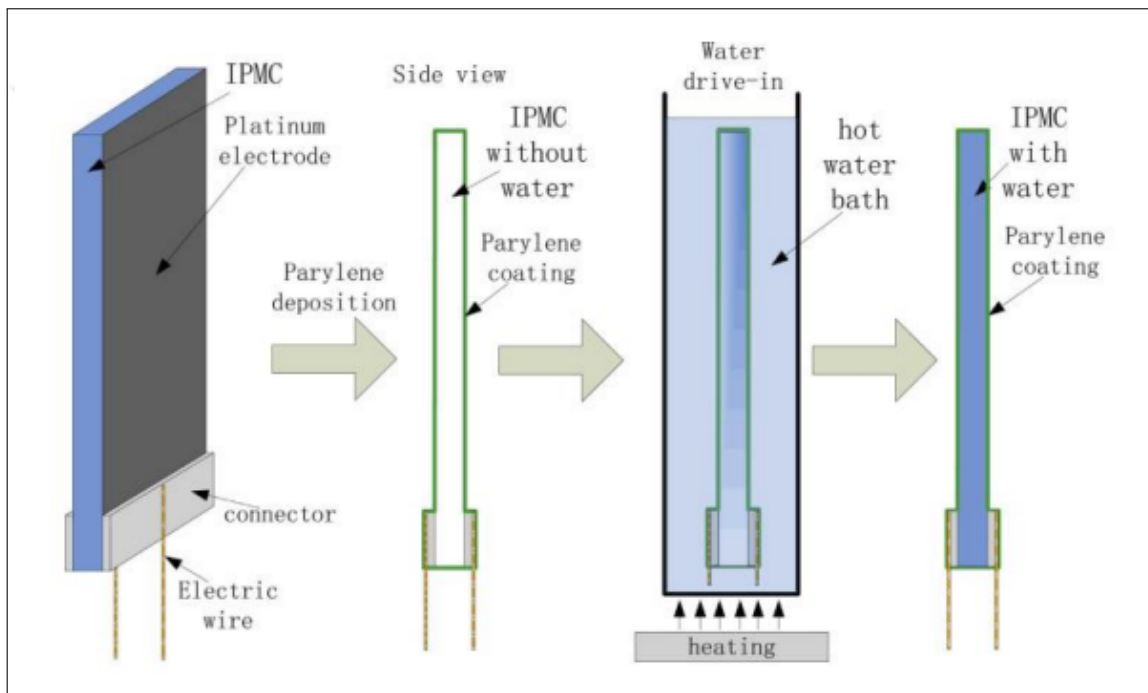


Figure 2.10 Fabrication procedure for IPMC encapsulation [9].

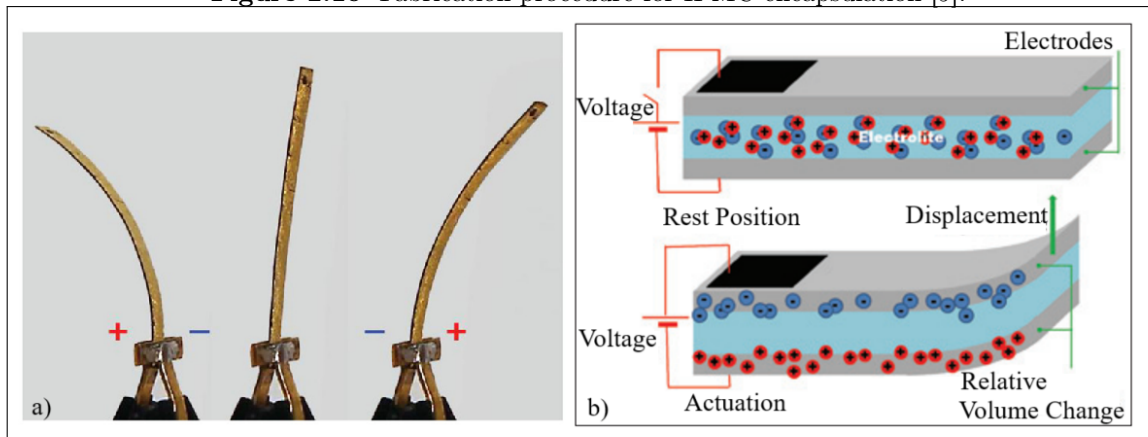


Figure 2.11 Bending Behavior (a) and Electrochemical Mechanism of IEAPs (b) [10, 11].

Through this work, efforts were made to produce electroactive polymer (EAP)

actuators that could mimic muscle movements. A literature review was conducted, focusing on two methods, and the materials and procedures required for their implementation were determined.

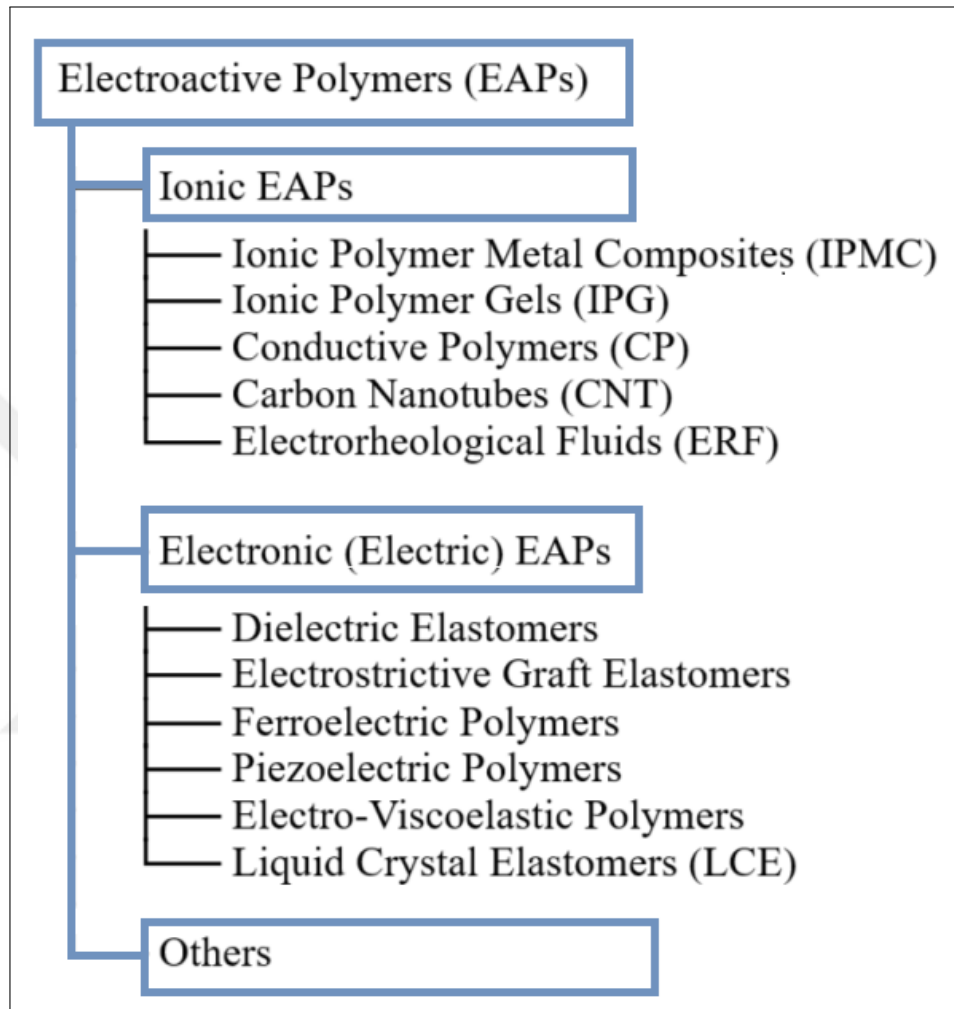


Figure 2.12 Different types of EAP materials [12].

Different types of EAP materials and various control mechanisms were tested to achieve the desired movement functions in the most effective way. The human hand has a highly advanced anatomical structure that provides exceptional movement capabilities. It consists of muscles, tendons, bones, and ligaments. A detailed examination of these structures suggested that designing based on these real attributes would result in a prosthetic hand that closely mimics the capabilities of a real hand. With these considerations, the prosthetic hand shown in Figure 2.11 was designed to be as realistic as possible.

The skeleton structure of the designed prosthetic hand was created by scanning real human hands in a clinical setting and reconstructing them in 3D. Each phalanx and metacarpal created in the Computer Aided Design (CAD) environment was scaled according to the real hand data obtained. The curvatures and endpoints in the design were specifically made to create biomechanically optimized support points. The endpoint of the hand was selected as the combination of approximately eight carpal bones.

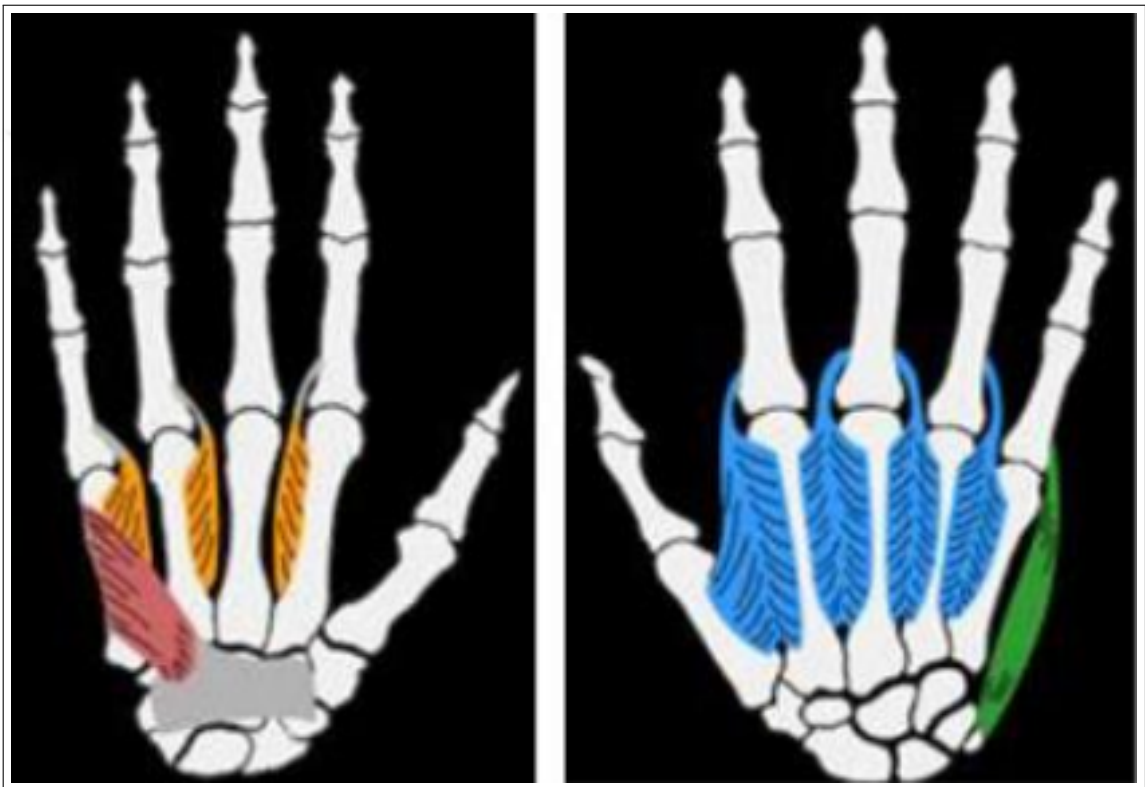


Figure 2.13 It is envisaged that IEAP actuators will be used instead of these muscles, which require less force than the arm region muscles [7].

Joints play a fundamental role in providing and supporting movement. In the design, these joints were chosen to be of two types: cylindrical (DIP, PIP, and CMC except for the thumb) and spherical (MCP and thumb CMC). The joints in the anatomical human hand contain additional constraints that had to be added to the design. The section of the finger near the palm is a tunnel-like ligament system resembling a pulley and synovial sheath structure. This tunnel structure was designed to hold the tendons close and tight to the skeleton on the inner and dorsal sides of the finger. This prevented the tendons from getting caught anywhere and provided efficient flexion and

extension movements to the finger.

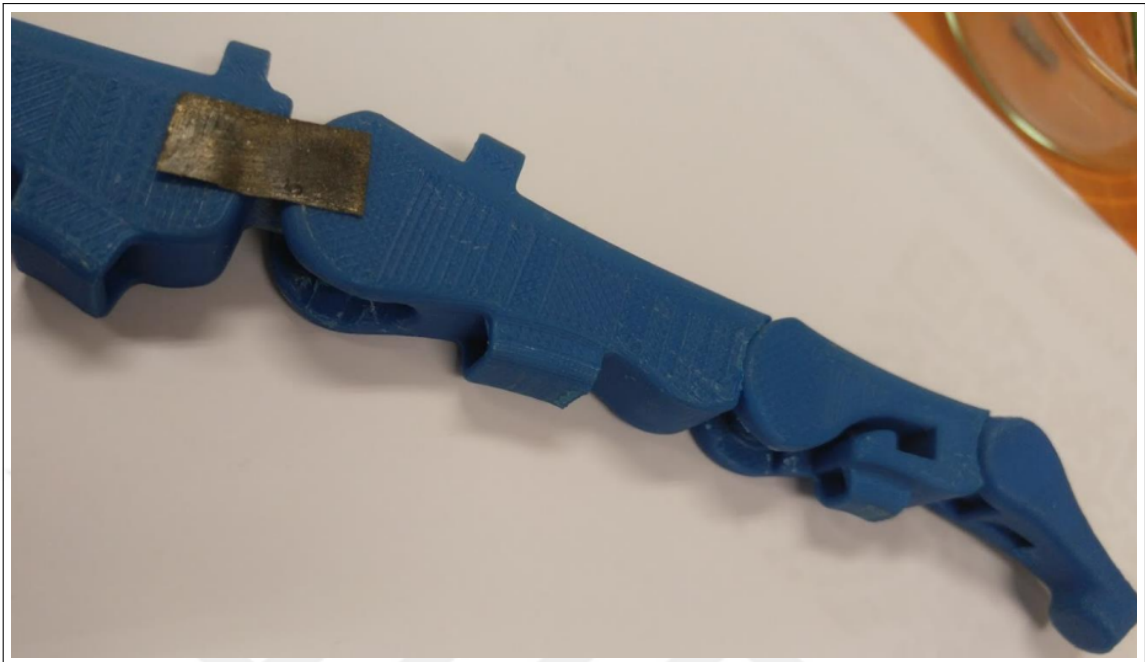


Figure 2.14 Finger prosthesis prototype and design for placement of IEAP actuator on both sides of the metacarpal.

In the design, brushless DC motors and electroactive polymers were used as actuators in place of muscles. Finger joint movement was achieved by the contraction of opposing extensor and flexor muscle pairs located in the forearm. Brushless DC motors were positioned in the forearm to replicate these muscles, being connected to the phalanges to generate greater force. Electroactive polymers were assumed to function as internal muscles within the palm, facilitating abduction and adduction movements of the fingers. When selecting these actuators, the criteria of low weight, compact size, and long lifespan were prioritized.

Following the identification of the production method for EAP actuators, the shape, size, and control approach were chosen to maximize the efficiency of these polymers as actuators. As initially planned and shown in Figure 2.14, it was proposed that EAP actuators would be placed on either side of the metacarpals to enable abduction and adduction movements. In this design, the EAP actuators replaced the SMA springs, becoming the primary actuators.

The prototype of the finger was produced using a rapid prototyping device, and the SMA springs were placed on the two sides of the phalanx to enable the MCP joint to perform abduction and adduction movements. Brushless DC motors were placed to allow flexion and extension movements at the DIP, PIP, and MCP joints, providing four degrees of freedom. Anatomically, the thumb has 5 degrees of freedom, the other 4 fingers have 4, and the wrist has 3 degrees of freedom. The electroactive polymers thought to be placed on both sides of the metacarpals to perform abduction or adduction movements when a voltage difference is applied (Figure 2.14).



Figure 2.15 a) Produced ionic electro-active polymers. b) Right and left bending motions of the IEAP when voltage is applied.

Ionic electro-active polymer (IEAP) consists of an ionic polymer with metal electrodes coated on both surfaces. In the literature, this structure is also referred to as an ionic polymer metal composite (IPMC) [9, 10, 12, 53–55]. When a voltage is applied to these two surfaces, ions move to one side according to the resulting electric field, causing the polymer to change shape. In our studies, Nafion 1110 (Dupont) polymer with a thickness of $254\ \mu\text{m}$ was selected.

To use the produced IEAPs as actuators, conductive wires were attached to both surfaces of the IEAP strips to apply electrical signals. In the study, the voltage in the range of 3-5V was applied by connecting positive and negative wires to the surfaces of the IEAP.

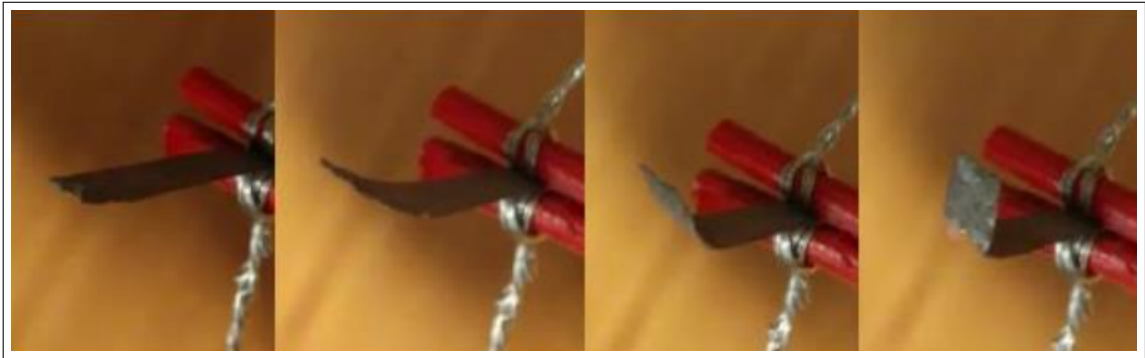


Figure 2.16 Bending Sequence of an IEAP Actuator Under Electrical Stimulation.

Following the project aimed at exploring the potential of EAPs, we found it necessary to revisit and compare alternative actuator technologies. Although various EAP materials and control mechanisms were tested, their limitations led us to reconsider other options. As a result, we conducted a comparative analysis of electroactive polymers (EAP), shape memory alloys (SMA), motors, and pneumatic systems. Each technology was evaluated for its strengths and weaknesses to determine its suitability for achieving human-like movement in prosthetic hands.

Ultimately, while EAPs demonstrated certain advantages, the challenges they presented prompted a shift back to SMA as the primary actuator technology. SMA provided a more reliable and practical solution. There are many different robotic hand designs with five or fewer fingers, each created according to the specific criteria of its inventors. These designs vary in actuation types, each offering advantages in certain areas and presenting challenges in others [49].

The multi-functionality of a prosthesis heavily depends on the performance of its actuators. For prosthetic applications, the actuator system plays a crucial role as it largely determines the system's autonomy, available grasping force, weight, size, and other factors such as noise. To enhance the functionality and efficiency of prosthetic devices, various actuation technologies beyond traditional motors are being explored. These alternatives offer distinct advantages in terms of weight reduction, power consumption, and simplified mechanical designs.

2.5 Detailed Study of Shape Memory Alloys

The Shape Memory Effect (SME) phenomenon, was first observed in 1932 by Swedish physicist Arne Olander in an alloy of gold (Au) and cadmium (Cd) [56], than In 1961, William Beuhler and his team at the U.S. Naval Ordnance Laboratory discovered that an alloy of nickel and titanium (Ni-Ti) also exhibited SME [57]. Over the years, SMAs have been extensively researched and developed, However, the potential of these materials began to grow in the 1980s. During this period, applications began to emerge in industries such as aerospace, biomedical devices, and robotics [17, 18, 58, 59]. As SMA applications became more complex, the need for advanced control methods became increasingly apparent. In the mid-1990s, neural networks began to be used to model and control the nonlinear behavior of SMA systems. By the early 2000s, neural networks were increasingly applied, enabling real-time control without the need for direct position sensors [60–62]. Today, the integration of neural networks continues to enhance the capabilities and efficiency of SMA-based systems, driving innovation across various industries.

While most of the research on SMAs has traditionally focused on their structure, fabrication, and fundamental behavior, many have also focused on various application areas and developing sophisticated control methods [21, 63–65]. Research has continued on how to effectively utilize the unique properties of SMAs by applying various control strategies. These strategies are designed to optimize SMA performance by precisely managing input parameters to control output parameters such as extension/contraction, force generation, and resistance change in response to direct and indirect heating, thereby enabling precise manipulation of output parameters in various engineering and biomedical applications [19, 65]. With the widespread use of artificial neural networks, the difficulties in controlling SMA have begun to be overcome and new models have been presented by researchers.

SMAs have been preferred primarily for their superelastic behavior (maintaining the austenite phase) and shape memory effect (controlling phase transitions) to achieve desired functionalities. Their high strength-to-weight ratio, biocompatibility, and cor-

rosion resistance further enhance their appeal [66]. These properties have made SMAs extremely useful and indispensable in various fields, including robotics, prosthetics, medical devices, aerospace, and civil engineering.

The superelasticity property is particularly crucial in applications like surgical instruments, implants, and prostheses. SMA wire can have a small cross-section in its deformed shape and can be introduced into an artery or body cavity with reduced risks [67–73]. The ability of SMA to produce force makes it suitable for actuators in robotic and mechatronic systems. Examples include grippers for precision handling, walking mechanisms for robots, and active control surfaces for adaptive wings in aerospace applications. There are also various robotic/prosthetic hand designs with five fingers or fewer for defined functions [19, 57, 71, 74–79]. Over the last two decades, recent advances in SMA material range and manufacturing technology, and the development of mechanical design possibilities have enabled the development of small-scale SMA actuators with complex designs in robotic hands, wearable devices, and micro-electromechanical systems (MEMS).

However, achieving precise motion control in SMA actuators remains a challenge due to their nonlinear behavior, hysteresis, and sensitivity to environmental changes. While various control models, such as proportional-integral-derivative (PID) controllers, model predictive control (MPC), and neural network-based approaches, have been employed to address these issues, each model has its limitations [63, 80]. PID controllers, for example, can struggle with the nonlinearities and time-varying properties of SMAs, while MPC offers predictive capabilities but may require extensive computational resources, making real-time application challenging. Neural network-based approaches have shown promise in capturing the complex dynamics of SMAs, but they too face challenges, particularly in terms of generalizability and adaptability to different SMA configurations and operating conditions.

The use of recurrent neural networks (RNNs) in controlling SMA actuators has gained significant attention due to the complex hysteresis and nonlinear behavior of these materials. Zakerzadeh [zakerzadeh2024modelling] demonstrated the effectiveness

of Long Short-Term Memory (LSTM) networks in modeling SMA hysteresis, providing accurate force predictions by capturing historical dependencies. However, while this approach excels in prediction, it lacks real-time adaptability for dynamic environments. Ghasemi et al. [25] and Gómez-Espinoza et al. [81] showcased how artificial neural networks (ANNs) and neural network direct control systems can adapt to the unique characteristics of SMAs, improving control performance and real-time adaptability. Yet, these studies primarily focus on specific SMA configurations, limiting their generalizability to other SMA applications.

NARX (Nonlinear Auto Regressive with External Input) and RNN (Recurrent Neural Network) models are two commonly used neural network models for controlling SMA springs [82–84]. These models effectively capture the non-linear behavior of SMA springs by incorporating external inputs and delayed feedback, considering previous inputs and outputs. Despite their effectiveness, there are limitations. For instance, NARX models, while powerful in capturing complex dynamics, may require extensive computational resources, making them less suitable for real-time applications where quick responses are critical.

Mai et al. [85] developed an adaptive inverse control strategy using dynamic neural networks (DNNs) to mitigate hysteresis. While effective, the sensitivity of this approach to precise initial modeling may limit its applicability in systems with significant parameter uncertainty. Nikdel and Badamchizadeh [86] emphasized the importance of robust control strategies for precise position tracking, though their approach does not explicitly address the challenges of time-varying SMA properties. Hannen et al. [80] introduced a hysteretic recurrent neural network (HRNN) integrated with sliding mode control to enhance robustness against uncertainties. While potentially beneficial, the increased complexity of this approach may pose challenges for real-time implementation. Bhargaw et al. [87] explored self-sensing position estimation using RNNs, simplifying control systems and improving actuator responsiveness. However, the accuracy of this approach may be affected in highly dynamic or noisy environments.

Therefore, control strategies that can overcome these limitations remain necessary, particularly in complex and demanding SMA applications. Ongoing research is focused on developing advanced control algorithms that can adapt in real time to changing conditions, compensate for SMA's inherent nonlinearities, and improve overall system reliability and performance.

Given these challenges and the inherent temporal dependencies in SMA behavior, neural network-based approaches, particularly Recurrent Neural Networks (RNNs), have emerged as promising solutions. RNNs are well-suited for modeling the complex, nonlinear behavior of SMAs, as they can capture the temporal dependencies between inputs (such as voltage and current) and outputs (such as force). By learning from data, these networks can effectively model the intricate relationships between input variables like temperature, voltage, and current and output variables like force and displacement. This capability allows for more accurate and responsive control, even in the presence of hysteresis and other nonlinearities.

2.5.1 Current Studies of The SMA Actuator Based Prosthetic Systems

Different research groups have been developed robotic hands or finger using SMA actuators. Well known SMA actuated upper limb prosthetic device is the Hitachi Ltd Hand, that developed in 1984. It had a load capacity of 2kg. Rutgers Hand, another SMA actuated hand was developed in 2002 with 20 degrees of freedom and comprised of five fingers. This hand can produce a 6.67N at the fingertip force.

Price et al, Implement a three-finger SMA actuated system with bias-type SMA wires (i.e., composed of an SMA element and a bias spring) directly routed through the finger joints in a traversing arrangement. to show proof of the concept. They used PID control due to the non-linear nature of SMA wires. They used PWM signals for Joule heating. [88]

A four-degree-of-freedom finger, which closely mimics the human finger, was

developed in 2006 [52]. In 2007, Kevin et al. were carried out on the transient response of SMA actuators. As a result they determined the selection of suitable SMA bundle sizes and SMA wire diameters for transient and steady state muscle performance [44]. In their studies they designed modular ease of assembly and ease of replacement of SMA wires 12 DOF four-finger. They locate SMA bundles in the Palm region to form a complete lower arm prosthesis [89]

Kevin et al., in their next studies, implemented the conductive forced cooling in variety materials, and due to their experiments, aluminium proved to be the most beneficial, reducing the 90% cooling time to approximately 1.9 seconds, compared to 3.4 seconds for natural cooling. The heating phase remains unaffected. It is shown that the use of aluminium heat sinks permits full actuation cycles at 0.3Hz, [44, 90].

K. Andrianesis et al. [51] established an experimental study for the SMA actuated finger, as a part of their whole design of a hand prosthesis in 2010. Their design will have a potential that can covers desired actuation, but their first experiments includes only a prototype of the whole hand and a testbed for one SMA actuated finger.

2.5.2 Advantages and Limitations of SMA Actuators

Advantages

- **Compact, lightweight, with high power/mass ratio and energy density** compared to a large selection of actuation technologies.
- **Ease of actuation and low voltage requirement** - they can be easily driven by electrical current via Joule heating. Also, the small voltages that are required to operate make them safe for human-oriented applications.
- **Clean, silent and spark-free operation** - In contrast to many actuators such as electric motors, SMA actuators operate with no friction or vibration, allowing extremely silent movements; this is a strong asset for the prosthetic applications,

where the conventional technology used remains quite annoying and uncomfortable for the users. They are also free of parts such as reduction gears and do not produce dust particles.

- **Long actuation life** - When used within sustainable strain and stress limits, SMA actuators can be expected to last hundreds of thousands of operation cycles.
- **High biocompatibility and excellent corrosion resistance** - This enables their use in an environment with high humidity or wet conditions [51] .

Direct-driven - Using SMA as actuators, there is no need for complex and bulky transmission systems. This drastically reduces the complexity of the hand's driving mechanism.

Limitations

- **Low displacement levels** - So, long lengths of SMA wire are required for large strains. However, using appropriate arrangements that convert the small strains into large motions, this limitation can be moderated.
- **Low power efficiency** - SMA operates through heat and as such is limited by the carnot efficiency model to at most 10%.
- **Low operating frequency** - The rate at which an SMA actuator can shift to the austenite phase and return to the martensite phase is limited by the slow heat transfer processes (low thermal conductivity) needed to promote the phase transformation of SMA. Typically, operation is faster for actuation (heating) than it is for relaxation (cooling). So, mostly the level of cycles per minute is dependent upon the rate of cooling of the wire. A variety of methods have been proposed to increase cooling speeds, such as water immersion, heat sinking, and forced air. However, even if these methods improve the bandwidth, they also cause an increase in power consumption, as more heat is required to actuate the wire within the cooling medium [51].
- **Control difficulties** - Hysteresis, nonlinearities, parameter uncertainties, and un-modeled dynamics introduce difficulties in the accurate control of SMA. The

SME is not a thermodynamically reversible process. Heat losses during the phase transformation (owing to internal friction or structural defects) cause hysteretic behavior of SMA as shown in Figure 1.1.

SMA Wires and Springs Shape Memory Alloys (SMAs), notably produced by major **manufacturers** like Dynalloy and Nitinol Devices & Components, are supplied in **various forms, such as wires, sheets, and springs**, for a wide range of industrial and biomedical applications. Among these, Nitinol is a particularly common alloy for medical and prosthetic devices, distinguished by its superior biocompatibility and mechanical properties. When comparing different SMA types, including Nitinol and copper-based alloys, Nitinol generally stands out for its superior flexibility and force output, making it highly suitable for prosthetic applications due to its transformation temperatures, mechanical properties, and fatigue resistance.

For effective prosthetic functionality, SMA actuators must exhibit several key characteristics: a lightweight design, sufficient force output, rapid response times, and consistent reliability over numerous heating and cooling cycles. Key considerations for their operation in prosthetics include ensuring adequate elongation to mimic muscle contraction for the necessary range of motion in prosthetic joints and achieving a working speed that allows for fast transition between austenite and martensite phases, balancing quick responsiveness with efficient heat dissipation. The generated force must be robust enough to emulate human muscle strength, offering high force-to-weight ratios that can be precisely tuned for specific daily tasks like gripping. Furthermore, the operational temperature of SMAs must remain within safe limits to ensure both actuator durability and user comfort. The inherent change in electrical resistance of SMAs with temperature can be leveraged for feedback and control, enabling precise real-time actuation. Regarding control systems, the wiring configurations are crucial for measuring resistance: a 4-wire system, which separates power and feedback circuits, offers finer control, while a 3-wire setup simplifies the design. Accurate temperature measurement is also vital for consistent performance and longevity; common methods include Resistance Temperature Detectors (RTDs), which provide precise measurements, and

cost-effective PTC (Positive Temperature Coefficient) or NTC (Negative Temperature Coefficient) thermistors, both of which can effectively regulate the heating cycles.

Considerations:

- **Elongation:** SMAs need to have sufficient elongation to mimic muscle contraction, allowing for the necessary range of motion in prosthetic fingers or joints.
- **Working Speed:** The transition speed between the austenite and martensite phases (heat-activated state changes) is crucial for ensuring that the prosthesis responds quickly enough to user input. Faster transition times are generally preferred, but must be balanced with heat dissipation concerns.
- **Generated Force:** The force output of SMAs must be sufficient to replicate human muscle strength. For instance, SMAs can produce high force-to-weight ratios, but their output needs to be fine-tuned for specific tasks, such as gripping or manipulating objects in daily activities.
- **Operation Temperature:** SMAs operate by cycling through different phases at specific temperatures. It is important that the operational temperature remains within safe limits, both for the durability of the actuator and the comfort of the prosthetic user.
- **Resistance Change:** SMAs exhibit changes in electrical resistance as their temperature changes. This property can be utilized for feedback and control purposes, helping to ensure precise actuation in real-time applications.
- **Resistance Measuring method, 4-Wire vs. 3-Wire:** The wiring configurations used in controlling SMA actuators can affect their performance and ease of control. A 4-wire system allows for separate power and feedback control circuits, whereas a 3-wire configuration simplifies the design but may limit fine control.
- **Temperature Measurement:** Accurate temperature measurement is vital for controlling SMA actuators, ensuring they operate within the desired temperature range for reliable performance and longevity.

RTD (Resistance Temperature Detectors): RTDs provide precise temperature measurements by changing resistance with temperature changes, making them a good option for controlling SMA actuators.

PTC/NTC Thermistors: These thermistors offer a cost-effective solution for temperature measurement. PTC (Positive Temperature Coefficient) thermistors increase resistance as the temperature rises, while NTC (Negative Temperature Coefficient) thermistors do the opposite, both of which can be used to regulate the heating cycles of SMAs.

2.5.3 Control of SMA Actuators: Challenges and Current Approaches

Over the last two decades, recent advances in SMA material range and manufacturing technology, and the development of mechanical design possibilities have enabled the development of small-scale SMA actuators with complex designs in robotic hands, wearable devices, and microelectromechanical systems (MEMS).

However, achieving precise motion control in SMA actuators remains a challenge due to their nonlinear behavior, hysteresis, and sensitivity to environmental changes. While various control models, such as proportional-integral-derivative (PID) controllers, model predictive control (MPC), and neural network-based approaches, have been employed to address these issues, each model has its limitations [63,80]. PID controllers, for example, can struggle with the nonlinearities and time-varying properties of SMAs, while MPC offers predictive capabilities but may require extensive computational resources, making real-time application challenging. Neural network-based approaches have shown promise in capturing the complex dynamics of SMAs, but they too face challenges, particularly in terms of generalizability and adaptability to different SMA configurations and operating conditions.

2.5.4 Neural Networks / Control Methods

The use of recurrent neural networks (RNNs) in controlling SMA actuators has gained significant attention due to the complex hysteresis and nonlinear behavior of these materials. Zakerzadeh (2024) demonstrated the effectiveness of Long Short-Term Memory (LSTM) networks in modeling SMA hysteresis, providing accurate force predictions by capturing historical dependencies. However, while this approach excels in prediction, it lacks real-time adaptability for dynamic environments. Ghasemi et al. (2013) and Gómez-Espinosa et al. (2019) showcased how artificial neural networks (ANNs) and neural network direct control systems can adapt to the unique characteristics of SMAs, improving control performance and real-time adaptability. Yet, these studies primarily focus on specific SMA configurations, limiting their generalizability to other SMA applications.

NARX (Nonlinear AutoRegressive with External Input) and RNN (Recurrent Neural Network) models are two commonly used neural network models for controlling SMA springs [82–84]. These models effectively capture the non-linear behavior of SMA springs by incorporating external inputs and delayed feedback, considering previous inputs and outputs. Despite their effectiveness, there are limitations. For instance, NARX models, while powerful in capturing complex dynamics, may require extensive computational resources, making them less suitable for real-time applications where quick responses are critical. Additionally, Mai et al. (2012) developed an adaptive inverse control strategy using dynamic neural networks (DNNs) to mitigate hysteresis, but the method's reliance on precise initial modeling may reduce its effectiveness in systems with significant parameter uncertainty. Nikdel & Badamchizadeh (2014) emphasized the importance of robust control strategies for precise position tracking, yet their approach does not fully address the challenges posed by the inherent time-varying properties of SMA materials. Hannen et al. (2012) introduced a hysteretic recurrent neural network (HRNN) integrated with sliding mode control for enhanced robustness against uncertainties. However, the complexity of this approach may limit its practical implementation in real-time applications. Bhargaw et al. (2021) explored self-sensing position estimation using RNNs, simplifying control systems and improving actuator

responsiveness, but this approach may struggle with accuracy in highly dynamic or noisy environments.

While these methods have improved performance, there is still a need for more robust and adaptive control solutions. This need is particularly pressing as SMA applications expand into more complex and demanding environments, where traditional control strategies may fall short. Ongoing research is focused on developing advanced control algorithms that can adapt in real-time to changing conditions, compensating for SMA's inherent nonlinearities, and improving overall system reliability and performance.

To address these challenges, neural network-based approaches, particularly Recurrent Neural Networks (RNNs), have emerged as promising solutions. RNNs are well-suited for modeling the complex, nonlinear behavior of SMAs, as they can capture the temporal dependencies between inputs (such as voltage and current) and outputs (such as force). By learning from data, these networks can effectively model the intricate relationships between input variables like temperature, voltage, and current, and output variables like force and displacement. This capability allows for more accurate and responsive control, even in the presence of hysteresis and other nonlinear effects.

LRNN Network

LRNN is a specialized artificial neural network designed to capture temporal dependencies in sequential data. Unlike traditional feedforward neural networks, LRNNs incorporate feedback connections, enabling them to process sequences of inputs and maintain information about previous inputs through internal states. In the LRNN, there is a feedback loop, with a single delay, around each layer of the network except for the last layer [MATLAB]. This design allows the network to retain information over time, making it well-suited for modeling dynamic systems. By leveraging this architecture, we aim to effectively capture the complex, non-linear dynamics of Shape Memory Alloy (SMA) behavior. The ability of this model to handle the inherent hysteresis and time-varying nature of SMA actuators is a key factor in its success. The recurrent connection enables the network to store information about previous inputs

in the current state, allowing the network to exhibit dynamic temporal behavior. The `layerDelays` parameter determines how far back in the time series the network can look when processing current inputs. Hidden Layer Sizes adjust to capture the complexity of the input-output data patterns.

2.6 Summary

A prosthesis is designed to replace the function and appearance of a missing limb or body part. To enhance dexterity, it is essential to mimic the structure of a real hand, including its joints, muscles, and tendon connections. While existing prosthetic designs often use motors, we chose to explore Shape Memory Alloys (SMAs) due to their muscle-like behavior, promising a more natural, human-like result with higher degrees of freedom. However, it quickly became clear that controlling such a system would be complex due to the nonlinear behavior of SMAs. Given these challenges, particularly their nonlinear properties, we turned to artificial neural networks as a potential solution. After reviewing various control methods in the literature, Layer Recurrent Neural Networks (LRNNs) emerged as a promising approach to address the complexities of SMA control. Despite advancements in this area, many examples in the literature still lack the precision and consistency required for practical applications. Experiments with both SMAs and polymers revealed that polymers had notable shortcomings. Therefore, we focused on SMAs and proposed a method to evaluate their effectiveness in improving prosthetic hand control.

3. METHODS

3.1 Overview of the Methodological Framework

This chapter outlines the methodological framework adopted to model and control Shape Memory Alloy (SMA) actuators. The inherently nonlinear and hysteretic behavior of SMA materials poses significant challenges for conventional control techniques. Accordingly, this chapter presents both the initial exploratory steps and the data-driven methodology used to predict and regulate actuator behavior under varying excitation conditions, focusing particularly on the use of recurrent neural networks (RNNs).

The experimental strategy consists of several steps: analyzing the relationship between temperature and electrical resistance of the SMA, designing the SMA actuator, developing a data acquisition system with integrated sensors, and preparing the collected data to train neural network models. It also includes developing both forward and inverse models to predict the output force based on applied voltage and to determine the voltage required to achieve a desired force. This section provides a comprehensive foundation for the subsequent development, training, and evaluation of control models by detailing the materials used, experimental setup, and data acquisition protocols.

The basic idea of this work is inspired by the unique behavior of SMAs, specifically their ability to return to a predefined shape and generate force when heated. This thermally induced structural transformation opens the potential for SMAs to be used as compact, silent actuators in biomimetic applications. However, effectively utilizing SMAs as actuators requires embedding them in a controllable system. Although this may seem straightforward at first glance, the inherent nonlinearities and hysteresis of SMA behavior posed significant challenges. To address these, numerous preliminary studies were conducted, spanning all stages from mechanical design to data-driven

modeling and control, resulting in the development of a workable methodology. The study was conducted in the following key steps:

- **Biomimetic Design:** CAD modeling was used to design prototype hands and fingers that closely mimic human anatomy. Initially, the design encompassed the entire hand, but due to practical challenges in controlling SMA actuators within a complex multi-Degree of Freedom (DOF) system, the scope was narrowed to focus on individual finger motion and then the SMA actuator itself.
- **Preliminary Studies and Exploratory Approaches:** Initial studies involved testing various SMA wires, springs, and commercial actuators to evaluate their suitability for mimicking finger movements. These experiments revealed that achieving full flexion required significant contraction, favoring spring-based designs over wires. The findings emphasized the need for a practical and standalone actuator, leading to custom designs and restructured electrical and sensing interfaces. These efforts laid the groundwork for capturing the temperature-resistance-force relationship essential for precise control.
- **Actuator Design and Integration:** This phase involved exploring various SMA configurations and addressing the practical challenges of their physical and electrical integration into prosthetic finger prototypes, including the design of mechanical interconnects that mimic natural tendons.
- **Data Acquisition System:** Various methods and sensors were employed to measure temperature and electrical resistance under different working conditions. A custom data acquisition system was developed to collect synchronized voltage, current, and force signals.
- **Data Processing and Modeling:** The collected data were preprocessed and analyzed using techniques such as curve fitting, nonlinear regression, and machine learning. NARX (Nonlinear Auto Regressive with External Input) and RNN architectures were explored to capture the nonlinear dynamics of SMA behavior.

Through numerous experimental attempts and iterative development, it was revealed that traditional control strategies were insufficient to capture the complexity of the input-output relationship. As a result, neural network-based methods were investigated, and finally, a practical and robust control methodology was obtained using Recurrent Neural Networks (RNNs). This enabled the realization of an efficient and adaptive force control scheme for SMA actuators.

3.2 Biomimetic Design and Evolution of Actuator System

3.2.1 Biomimetic Hand and Finger Design and Modeling

The design process began with a deep focus on the anatomy of the human hand, including careful study of muscle and tendon relationships, types of connections, and structural complexities. Muscle-force relationships and various muscle structures and types were extensively investigated. This anatomical understanding was crucial to developing a biologically inspired hand CAD model based on CT cross-section reconstructions of the human hand. This initial comprehensive design effort was supported by the TÜBİTAK 1001 "Cognitive Controlled Myoelectric Hybrid Prosthetic Hand" project.

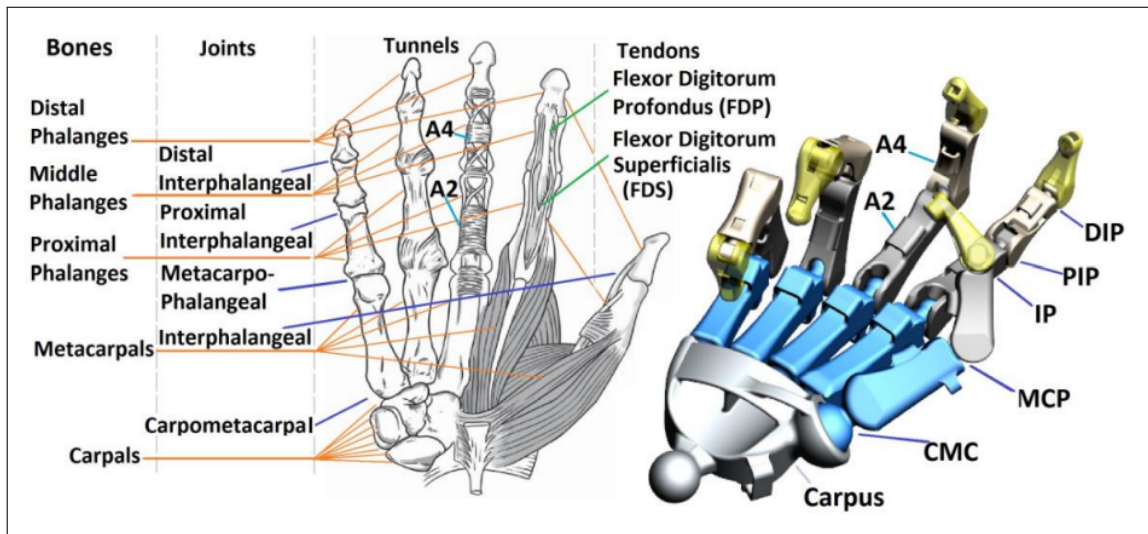


Figure 3.1 Structures of human hand and its mechanical design [13,14].

The hand and wrist, consisting of 27 individual bones, were meticulously modeled. The eight small carpal bones of the wrist, collectively known as the carpus, were designed to articulate with the ulna and radius at the proximal end of the wrist and the five metacarpal bones on their distal surfaces. Each finger and thumb, its phalanges, and metacarpals were designed to scale according to anthropomorphic data obtained from the subject. The curvatures and tips of these bones were meticulously designed to provide biomechanically efficient fulcrums. The proximal end of the designed hand was created by fusing eight carpal bones. The first and second finger joints were designed as rotary joints, while the third joint was modeled as a condyloid joint.

The roles of both extrinsic and intrinsic muscles during movement were investigated. This included examining the force requirements for various types of grasping and gestures and the tendon displacements required for each of these types of grasping.

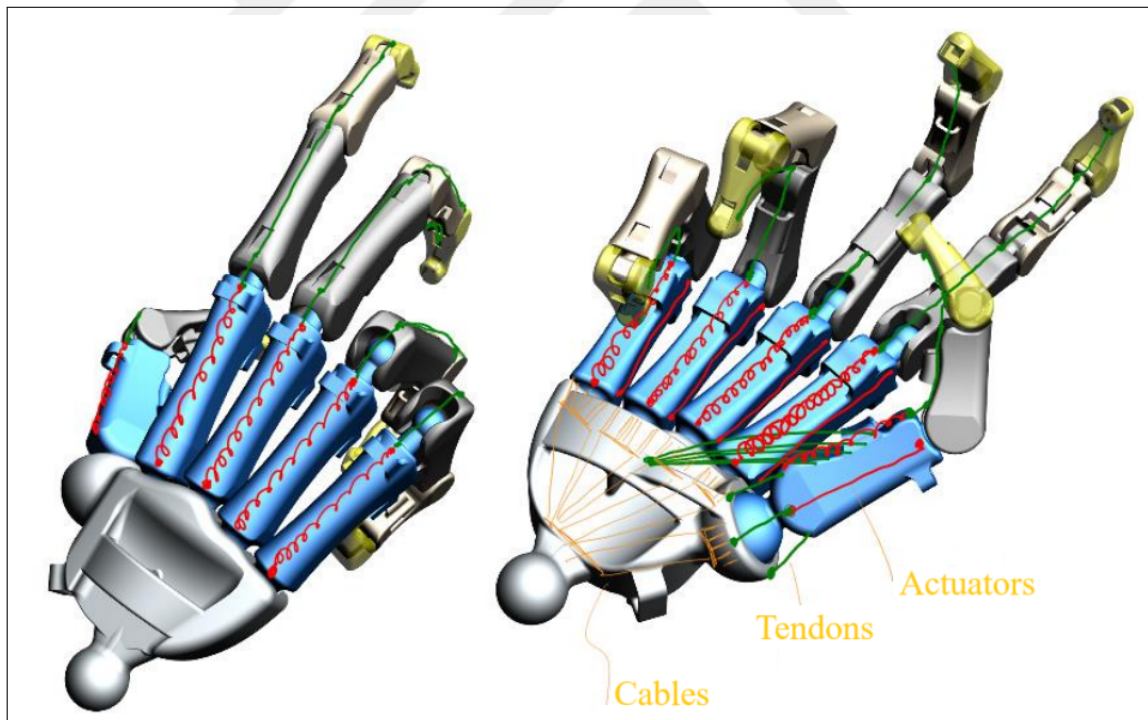


Figure 3.2 CAD-based prosthetic hand design overlaid with manually sketched SMA spring placements. The illustration combines anatomical modeling with conceptual actuator positioning to simulate tendon-like flexor pathways [13, 14].

While the design commenced with a comprehensive prosthetic hand, later stages of the project revealed significant difficulties in effectively controlling the integrated SMA actuators within such a complex multi-degree-of-freedom system. This prompted

a re-evaluation and subsequent narrowing of the study's focus, transitioning from the complete prosthetic hand design to concentrating on individual finger motion and ultimately to a meticulous investigation of the SMA spring actuator itself.

Table 3.1
Range of Motion, Velocities and Force Capabilities of Human Index Finger.

Phalanges	Joints	Tendons	Range of Motion	Angular Velocities	Angular Accelerations	Force Within each joint
Proximal Phalax	MCP	FDS / FDP	-20° - 90°	≈ 240 °/s	≈ 400 °/s ²	25,8
Intermediate Phalax	PIP	FDS / FDP	0° - 100°	≈ 240 °/s	≈ 400 °/s ²	32,2
Distal Phalax	DIP	FDP	0° - 80°	≈ 240 °/s	≈ 400 °/s ²	56,6
Thumb	CMC		-40° - 90°			
	MCP		0° - 80°			
	IP		20° - 90°			

The initial design phase focused on developing a CAD-based anatomical model of the prosthetic finger, inspired by the biomechanics of the human hand. Using anthropometric data and CT-derived anatomical references, the phalanges and joints were modeled to reflect realistic proportions and ranges of motion. In this model, various SMA actuator configurations consisting of wires and springs were virtually placed to mimic tendon-like alignments.

While the initial goal was to integrate SMA actuators into a full hand structure, early simulations and prototyping revealed significant challenges in controlling SMA elements within such a complex, multi-degree-of-freedom system. As a result, the focus was narrowed to finger-level implementation, where SMA actuators were evaluated in isolated segments.

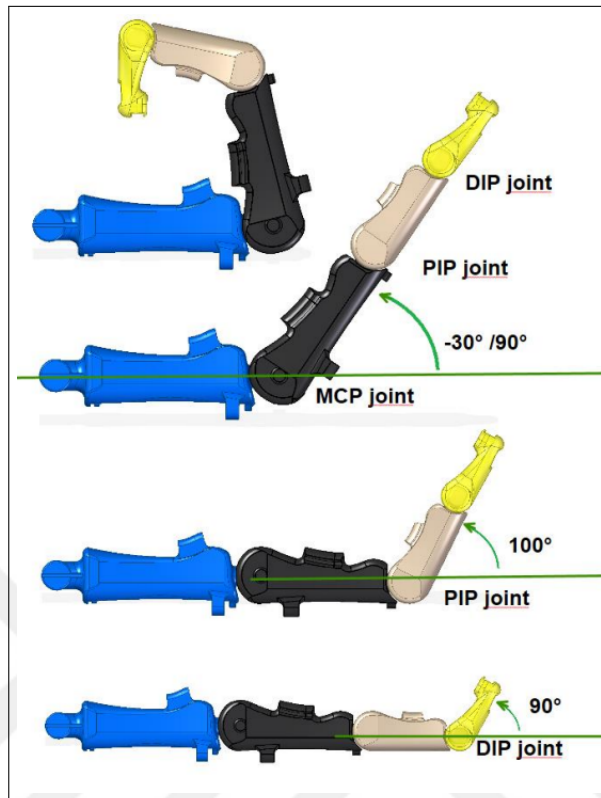


Figure 3.3 Range of Motion Analysis of Index Finger Prototype [13].

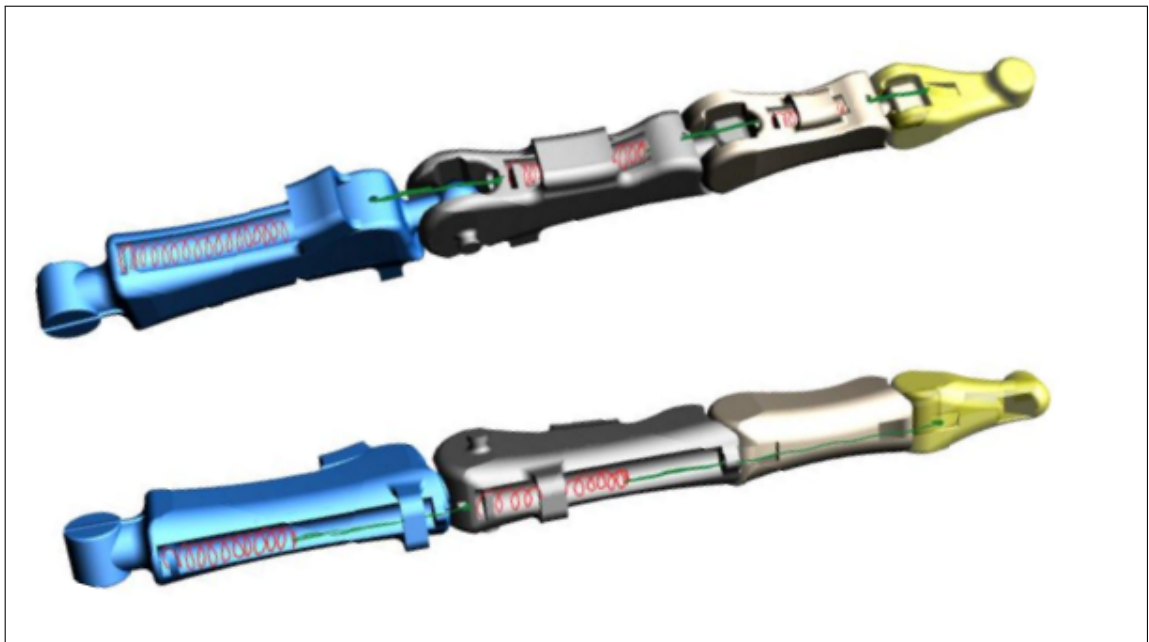


Figure 3.4 Design of an SMA-actuated index finger and schematic planning for placing actuators along phalanges [13, 14].

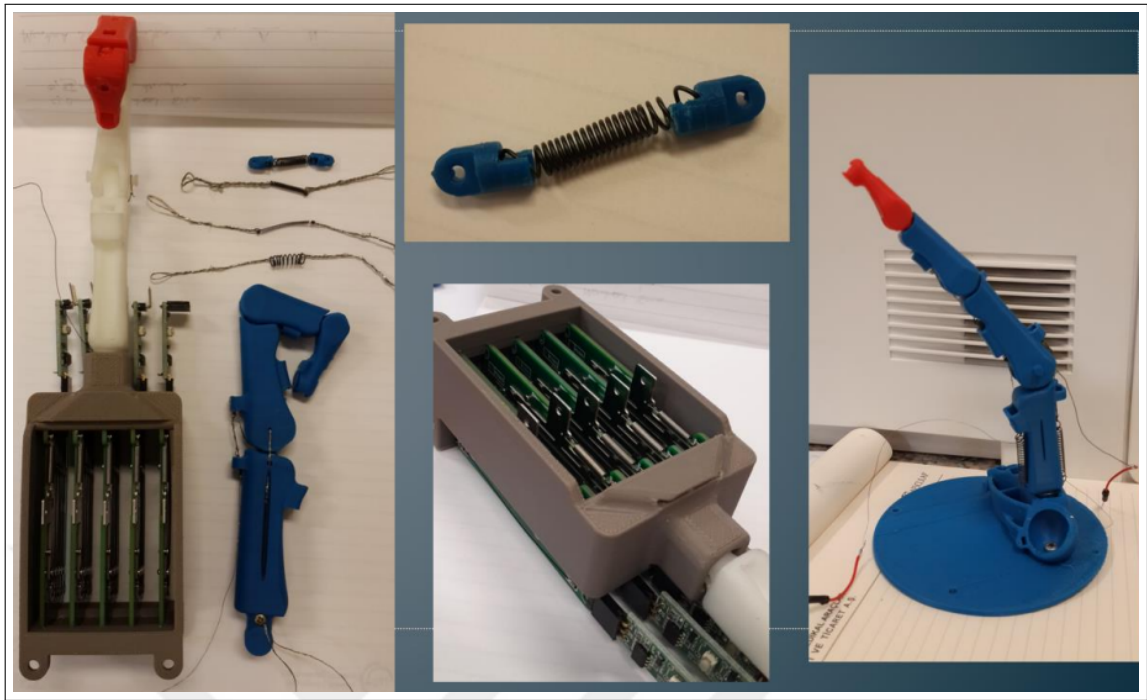


Figure 3.5 Design of SMA-actuated index finger and SMA actuator placement on metacarpals [13].

The CAD environment enabled iterative evaluation of actuator placement, contraction paths, and attachment points. Particular attention was paid to aligning the actuator trajectories with biological flexor tendon pathways, allowing simulated motion at the MCP, PIP, and DIP joints. These efforts led to the preference for spring-based SMA actuators, which have greater contractile capacity and better adaptability to curved anatomical geometries.

Finally, the ongoing difficulties in achieving precise and reliable control even at the finger level highlighted the need for investigation of the actuator itself. This led to the development of stand-alone SMA actuator designs that are separated from the prosthetic finger model for more focused experimentation and control system development.



Figure 3.6 Standalone SMA actuator prototype designs fabricated for controlled modeling experiments.

Although the initial design targeted the integration of SMA actuators into a full prosthetic hand, early prototyping and CAD-based simulations revealed considerable difficulties in reliably controlling these actuators within such a complex, multi-DOF system. These challenges—primarily stemming from the nonlinear and hysteretic nature of SMA behavior—led to a progressive narrowing of focus: first to individual fingers, and eventually to the actuator itself.

As a result, the research direction shifted towards isolating the SMA actuator from the full prosthetic assembly. This approach enabled more precise characterization and systematic modeling of actuator behavior. Several standalone SMA actuator prototypes were designed and tested with the explicit goal of understanding their dynamic properties and improving their controllability. These efforts laid the groundwork for the

development of data-driven models and robust control strategies based entirely on the SMA actuator's intrinsic dynamics—independent of higher-level prosthetic mechanics or integration.



Figure 3.7 Spring SMA actuator placement for force measurement setup.

3.3 Temperature and Resistance Relationship

It is reported that SMA electrical resistance is relatively higher in the martensite phase than in the austenite phase [91, 92]. For each phase alone SMA shows a linear proportional resistance change due to temperature change, and the rate of resistance change is different for both phases. However, during the transition between phases, resistance change is inversely proportional to temperature. Figure 1.1 shows the change in SMA resistance due to temperature for martensite phase (I), transition phase (II), and austenite phase (III). In regions I and III, there are proportional changes but at different rates, and in region II the resistance starts to reduce, and in a portion of this phase the resistance changes inversely proportional to temperature.

In figure 1.1, it is seen that if there is a way to observe resistance change while heating the material, the phase of the material can be detected and characterized for operation in a safe range.

To control the force generated when the SMA is excited, measurements were conducted in various scenarios using a data acquisition and control system that applies voltage at certain intervals and levels and measures the force generated in response. The collected data was then transferred to MATLAB in real time. The collected data was prepared for both forward and inverse models for RNN training in MATLAB. Monitoring the SMA behavior provides valuable information about the current phase and the progress of the phase transformation. This information, together with the voltage and current values, is given as input to the RNN to improve the ability to predict force output and adjust control signals for precise operation.

3.4 Preliminary Studies and Exploratory Approaches

The design and integration of SMA (Shape Memory Alloy) actuators into prosthetic finger prototypes required meticulous attention to both their mechanical connections that mimic natural tendons and the critical electrical interfaces for actuation and sensing. This phase involved exploring various SMA configurations and addressing the practical challenges of their physical and electrical integration.

For initial experiments, a variety of SMA actuators, wires, and springs were used for the initial prototype of the finger design. Five Miga Motors SMA actuators were used to analyze the concept's specifications and requirements (Figure 3.5). Additionally, experiments were conducted with SMA wires and springs of different sizes and diameters to observe the SMA's behavior and the kinematics of the initial setup. At the end of these experiments, it was observed that simulating finger movement in full flexion required a significant length reduction from the actuator. It was thought that it would be more efficient to use a spring instead of a wire. In addition, all actuators required different combinations of designs to mimic specific finger movements such as full flexion, half flexion, and extension at the MCP, PIP, and DIP joints.

Starting from the hand design and focusing on the finger and then the SMA actuator itself, the studies revealed the need for an easy, practical, and stand-alone design

for the SMA actuator. The different designs also necessitated redesigns, including the electrical signals and sensor connections that would stimulate the actuator. Different methods were also tried to measure and collect this data that needed to be measured to capture the temperature, resistance and force relationship.

All these preliminary studies were important stages of this study and ultimately paved the way for the SMA actuator to be applied to different scenarios in real time in a practical way at the end of this study.

3.4.1 Measurements

Various methods and sensors were employed to measure temperature and electrical resistance, and generated force under different working conditions. A custom data acquisition system was developed to collect synchronized voltage, current, and force signals.

Temperature Measurements

One of the primary challenges in working with SMA wires and springs is achieving accurate real-time temperature measurement. Conventional temperature-sensitive components such as NTC and PTC thermistors are commonly used in various applications; however, their response times are too slow for SMA systems, which require sub-second thermal feedback due to the rapid heating behavior during actuation.

Infrared temperature sensors offer faster response times and are theoretically suitable for real-time applications. However, they struggle to accurately detect the temperature of thin SMA wires due to limited spatial resolution and targeting difficulties. Thermal cameras provide broader visual temperature mapping across multiple points, yet they also suffer from inherent latency and the added complexity of image processing to track the exact location and moment of peak temperature on small-diameter wires.

Due to these limitations, indirect temperature estimation methods are preferred. A more viable approach is based on the well-established principle that the electrical resistance of SMA materials varies with temperature. By continuously monitoring the resistance of the SMA wire or spring, it is possible to infer the temperature indirectly.

However, this method introduces its own challenges. SMA components used in this study typically exhibit low resistance values in the range of 0.8–3 Ω , and the thermal sensitivity results in only about a 10% change in resistance. Detecting such small variations in real-time requires highly precise measurement systems. While Wheatstone bridges can be used to measure small resistance changes, the setup becomes unreliable at high currents: self-heating effects alter the resistances of the bridge elements, leading to unpredictable results.

A more stable solution involves calculating resistance using synchronized voltage and current measurements. This approach avoids the complications of component heating and enables accurate real-time estimation of the actuator's temperature.

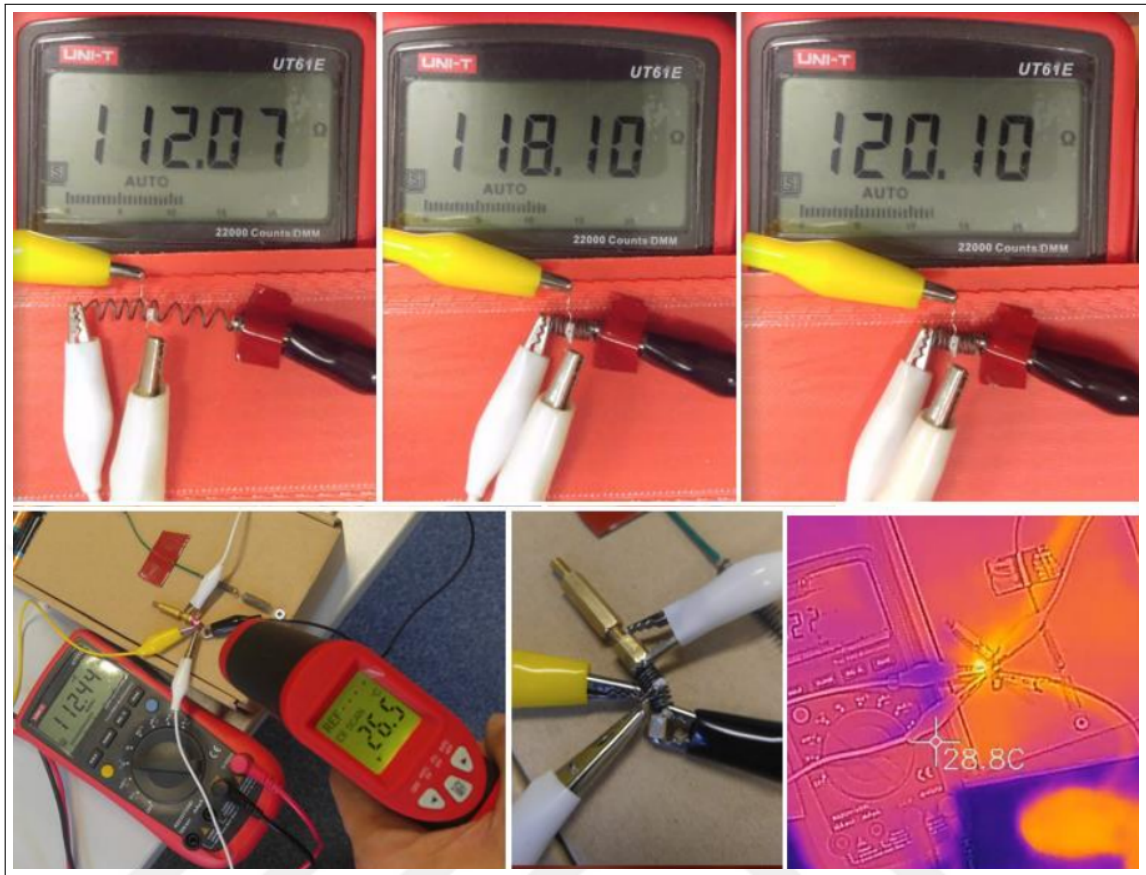


Figure 3.8 Measuring temperature setups with PTC, infrared devices, or thermal camera.

SMA wires and springs must be securely connected to signal (electrical) wires to ensure both mechanical stability and reliable electrical conductivity. These connection points should be strong enough to withstand the generated force without affecting the elongation behavior of the SMA, thereby preserving actuator performance.

Soldering may appear to be a straightforward solution; however, the high temperatures from the soldering iron can alter the intrinsic properties of the SMA material, negatively impacting its performance. As a low-temperature alternative, ultraviolet (UV) curing was also tested. While this method avoids thermal damage, it often results in incomplete conductivity and weak bonding at the joint. Another method explored was mechanical fastening using screws. This approach proved to be both thermally safe and mechanically robust. Consequently, in this study, both ends of the SMA springs were mounted using screwed terminals, ensuring consistent performance throughout the experiments.

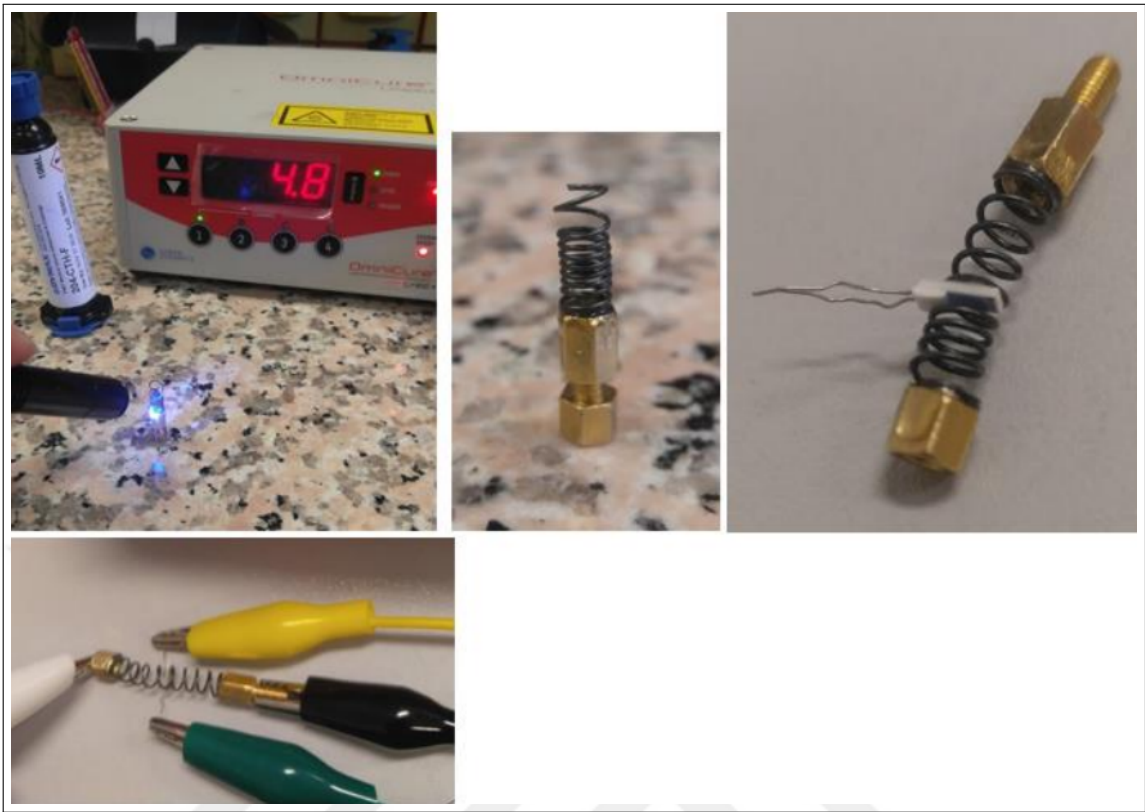


Figure 3.9 UV curing method applied at the junction between SMA springs and electrical wires. Although this technique avoids thermal damage that may occur with soldering, it often results in poor electrical conductivity and insufficient mechanical strength.

Real-time temperature measurement of SMA springs is challenging due to the slow response time of conventional temperature sensors. While methods such as PTC thermistors, infrared devices, or thermal cameras can be employed, these systems often introduce delays that are intolerable for precise control. Since temperature changes directly induce corresponding changes in the electrical resistance of SMA material, measuring resistance offers a more efficient alternative to conventional temperature measurement techniques.

This resistance variation can directly indicate the phase transformation between the martensite and austenite phases. In this study, the SMA wires and springs used exhibit resistance values ranging from 0.9 to 5 ohms. Consequently, a key challenge is accurately measuring resistance changes smaller than 0.1 ohm in real time to prevent overheating and ensure the actuator operates within its safe range.

Some alternative studies to control temperature

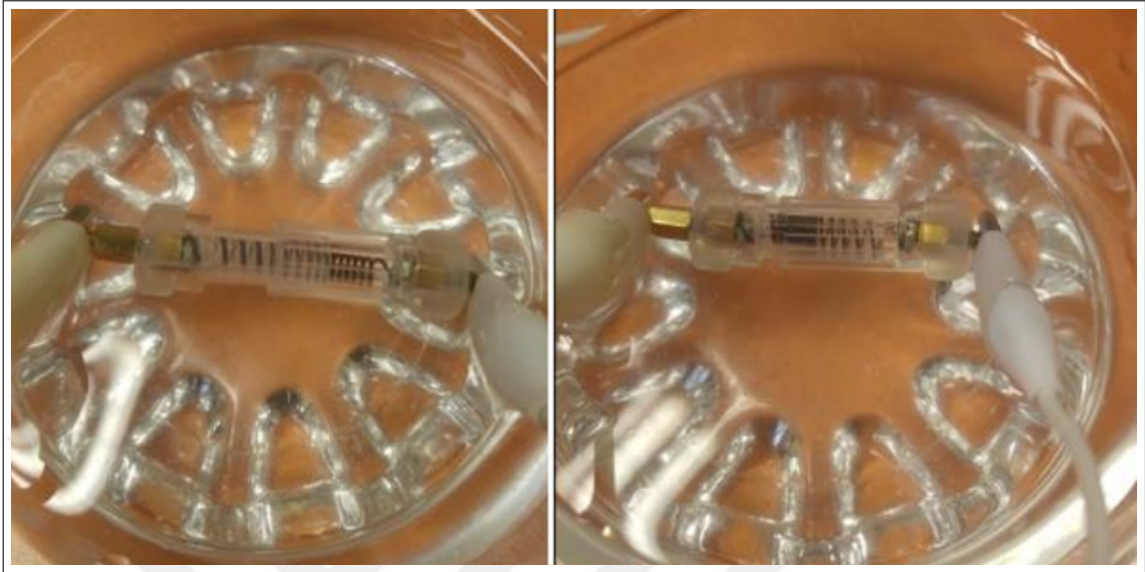


Figure 3.10 Water bath used for rapid thermal stabilization of SMA actuators.

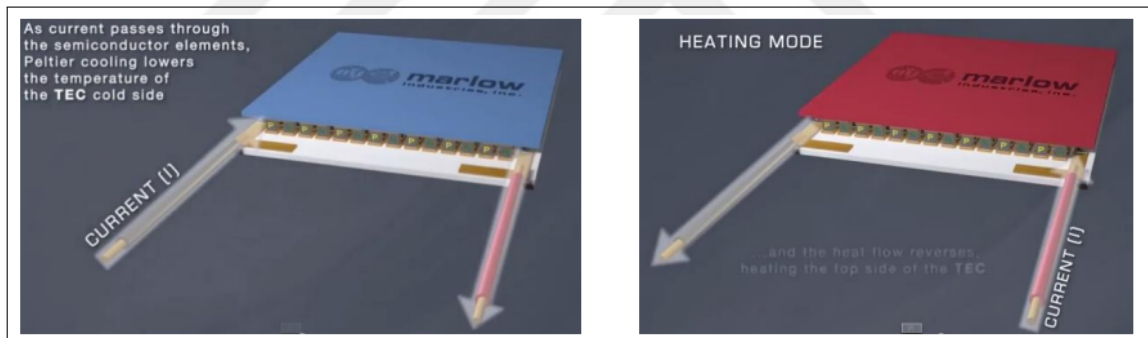


Figure 3.11 Peltier module-based cooling and heating system for SMA temperature control [15].

Thermoelectric couples are solid-state devices capable of generating electrical power from a temperature gradient, known as the Seebeck effect, or converting electrical energy into a temperature gradient, known as the Peltier effect. The Peltier effect bears the name of Jean-Charles Peltier, a French physicist who in 1834 discovered the calorific effect of an electrical current at the junction of two different metals. When current flows in one direction, the module enables cooling on one side and heating on the other. Reversing the current reverses the thermal effect. This bidirectional control provides a solid-state method for thermal regulation of actuators.

Resistance Measurements

Because of the slow response time of conventional temperature sensors, real-time temperature measurement of SMA springs presents a significant challenge. While methods like PTC thermistors, infrared devices, or thermal cameras can be used, all such systems introduce delays that are often intolerable for precise real-time control. Given that temperature change directly forces a change in the electrical resistance of SMA material, measuring this resistance change offers a more efficient alternative to conventional temperature measurement techniques.

This resistance change can provide valuable insights into the phase transformation between the martensite and austenite phases. In this proposed study, SMA wires and springs exhibit resistance levels ranging from 0.9 ohms to 5 ohms. A key challenge lies in accurately measuring resistance changes smaller than 0.1 ohm in real-time to prevent overheating and ensure the actuator operates within safe parameters.

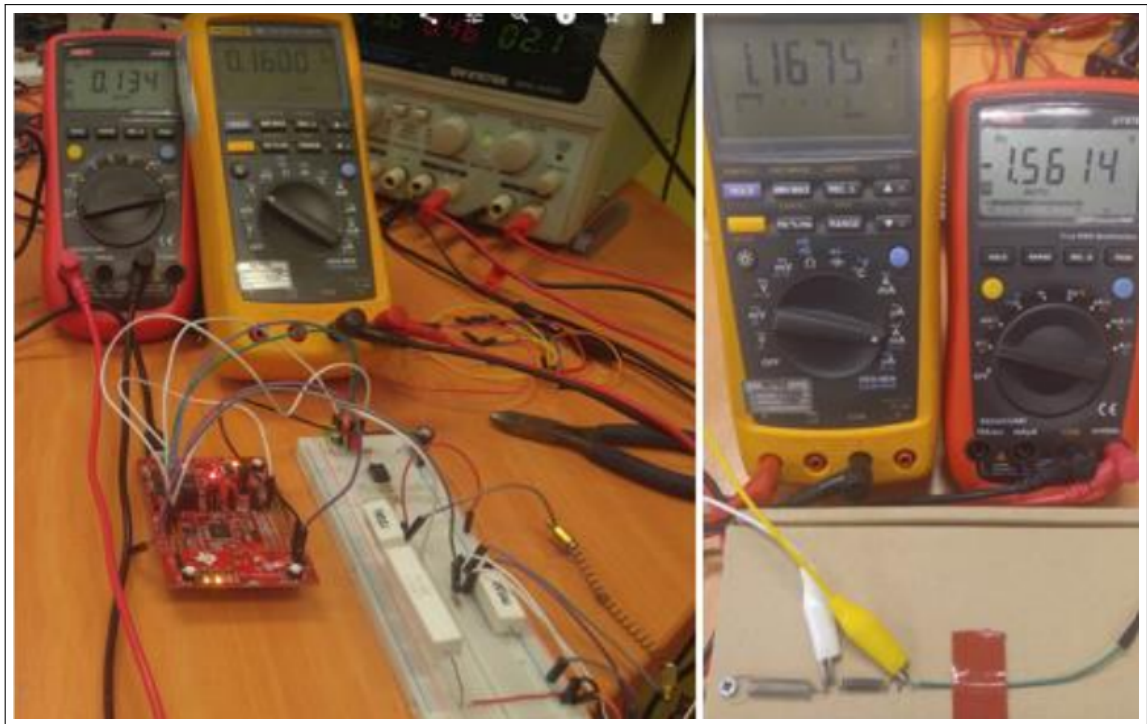


Figure 3.12 Measuring resistance change with voltage divider and Wheatstone bridge.

Force Measurements

Initial force measurements were conducted in a laboratory environment using specialized devices designed to characterize the spring's properties. While these systems provided insights into the Shape Memory Alloy (SMA) spring's behavior, such as its force generation upon heating, their connection limitations and sensitivity to environmental conditions rendered them unsuitable for real-time applications. Nevertheless, these complex systems were employed in the initial experiments to thoroughly understand the SMA's response to heat, its force output, and its overall characteristics.

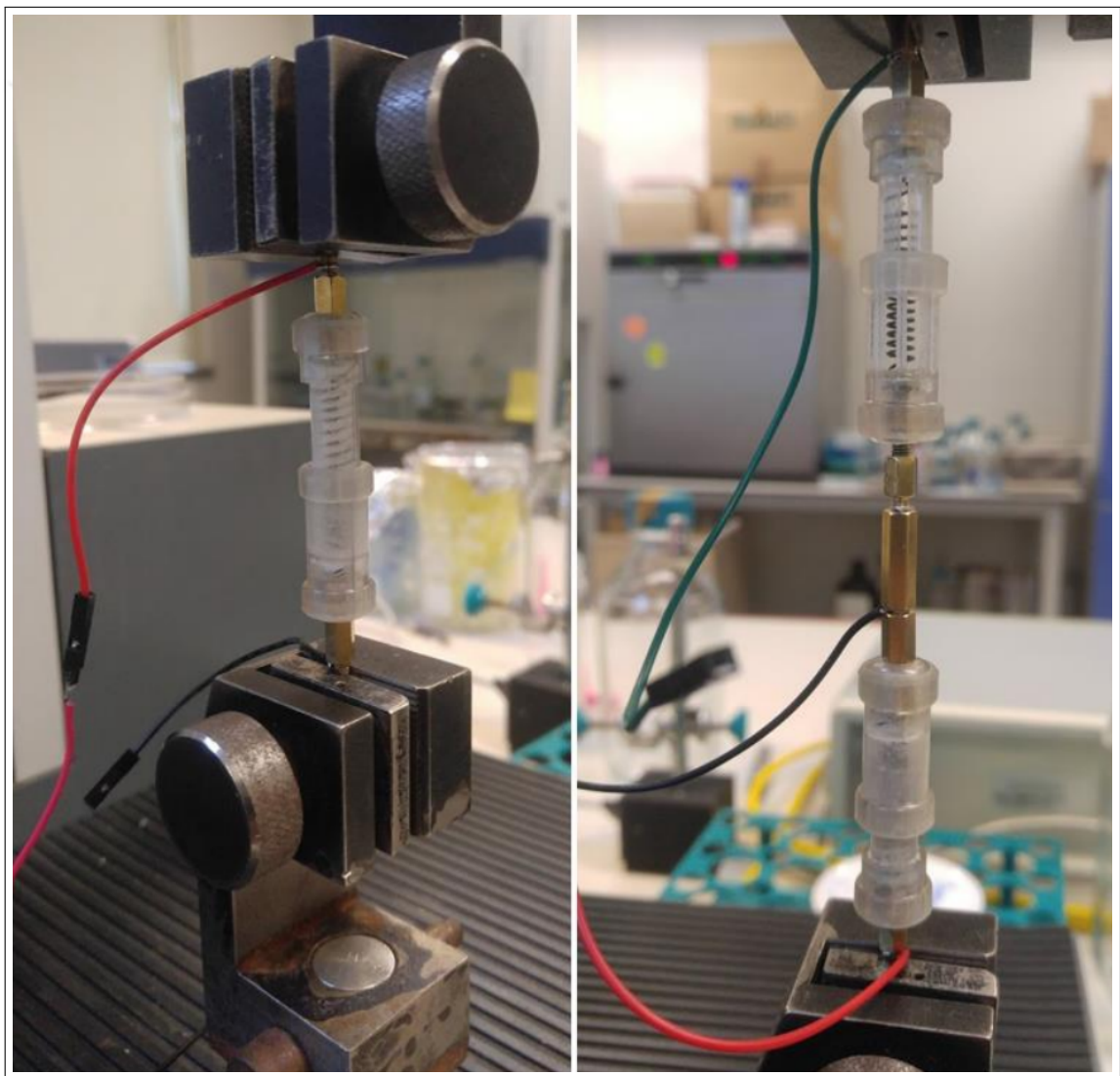


Figure 3.13 Experimental setup of SMA spring load test.

These preliminary results highlighted the necessity for a more practical force measurement method. Subsequent measurements continued with a more compact

palm-sized force meter, which, despite its smaller form factor, still allowed for effective measurement. However, the need for an even more practical approach persisted. Ultimately, the integration of a Load Cell provided a solution that occupied less space and enabled direct, in-situ force measurement. Consequently, our data collection system became compact and highly practical with the inclusion of the Load Cell.

The spring is mounted vertically and connected to a rigid test fixture, enabling controlled thermal activation and force observation. Electrical leads deliver current through the SMA, while the spring's contraction is mechanically constrained to measure the resulting force. These measurements were conducted in a laboratory environment using specialized devices designed to characterize the spring's properties. The laboratory-based tests presented in Figure 3.14 were designed to extract the characteristic properties of the Shape Memory Alloy (SMA) spring under controlled thermal and mechanical conditions. During these experiments, the temperature was gradually increased in a stepwise manner to closely monitor the SMA's contraction behavior, force generation, and thermal hysteresis characteristics. These measurements were conducted in a specialized setup that allowed precise alignment, mechanical fixation, and accurate current control, thereby enabling repeatable and detailed data acquisition.

Although this configuration was effective for characterizing the SMA's response, it required a complex laboratory environment and lacked portability. As a result, the need for a more practical and field-deployable system became evident, especially for real-time control applications in wearable or embedded actuator systems. This motivated the transition to more compact measurement tools and eventually to the integration of load cells in later stages of development, enabling in-situ force monitoring under operational conditions with minimal hardware complexity.



Figure 3.14 Detailed view of spring load testing mechanism. Detailed view of a palm-sized digital force gauge used in early-stage spring load measurements. The SMA spring is attached between fixed and moving ends, and the force is recorded as the spring contracts upon electrical activation. This compact device enabled practical measurements before transitioning to an integrated load cell system.

The SMA actuator was designed with careful consideration of the practical constraints associated with connecting electrical wires to the SMA element and ensuring both mechanical stability and reliable electrical conductivity. The configuration enables secure fixation of the SMA spring at both ends using mechanical screws, thereby avoiding thermal damage caused by soldering. This setup allows the spring to elongate and contract freely during operation while maintaining robust electrical connections. Additionally, the design facilitates precise resistance measurements across the SMA, which are critical for monitoring temperature-dependent phase transformations and enabling closed-loop control. This robust mechanical and electrical integration ensures repeatable operating performance and better data acquisition throughout test cycles. Additionally, the modular design facilitates rapid replacement and flexible reconfiguration of SMA actuators with different geometries, thus supporting a wide range of experimental protocols and extended operational tests.

Mechanical Refinements and Initial SMA Actuator Integration

In subsequent studies, the mechanical design of the finger and hand was refined and redesigned, taking into account detailed anatomical features and insights from initial design explorations. Specific improvements included:

- All joints of the phalanges were changed from hinge joints to more functionally appropriate ball joints.
- Tendon attachment points and internal channel structure in the phalanges were optimized to ensure efficient movement capabilities.

For actuator integration, SMA wires were strategically placed within the metacarpals to mimic the function of the intrinsic muscles found in real human fingers, specifically the palmar interossei (PI) and dorsal interossei (DI). In this design, two SMA actuators were placed on either side of the metacarpals to mirror their anatomical counterparts. These SMA springs can be easily activated with low energy (e.g., two AA batteries, 3V), which are expected to provide instantaneous abduction and adduction when voltage is applied to their pins. Initial experiments were conducted with various Shape Memory Alloy samples to understand their properties and identify new SMA actuator types or structures that could meet our specific demands, especially regarding heating, cooling, force generation, and displacement properties for efficient use.

For initial experiments, samples of various SMA actuators, wires, and springs were utilized for the first prototype of the finger design. Five Miga Motors SMA actuators were used to analyze features and requirements of the concept (Figure 3.16). Additionally, experiments were performed with different sizes and diameters of SMA wires and springs to observe the behaviors of SMA and kinematics of the initial setup. At the end of the experiment, it was observed that mimicking finger motion at full flexion required a substantial length contraction from the actuator. Furthermore, all actuators contracted combinatorially to mimic specific finger movements, such as full flexion, half flexion, and extension at the MCP, PIP, and DIP joints. These experiments highlighted that detailed kinematic analyses were indispensable for determining the desired contraction length of the actuating units.

Prototyping, Simulation, and Initial Experimental Validation

The prototype finger was fabricated through rapid prototyping of ABS plastic (Figure 3.15 c). Tendon motion through the synovial sheath (tunnels) was imitated using a cable and pulley system, (Figure 3.15 d). ADAMS software was used for the dynamic simulation of the mechanical design.

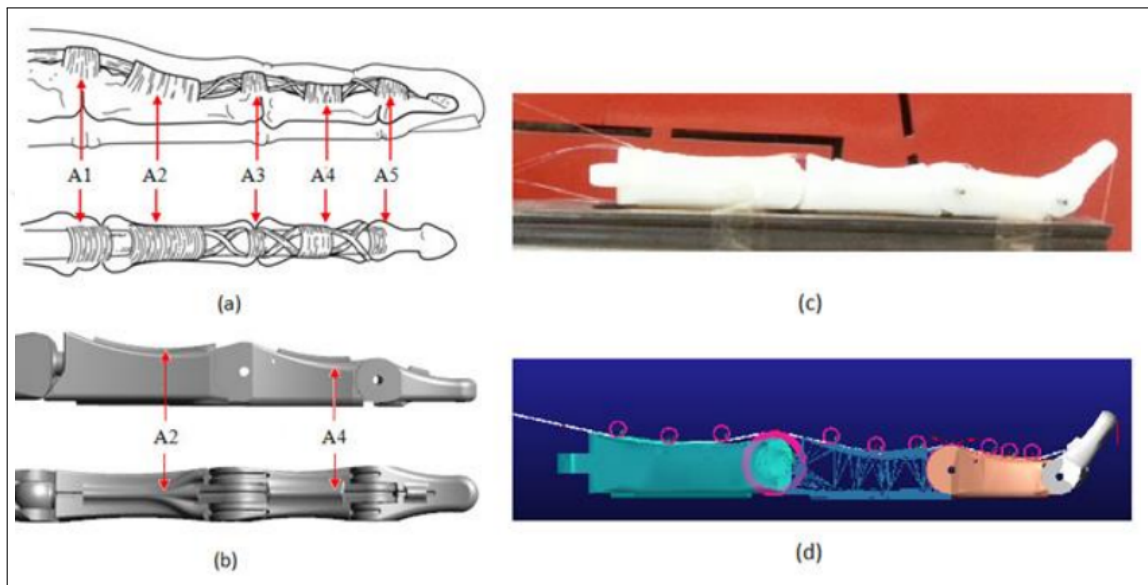


Figure 3.15 a) Pulleys of typical human finger, b) designed prototype, c) test-bed of prototype, d) simulated model [13].

Table 3.2

Forces of Applied on Fingertip and Measured on FDP Tendon.

Force Applied on Fingertip (N)	Force Measured in FDP Tendon for the Fingers (N)		
	Human	Prototype	Simulated
2	7.5	8.7	4.9
5	13.5	16.9	12.5
10	23.7	24.8	22.1

For mechanical testing, a test bed for the targeted load-lifting task was constructed (Figure 3.15 c). To measure tendonal force and angular displacement, the prototype finger was placed at an angle on the table with the finger attached to a load. To assess the validity of the simulation, the task was repeated in an ADAMS simulation for a number of motions.

A specially developed experimental platform was utilized to simulate load-pulling tasks similar to those performed by the flexor digitorum profundus (FDP) tendon. The range of motion and tendon tension generated by the prototype were then compared with those of a human index finger. This provided valuable information about the mechanical accuracy of the biomimetic design and was instrumental in determining the target forces and sufficient extension-shortening area required from the actuator [13,93].

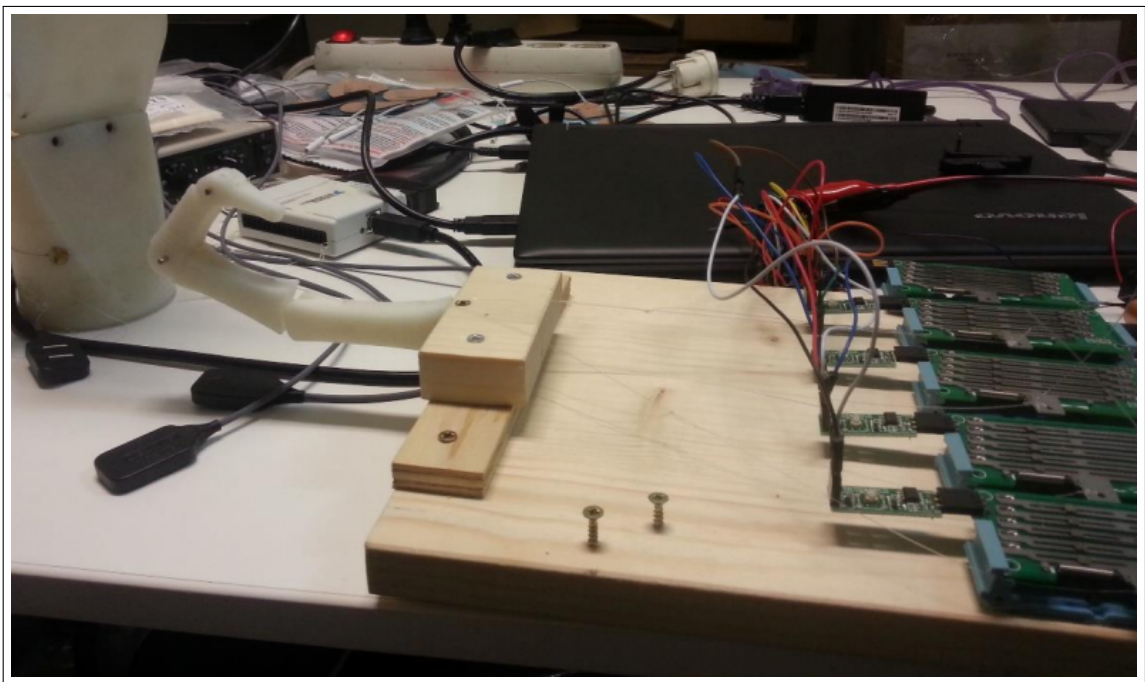


Figure 3.16 Experimental setup of SMA actuated index finger prototype.

Reduction to Finger-Level and Single-Actuator Modeling

Due to practical challenges in controlling SMA actuators within a complex multi-DOF system, the scope was narrowed to focus on individual finger motion. Eventually, the system was simplified further to a single SMA spring actuator, enabling better isolation and understanding of its nonlinear behavior.

The SMA actuator was designed with careful consideration of the practical constraints associated with connecting electrical wires to the SMA element and ensuring both mechanical stability and reliable electrical conductivity. The configuration en-

ables secure fixation of the SMA spring at both ends using mechanical screws, thereby avoiding thermal damage caused by soldering. This setup allows the spring to elongate and contract freely during operation while maintaining robust electrical connections. Additionally, the design facilitates precise resistance measurements across the SMA, which are critical for monitoring temperature-dependent phase transformations and enabling closed-loop control.

3.4.2 Modeling and Control Approaches

This section details the various modeling and control strategies explored to manage the complex behavior of Shape Memory Alloy (SMA) actuators. Initially, conventional methods like polynomial fitting and linear/nonlinear regression were employed to empirically establish relationships between voltage, resistance, and force. However, these basic models proved inadequate, primarily due to their inability to generalize across varying dynamic conditions and the inherent nonlinearities and noise present in SMA data. Similarly, while traditional PID controllers were implemented and tuned for position and force regulation, they struggled with the transient nonlinearities of SMA, failing to provide the required precision for dynamic control. These limitations collectively prompted a strategic shift towards more sophisticated data-driven, machine learning approaches, specifically focusing on neural networks to capture the complex input-output dynamics.

3.4.3 Fitting, Regression, and Neural Network Architecture

In the early stages of this study, polynomial fitting, linear, and nonlinear regression methods were extensively used to identify relationships within the collected data. Despite these efforts, a robust, generalized equation or model could not be established due to the inherent noise from inactive parts of the system and the pronounced nonlinear behavior of the SMA. Although fitting was applied piecewise to different phase transformations of the SMA, a universally applicable generalization for every scenario remained elusive.

Linear regression provided an initial baseline understanding of voltage-resistance and voltage-force trends, but its inability to model phase transitions, hysteresis, and saturation effects limited its predictive power. Nonlinear regression techniques, including exponential and multi-variable polynomial models, showed better curve fitting in isolated ranges but failed to generalize across full operational conditions. Furthermore, sensitivity to noise—especially in low-force or transition regions—caused instability in fitted models. As a result, these regression-based approaches were found insufficient for modeling SMA actuators operating in dynamic, real-time conditions.

Acknowledging these challenges, the literature guided us towards neural network algorithms, which have demonstrated effectiveness in controlling SMA springs' force output, especially under nonlinear and time-variant scenarios. Unlike conventional modeling methods, neural networks are capable of learning complex patterns directly from data without explicitly defined equations, making them highly suitable for this type of system.

In this context, various neural network architectures were investigated. Beyond standard feedforward neural networks, alternative structures such as radial basis function networks and self-organizing maps were reviewed. However, particular focus was given to dynamic networks like NARX (Nonlinear AutoRegressive with Exogenous Inputs) and Recurrent Neural Networks (RNN), which are specifically designed to capture temporal dependencies and state-based behaviors in systems like SMA actuators.

NARX models operate by regressing future outputs based on past values of both inputs and outputs. While this structure enables memory-like behavior, its performance is highly sensitive to the number and selection of delays. NARX networks also require careful configuration of training parameters to avoid overfitting, and their reliance on past output feedback can become problematic in closed-loop control if prediction errors accumulate.

RNN models, on the other hand, possess internal memory states and recurrent feedback loops that allow them to learn sequences and dynamic responses more nat-

urally. Their architecture is inherently suited for time-series modeling and adaptive control applications. However, training RNNs can be computationally intensive, and they are prone to vanishing or exploding gradient problems—particularly in long sequences. These issues necessitated the use of truncated sequences, gradient clipping, and appropriate weight initialization strategies during training.

To address these limitations, a specialized variant of RNN—Layer Recurrent Neural Network (LRNN)—was selected as the final architecture for both forward and inverse modeling tasks. The LRNN integrates layer-wise memory and delay units, offering a balance between learning temporal patterns and maintaining training stability. In the forward model, the LRNN was trained to predict the force output from a given voltage input, whereas in the inverse model, the goal was to determine the required voltage to achieve a target force. The inverse architecture employed modified input structuring with shifted force signals to improve temporal generalization.

This staged modeling transition—from regression to neural network models—was critical for achieving the desired performance and adaptability in controlling SMA-based actuators. The experimental results and simulation comparisons between methods, which are presented in subsequent chapters, support the superiority of LRNN-based models in terms of generalization ability, prediction accuracy, and suitability for real-time control implementations.

3.5 Actuator Design and Data Acquisition System

3.5.1 Material

In this study, NiTi-based SMA springs supplied by “Kellogg’s Research Labs” (Moultonborough, USA) were used [94]. The main reason for preferring the spring form compared to SMAs in wire form is the potential to obtain larger displacement ranges. While SMA wires shorten in length by 6-8% when heated, this small shortening can be mechanically amplified in the axial direction and converted into significantly

larger displacements, thanks to the helical spring structure. This provides a wide range of motion for applications such as precise positioning, robotic joint control, etc [17–19,58,59,65]. In the study, a spring with a length of 10 mm, a diameter of 0.5 mm, a pitch of 0.5 mm, a mandrel size of 3.2 mm, and a transformation temperature of 45 °C was selected.

A transformation temperature of 45 °C ensures that the material is in the martensite phase at room temperature, easily transitions to the austenite phase upon stimulation, and provides instant force generation. Choosing the transformation temperature close to ambient temperature facilitates cooling to the martensite phase when the excitation is terminated. This simplifies the process by reducing energy consumption and the time between working cycles. Since the transformation temperature of the SMA spring is selected slightly above room temperature, it is in the martensite Phase (Phase I) at room temperature. The test starts in Phase I and immediately reaches Phase II, and the resistance starts to decrease until the end of Phase II. Then the resistance increases again, meaning that it reaches phase III. Excitation is stopped at the beginning of this phase to prevent overheating, rapid deterioration of shape memory properties, and premature fatigue.

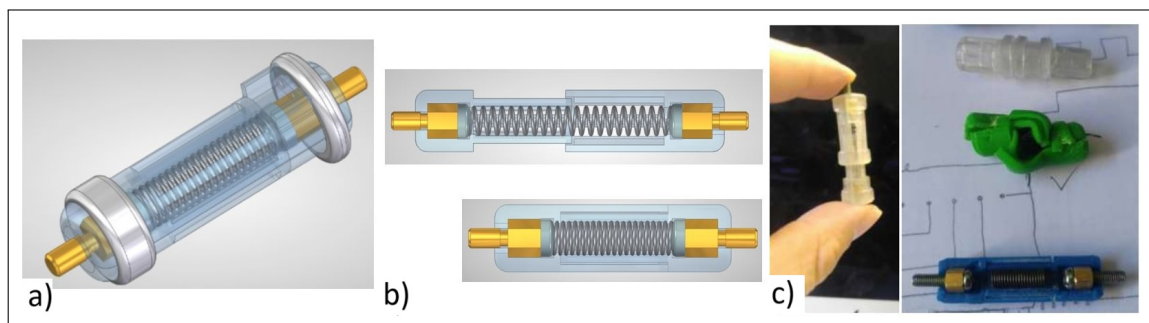


Figure 3.17 SMA actuator design drawings (a) and (b), and 3D prototypes of the design shown in (c). The green one was damaged due to overheating, as seen inside the blue prototype.

3.5.2 Data Acquisition System, Experimental Setup

To monitor and record the behavior of the SMA actuator, a control unit was designed, as shown in Figure 3.18. This unit comprises an SMA spring actuator, an SMA

driver circuit, sensors for force, current, and voltage, and a fixation block. This system facilitates data collection without disturbing the SMA actuator functions for training RNN models. The voltage and current of the SMA spring are monitored by sensors (INA260 Digital Current and Voltage Monitor [16]). The INA260 is a current-sensing amplifier that can measure both the voltage levels and current of the load [16] and send the results to the microcontroller unit via the I2C serial communication protocol. A force sensor (HX711 load cell amplifier) is used to measure the force generated by the SMA actuator under constraint, as shown in Figure 3.18. The experimental parameters are controlled by a microcontroller (CC3200) connected to a mobile phone via Wi-Fi using an Android application (Blynk) for user interface and control. A digital potentiometer controlled by the microcontroller is used to generate different voltage levels.

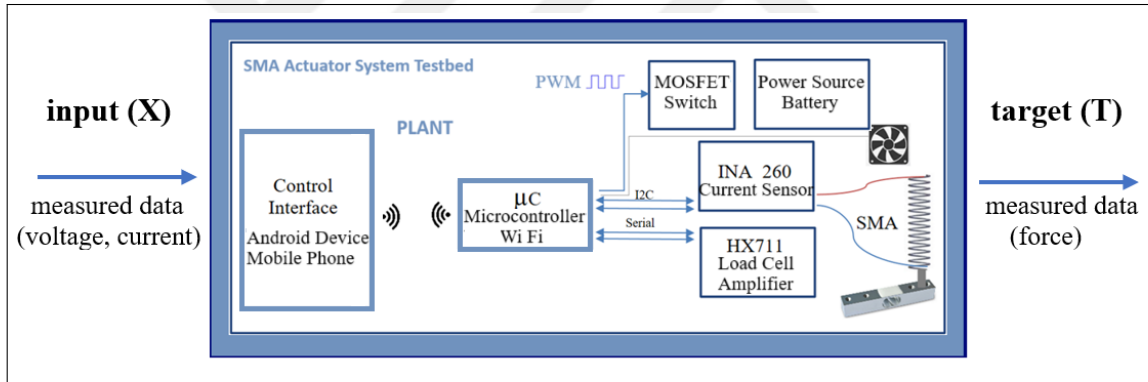


Figure 3.18 Block diagram of the SMA actuator calibration and operation setup. The CC3200 microcontroller, equipped with a WiFi module, receives control signals from an Android device via WiFi, enabling remote control and data transmission. The microcontroller receives control signals from an Android device via WiFi. It measures and monitors the current flowing through the SMA spring and the voltage applied across it using the INA260 voltage and current sensor. Additionally, it measures the force generated by the SMA actuator using the HX711 force sensor. The microcontroller then calculates the resistance change of the SMA spring based on the measured voltage and current values for calibration and operation, ensuring it stays within a safe range.

3.5.3 INA260 Voltage/Current and HX711 Force sensors

The INA260 is a digital current and voltage monitor that includes an integrated precision shunt resistor and can measure current, voltage, and power and transmit data via an I²C or SMBus™ compatible interface. The data readout time can be configured

as fast as $140\ \mu\text{s}$ or as long as $8.244\ \text{ms}$ and can read and average between 1 and 1024 samples.

The HX711 is a high-precision analog-to-digital converter (ADC) integrated circuit used with load cells. It converts small voltage changes from load cells into digital signals that can be processed by microcontrollers. The HX711 sensor can perform high-resolution measurements with its 24-bit ADC structure and can be easily integrated into microcontroller systems due to its low power consumption and serial communication features. The sampling rate can be set to a maximum of 80 SPS (samples per second). The sampling rate of the designed system in this study is limited to 80 samples per second due to this force measurement limitation.

3.5.4 CC3200

To monitor and record the behavior of the SMA actuator a controller unit comprising an SMA spring actuator, an SMA driver circuit, force, current and voltage sensors, and a fixation block is designed as shown in Figure 3.18. This system facilitates the collection of data, without perturbing the SMA actuator functions, for the training of the RNN models. The voltage and current of the SMA spring are monitored with sensors (INA260 Digital Current and Voltage monitor [16]). A force sensor (HX711 load cell amplifier) is used for measuring the generated force by the SMA actuator under constraint as shown in Figure 3.18. The experiment parameters are controlled by a microcontroller (CC3200) that is connected to a mobile phone via wi-fi with an Android application for user interface/control [95].

The INA260 is a digital current and voltage monitor that integrates both a current sense amplifier and an analog-to-digital converter (ADC) into a single package. It is capable of measuring both the bus voltage and the current flowing through a shunt resistor and transmits these measurements via the I²C serial communication protocol to a host processor or microcontroller unit (MCU) [16]. With an embedded wireless module and a microcontroller, “CC3200” [95] is used for the system. “CC3200” can

be programmed via Energia [96]. An android device with a “Blynk” [97] application is used to control and visualize measured bus voltage and sense the resistor’s current, and voltage directly.

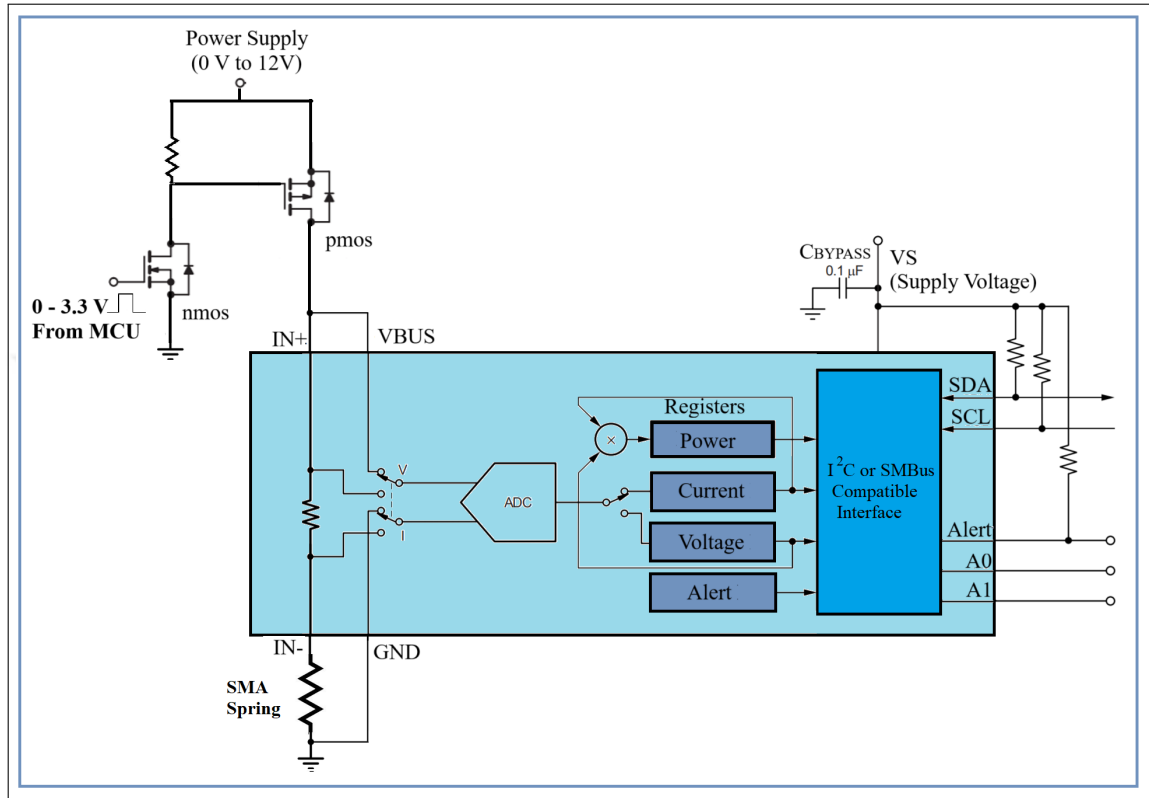


Figure 3.19 Block diagram illustrating the role of the INA260 in measuring current and voltage. The diagram also demonstrates how the Shape Memory Alloy (SMA) spring is stimulated using electrical input. The INA260 communicates measurements via I²C to a microcontroller [16].

Voltage, current, and force values are taken in real time. The SMA spring was stimulated for 8 seconds to heat and allowed to cool and return to its initial condition. The sampling rate is limited by INA260 capability, the maximum being 79 samples per second. Each experiment was continued for 120 seconds, and that was repeated 10 times.

3.6 Data Collection and Processing

3.6.1 Data collection

In this study, an "SMA Spring Actuator" was designed, utilizing a shape memory alloy (SMA) spring as the active component. The "SMA Actuator System", specifically designed for data collection and control, was employed to measure the force generated in response to various voltage levels applied under different conditions. The collected data was then used in the subsequent analysis. In the experiments, a voltage in the range of 0-3 V was applied to the SMA spring. The voltage applied to the spring, the current passing through it, and the generated force values were measured in real time with the data collection system. The SMA spring was stimulated to heat for 8 seconds or more and allowed to cool down and return to its initial condition. The sampling rate is limited by the HX711 force sensor capability, with a maximum of 80 samples per second. Each experiment lasted for 120 seconds and was repeated 10 times (or a varying number of times). The measured voltage, current, and force values, along with the control parameters, were transferred to MATLAB via the serial port using the CC3200.

3.6.2 Data Structure

The data structure for each test scenario, comprising control parameters and measured values, was recorded as a MATLAB data file. This file stored 7 different features for each sample. The data was marked to distinguish between active and inactive periods. The active period corresponds to when the SMA spring was excited (voltage applied, heating active, and force generated). The inactive period corresponds to when the stimulus was removed and cooling occurred. The data included values such as digital potentiometer value, measured voltage, current, calculated resistance (voltage/current), measured force, number of samples, and active state.

When the active time was 8 seconds, 112 seconds were allocated for cooling.

A longer time was allocated for passive cooling to ensure the heated spring cooled completely. An active and non-active period together lasted for a total of 120 seconds. With a sampling rate of approximately 80 samples per second and a total test duration of 120 seconds, each test dataset contained around 9600 samples for each of the measured features (voltage, current, force, etc.). It was tested in scenarios where active and non-active times were different. Only a 10-point moving average smoothing was applied to the collected data. Initially, we attempted to correlate the resistance to change with the generated force. However, this proved difficult due to significant outliers and noise, likely caused by the sequential reading of voltage and current during rapid changes. Using the data almost as it was for the relationship between only the voltage and the force formed, instead of the resistance, provided a more practical way.

Data sets were repeated for both training and testing in different scenarios. Both forward and inverse models were trained and tested with the dataset in four different scenarios.

Table 3.3
Test Parameters for both training and testing in different scenarios.

Test	Active Period/Warm-up	Cool-down	Voltage Levels	Reps
1	8 sec/Allowed	112 sec	4	3
2	8 sec/Allowed	112 sec	4	2
3	8 sec/Allowed	12 sec	Different	1
4	10 sec/Allowed	10 sec	Repeated	14

3.6.3 Data Preparation and Preprocessing, RNN Model

MATLAB was chosen as the development environment, where LR was utilized as a type of recurrent neural network (RNN). LRNN is a specialized artificial neural network designed to capture temporal dependencies in sequential data. Unlike traditional feedforward neural networks, LRNNs contain feedback connections, allowing them to process sequences of inputs and retain information about previous inputs through internal states. In LRNN, there is a feedback loop around each layer of the network,

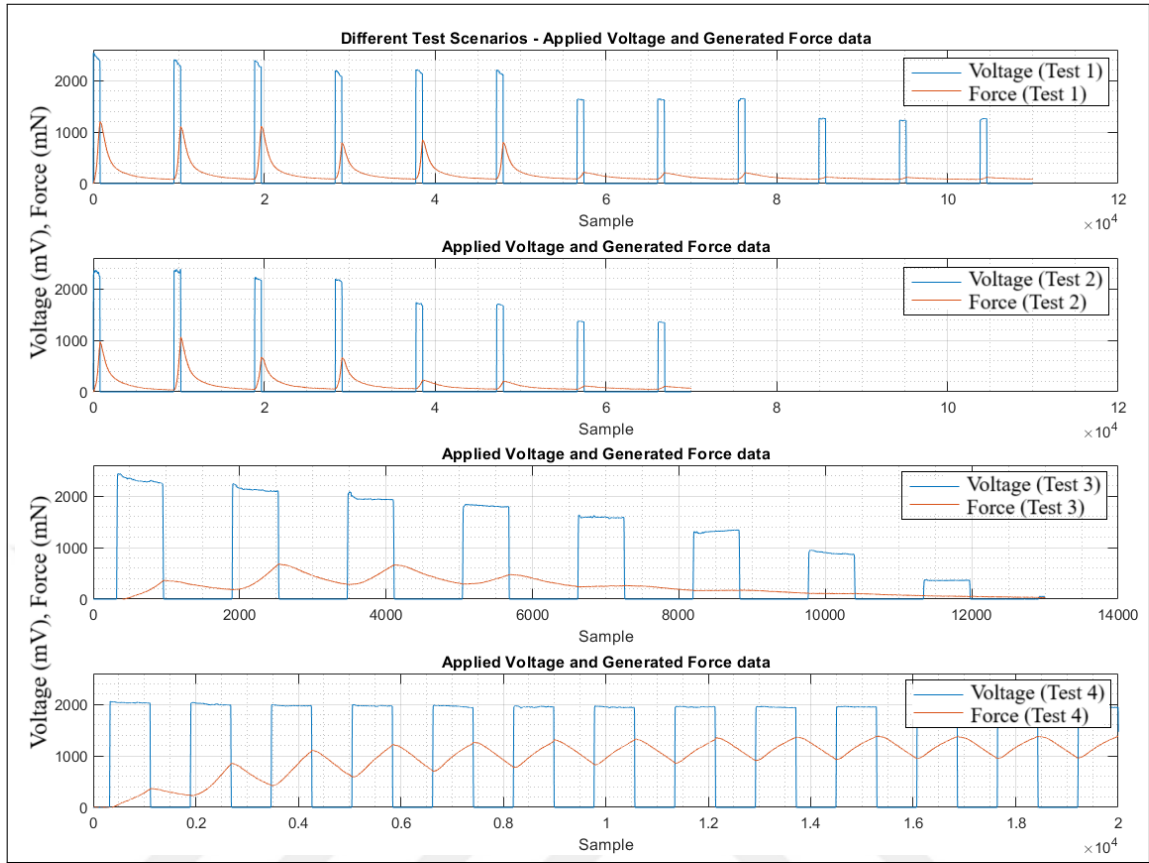


Figure 3.20 The graph shows the force and voltage data obtained with the SMA Actuator System in four different scenarios. These scenarios were designed to capture the dynamic behavior according to the difference between the cooling times. The first two scenarios with long cooling times were used to examine the steady-state behavior, and the last two scenarios with short cooling times were used to examine the dynamic responses.

except the last layer of the network, with a single delay [98]. This design allows the network to retain information over time, making it well-suited for modeling dynamic systems. By utilizing this architecture, the aim is to capture the complex, nonlinear dynamics of SMA behavior effectively. The ability of this model to handle the inherent hysteresis and time-dependent nature of SMA actuators is a key factor in its success. The forward model, which is trained with input voltage and output force values to estimate the force produced by the SMA actuator in response to a given input voltage, is called the forward model, and the model, which is trained with input force and output voltage data to find the voltage that should be applied to create a desired force, is called the inverse model. In both forward and inverse models, the LRNN architecture created with the layrecnet function of MATLAB was used.

The recurrent connection enables the network to store information about previous inputs in the current state, allowing the network to exhibit dynamic temporal behavior. The `layerDelays` parameter determines how far back in the time series the network can look when processing current inputs. Hidden layer sizes adjust to capture the complexity of the input-output data patterns. In our forward model layer, delay size is kept at 5, allowing the network to learn the relationship between input (voltage) and output (force). However, in the inverse model, the relation is more complex to capture; the input data (force) is concatenated with its time-shifted versions to better capture this complexity. Despite this added complexity, the layer delay size is still kept at 5. The hidden layer size is set to 10 neurons for both the forward and inverse models. The Bayesian Regularization algorithm was selected as a transfer function due to its superior ability to prevent overfitting and enhance generalization, especially in scenarios with small or noisy datasets, compared to other algorithms like Levenberg-Marquardt (`trainlm`) or Scaled Conjugate Gradient (`trainscg`).

3.7 Modeling

3.7.1 Forward Model

The forward model is designed to estimate the force generated by the SMA actuator based on a given input voltage. In this model, which has a recurrent layer structure, we aimed to capture the time-dependent dynamics of the SMA actuator using a feedback delay of 5 time steps. In this way, the network becomes sensitive not only to the instantaneous voltage value but also to the voltage values in the past 5 time steps, which helps to model the hysteretic behavior of the SMA. The single hidden layer contains 20 neurons, and this size provides enough capacity for the network to learn the nonlinear relationships between voltage and force while also aiming to balance overlearning. During the training process, the network learns these complex patterns from experimental data with the Bayesian Regularization (`trainbr`) algorithm. This training algorithm is effective in preventing overlearning and increasing the ability of the model to generalize to new, unseen data. While the model uses the tanh activation function

as the default in its hidden layer, the output layer is designed with a linear activation function. Linear activation allows the force value to be in a continuous range, which is suitable for regression tasks. As a result, the trained forward model can produce accurate force estimates for unseen voltage inputs presented to it. This structure of the forward model is especially ideal for scenarios where the applied voltage is known, and the goal is to predict the resulting force. In control applications, knowing the expected force output based on a given voltage input allows for the design of precise and efficient control strategies for the SMA actuator. For example, in a robotic system, more precise motion control and energy efficiency can be achieved by predicting the force required to perform a certain task. The training period is limited to a maximum of 200 epochs.

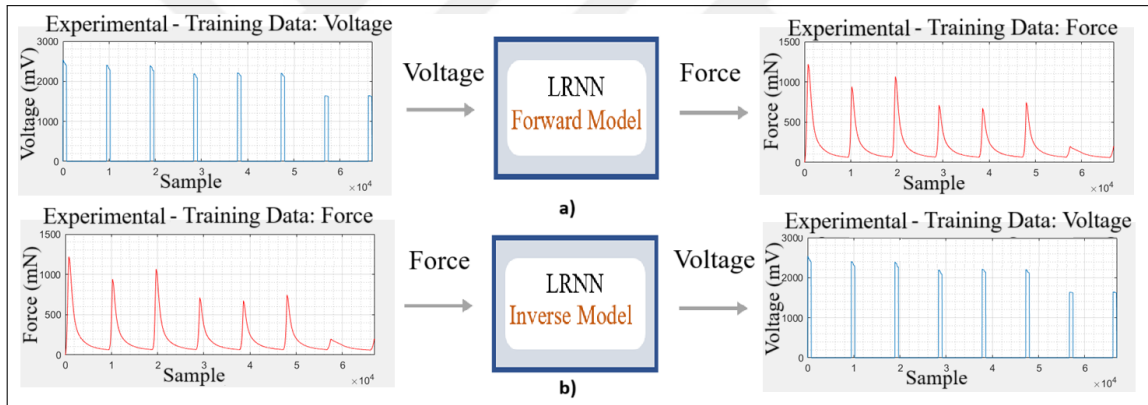


Figure 3.21 a) The forward model, designed to predict the force generated by the SMA actuator based on a given input voltage, utilizes a single hidden layer with 20 neurons and a 5-step feedback delay. b) The inverse model, designed to predict the required voltage to achieve a desired force output, employs two hidden layers with a 6-step feedback delay to capture the more complex relationship between force and voltage. Both models use Layer Recurrent Neural Networks (LRNNs).

3.7.2 Inverse Model

In this model, force is used as input, and the model is trained to output the voltage required to produce this force. However, this relationship is more complex. To overcome this complexity, in addition to the force data, "time-shifted" versions are also added to the input of the inverse model. In this way, the inverse network can learn the complex and difficult-to-invert behavior of the SMA more effectively. In addition to the shifted inputs, a 6-time-step feedback delay is used for these inputs,

similar to the forward model. This is so that the inverse model can better capture the time-dependent and hysteretic behaviors of the SMA actuator in modeling a more complex relationship, such as the transition from force to voltage. The inverse model has a deeper architecture with two hidden layers, and different numbers of neurons are implemented in each layer. This deeper structure allows the inverse model to learn the more complex "force $\rightarrow$ voltage" relationship more effectively compared to the forward model. This design of the inverse model is particularly important when it is necessary to follow a desired force trajectory or obtain a specific force value precisely. For example, in a prosthetic hand application, the inverse model can predict in real time the correct voltage levels that should be applied to the SMA actuators to obtain the user's desired grip force.

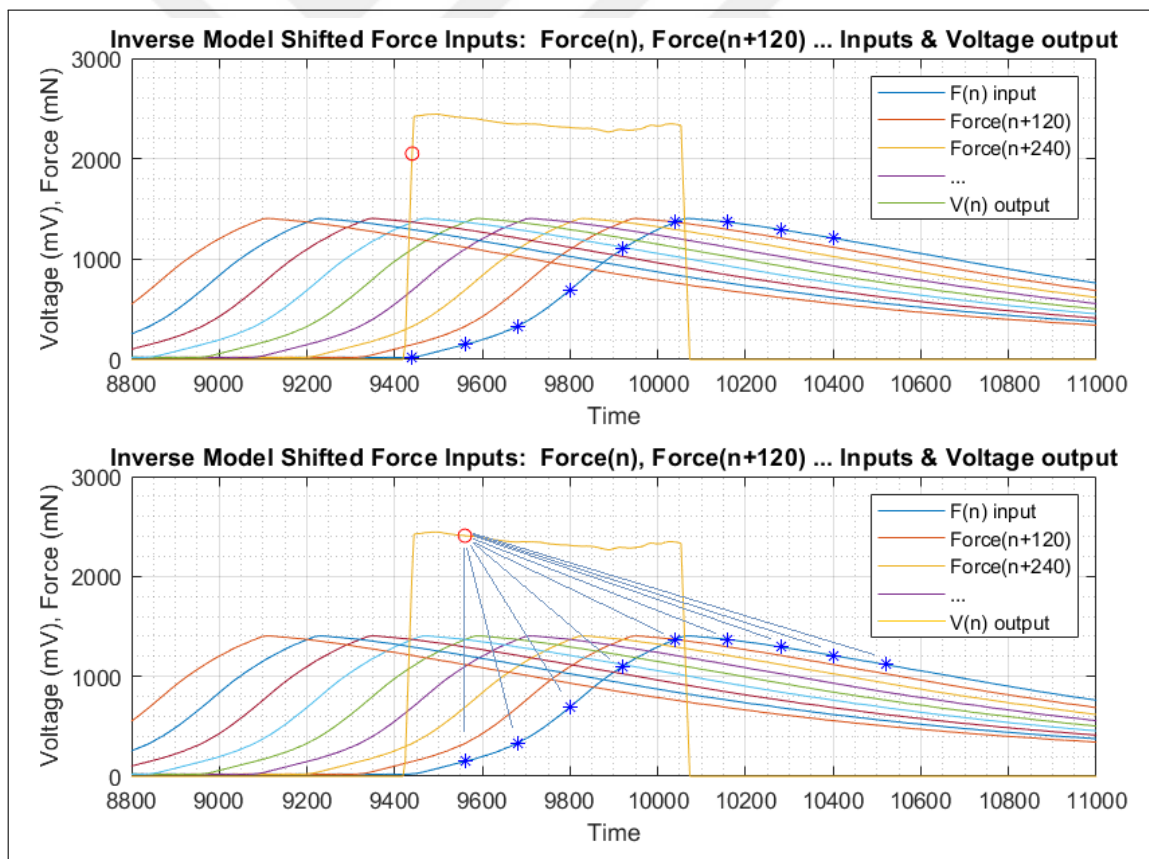


Figure 3.22 The input force data are combined with their time-shifted versions for the inverse model. This enhanced input structure enables the network to predict the future behavior of the SMA actuator while accounting for its dynamic hysteresis properties.

Figure 3.22 shows the data structure applied to the input layer of the inverse

model in detail. This structure allows the inverse model to make a more accurate and dynamic stress estimate by using not only the instantaneous desired force value but also the force information of future time steps.

3.8 Inverse Model-Forward Model Connection Simulation

The relationship between the inverse model and the forward model is crucial for achieving precise control of the SMA actuator. The diagram below represents this connection using LRNN (Layer Recurrent Neural Network) models for both the inverse and forward models. 1. Inverse Model (LRNN Inverse): The desired force (F_{desired}) is input into the inverse model. The LRNN inverse model then estimates the necessary voltage ($V_{\text{estimated}}$) that should be applied to the actuator to achieve the desired force. 2. Forward Model (LRNN Forward): The estimated voltage is then fed into the forward model to predict the force output ($F_{\text{estimated}}$) that would result from these inputs. 3. Comparison: The key step in this process is comparing the estimated force ($F_{\text{estimated}}$) with the desired force (F_{desired}). This comparison allows for the validation of the control strategy and adjustment of the inputs if necessary to ensure the desired force is achieved. This connection between the inverse and forward models enables a closed-loop control system, where the inverse model determines the input needed, and the forward model verifies the output, ensuring accurate and reliable control of the SMA actuator.

(i) **Inverse Model (LRNN Inverse):**

- The desired force (F_{desired}) is input into the inverse model.
- The LRNN inverse model estimates the necessary voltage ($V_{\text{estimated}}$) that should be applied to the actuator to achieve the desired force.

(ii) **Forward Model (LRNN Forward):**

- The estimated voltage ($V_{\text{estimated}}$) is then fed into the forward model.

- The forward model predicts the force output ($F_{\text{estimated}}$) that would result from these inputs.

(iii) **Comparison:**

- The key step in this process is comparing the estimated force ($F_{\text{estimated}}$) with the desired force (F_{desired}).
- This comparison allows for the validation of the control strategy and adjustment of the inputs if necessary to ensure the desired force is achieved.

In the "Inverse Model - Forward Model Connection" method, the simulation of the connection between the inverse and forward models using Layer Recurrent Neural Networks (LRNN) was conducted in MATLAB Simulink. MATLAB Simulink provides a graphical environment that allows for the modeling and simulation of dynamic systems. In this case, the LRNN models were implemented to create a system where the desired force (F_{desired}) is inputted into the inverse model. The inverse LRNN then calculates the estimated voltage ($V_{\text{estimated}}$) and current ($C_{\text{estimated}}$) required to achieve this force. These estimated values are subsequently fed into the forward LRNN model, which simulates the system to produce the estimated force ($F_{\text{estimated}}$). By comparing F_{desired} with $F_{\text{estimated}}$, the accuracy and performance of the control strategy can be evaluated. This simulation approach provides a powerful tool for testing and refining control strategies before implementation on a physical SMA actuator system, ensuring that the desired force output can be achieved reliably.

In this simulation scenario, the desired force value (F_{desired}) is given as input to the inverse LRNN model as a control signal. The inverse model calculates the estimated voltage (V_{estimate}) and values that should be applied to the SMA actuator to produce this desired force. This estimated voltage value is then applied as input to the forward LRNN model to simulate the behavior of the system. The forward model predicts the expected force output (F_{estimate}) from the system in response to this estimated voltage. In the evaluation phase of the simulation, the force predicted by the forward model (F_{estimate}) is compared with the initially desired force (F_{desired}) given to the system. This comparison is critical to measuring the accuracy and

effectiveness of the developed control strategy. If the estimated force is close enough to the desired force, this means that the control strategy performs successfully in the simulation environment. This approach allows the developed control strategies to be tested extensively and necessary improvements to be made before they are tested on a real SMA actuator system, thus increasing the reliability and performance of the system in real applications.

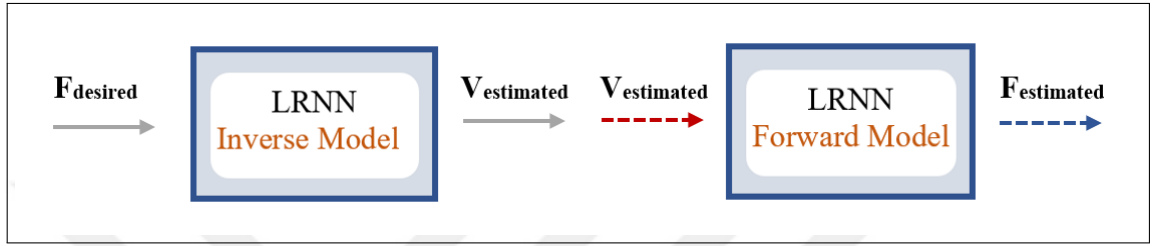


Figure 3.23 Inverse Model- Forward Model Connection is designed to verify whether the system can predict the correct voltage levels to produce the desired force at the output of the system in the simulation environment.

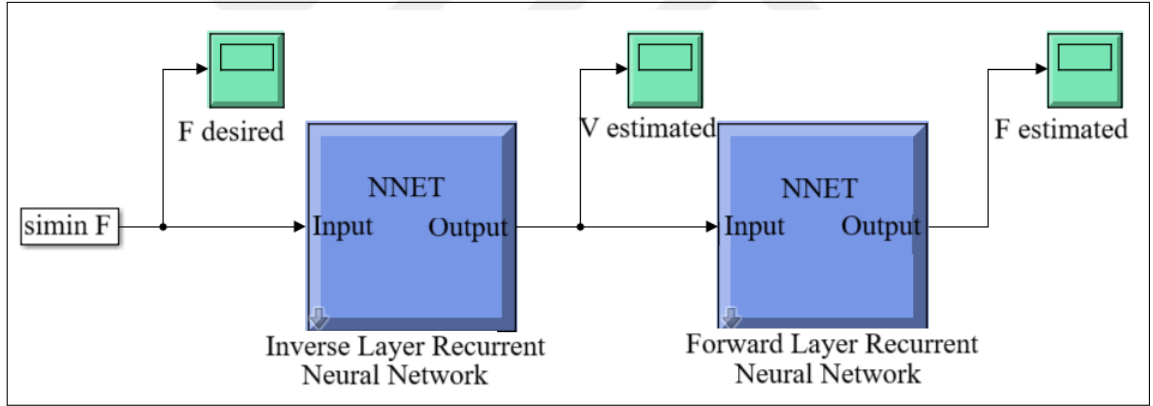


Figure 3.24 Simulink models were used to verify the system's voltage estimate for the desired force due to their visual and block-based architecture that facilitates synthetic signal input and response analysis.

3.9 Test: Inverse Model - Plant (SMA Actuator System)

After the simulation of the connection between the inverse and forward LRNN models in the MATLAB Simulink environment, tests were performed on the SMA actuator system to evaluate the real-world performance of the developed control strategy. The main purpose of this stage is to verify the validity of the simulation results and to observe how effectively the inverse LRNN model works when applied to a real system. In this test setup, the desired force ($F_{desired}$) is given as input to the inverse LRNN

model as a control signal. Using the "force $\rightarrow$ voltage" relationship learned in its training, the inverse model calculates the estimated voltage ($V_{\text{estimated}}$) value that should be applied to the SMA actuator system to produce this desired force. These estimated voltage values are applied to the physical SMA actuator system in real time. The SMA actuator system produces a force in response to the applied voltage. This measured actual force (F_{actual}) value is compared with the desired force (F_{desired}) given to the system at the beginning. This comparison process provides the opportunity to numerically evaluate the accuracy of the inverse LRNN model and its effectiveness in controlling the SMA actuator system in real time. The primary focus of the tests is to examine how close the measured true force (F_{true}) value is to the desired force (F_{desired}) value and the agreement between them.

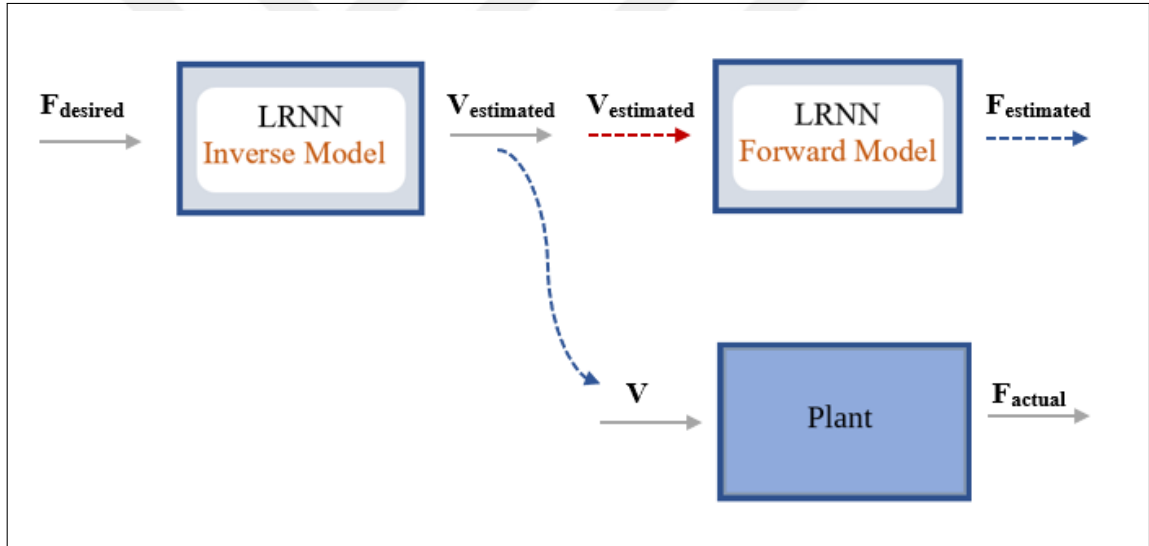


Figure 3.25 Simulation: Inverse Model - Forward Model Connection. To validate if the system can estimate the right voltage levels to generate the desired force at the output of the system in the simulation environment. Inverse Model—Plant (SMA actuator system) connection: The desired force (F_{desired}) is input into the inverse LRNN model, which predicts the corresponding voltage ($V_{\text{estimated}}$) needed to generate the specified force for the plant.

3.10 Generalization capability

Training was continued in various scenarios to ensure generalization by demonstrating that the developed control system responded correctly to different inputs that it had not seen before. In these tests, the system was subjected to various input profiles, including step changes and sinusoidal signals with desired forces. These scenarios

represent real-world operating conditions where the control system may encounter unexpected or previously unobserved inputs.

The performance of the system was analyzed by comparing the actual force generated by the SMA actuator with the desired force under each test scenario. Successful generalization will be demonstrated by the ability of the system to accurately track the desired force in all test cases.

The results showed that the inverse LRNN model can maintain high accuracy and robustness under different input conditions when combined with the SMA actuator system. This confirms the strong generalization ability of the model and makes the system suitable for practical applications.

3.11 Summary of the Methodology

This chapter provided a detailed walkthrough of the methodological evolution from full prosthetic design to single-actuator modeling and control. Through systematic experimentation and neural network modeling, an adaptive force control scheme was developed that is suitable for SMA actuators and holds promise for broader prosthetic applications.

4. EXPERIMENTS AND RESULTS

Data was collected in four different scenarios with the SMA Actuator System, designed for data collection and control. Forward and inverse models were trained with one of these data sets and tested with the other data sets. The success in the model outputs of these different data sets will also show the generalization ability. Data sets were repeated for both training and testing in different scenarios. Both forward and inverse models were trained and tested with the dataset in four different scenarios.

Due to a significantly delayed response, differential gain makes the PID controller unstable. K_d is set to 0 to avoid total loss of control. Strong inherent hysteresis makes conventional PID tuning very difficult, making the method unemployable. P and I values are chosen as 4 and 0.0001 that the respectively, so that the overall system does not break and some observable response could be achieved.

4.1 Forward Model Training Results

The forward model has a single hidden layer containing 20 neurons and a 5-step delay at the input. The results of the model trained with Set 1 are shown below. The graph compares the actual force values with the force outputs predicted by the model for four different data sets.

The high R -value (0.99992) and mean squared error (MSE) of 46 obtained show that the model was trained very successfully. The Forward LRNN model learned and predicted the training data with almost perfect accuracy. The low MSE value of 46 confirms that the prediction error is minimal. The decrease in the gradient value and the maximum epoch number reached show that the training algorithm achieved good convergence. The regression graph also supports these findings, visually confirming that the model predictions are in high agreement with the actual values. While the

perfect fit on Test 1 (training data) demonstrates the model's learning ability on the data it was trained with, the high R-values and generally low MSE values obtained for Test 2, Test 3, and Test 4 data, which were not seen during training, indicate that the model also exhibits strong generalization ability. This shows that the model can make accurate predictions not only for the data it was trained on but also for new, unseen data, which is a critical feature for the practical applicability of the model.

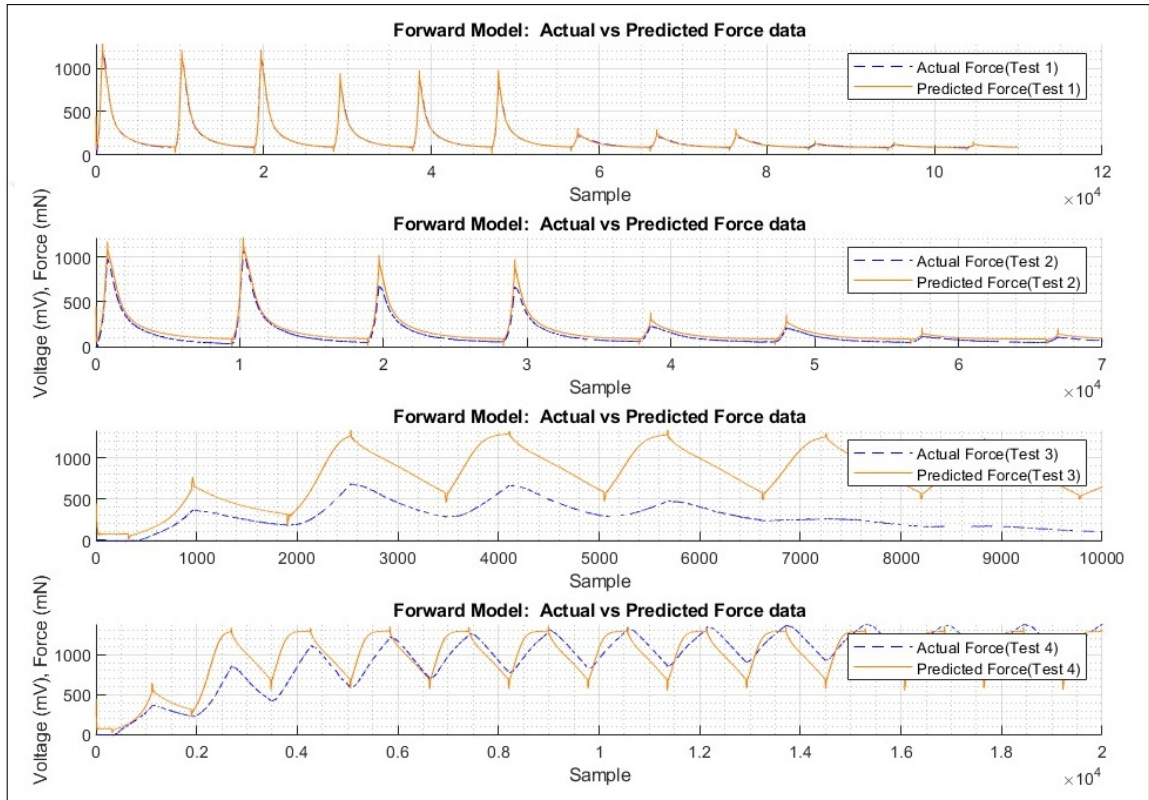


Figure 4.1 The graph shows the actual force values and the force outputs predicted by the forward model trained with Dataset 1, corresponding to the inputs of four separate datasets.

The performance comparison of the forward model on different data sets is shown in Figure 4.1. The model shows excellent compliance on the training data (Test 1), while it also provides high accuracy on Test 2, Test 3, and Test 4 data that were not seen in training, demonstrating a strong generalization ability.

The forward model showed similar success when trained with one of the other data sets and tested with other scenarios. The high accuracy achieved in the training and testing processes performed in different scenarios confirms the generalization ability

and stability of the model. The success of the Forward model, which was trained repeatedly, is shown below for each training. Each training result showed that the LRNN architecture is suitable for this problem for the Forward model.

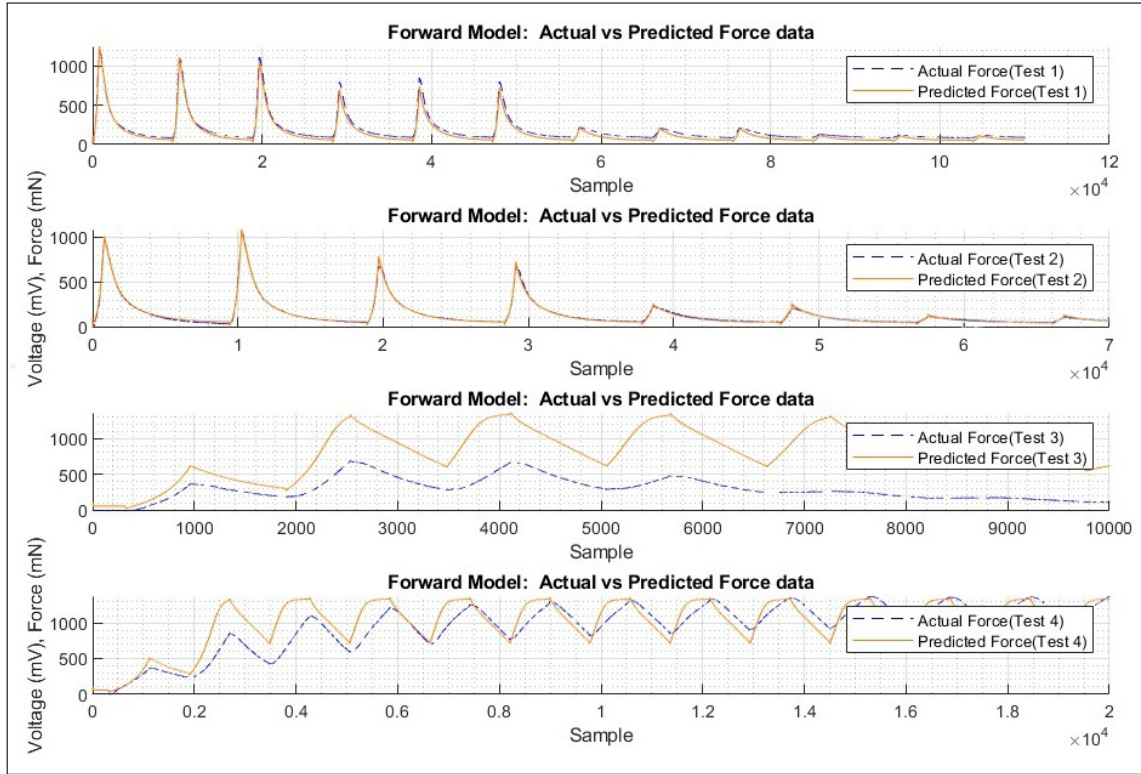


Figure 4.2 The graph shows the actual force values and the force outputs predicted by the forward model trained with Dataset 2, corresponding to the inputs of four separate datasets.

The performance of the forward model across different datasets is compared in the following. The model shows an excellent fit to the training data (Test 3) while also providing high accuracy on Test 1, Test 2, and Test 4 data, which were not seen during training, thus exhibiting a strong generalization ability.

The results of repeated Forward model training are summarized below:

As seen in the forward model training results, the R-values were consistently high across different datasets, ranging from 0.99789 to 0.99944, and the MSE values were generally lower compared to the inverse model. This suggests that the forward model might have been easier to train or inherently more predictable for this system. However, the inverse model also demonstrates acceptable performance with an R-value of 0.99891.

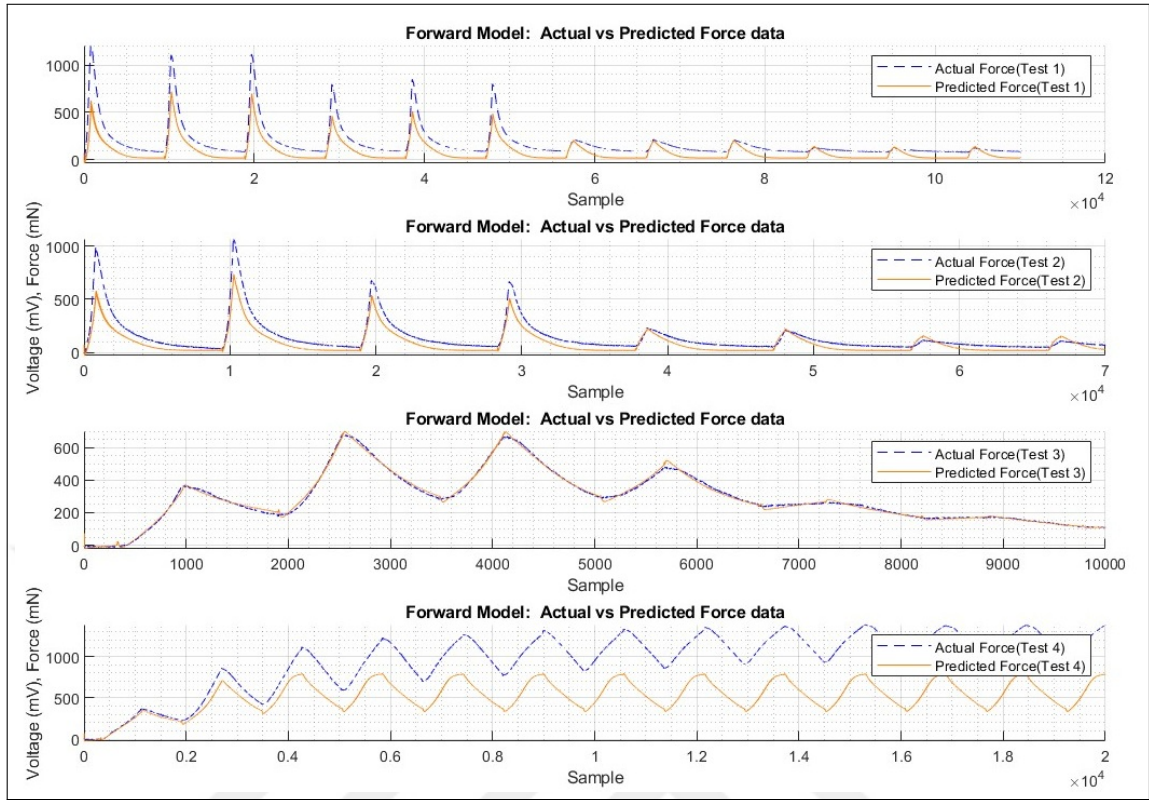


Figure 4.3 The graph compares the forward model's force predictions (trained on dataset 3) with the actual force values from other datasets, demonstrating its prediction success.

Table 4.1
Forward Model Training Results.

Training	Set	R value	MSE
1	1	.99845	9 .5344
2	1	.99852	8 .9537
3	1	.99944	3 .6256
4	1	.99824	10 .8880
5	2	.99803	9 .6867
6	2	.99789	9 .3674
7	3	.99840	8 .2966
8	3	.99928	4 .4062
9	4	.99889	15 .6869
10	4	.99789	9 .8890

The table above shows the best training performance achieved for both the forward and inverse models. As can be seen, the forward model achieved a slightly

higher R-value and a significantly lower MSE compared to the inverse model.

Training Success of Forward LRNN Model Trained with Dataset 1. This figure shows the high R value (0.99944) and low MSE value (32.6256) obtained after 200 epochs of training. These impressive results prove that the model learned the training data with almost perfect accuracy and exhibited strong regression performance.

When the results of repeated training are examined, it is seen that the forward model consistently exhibited high performance in each trial. In all ten different training scenarios presented, regression R-values ranged from very high values such as 0.99789 to 0.99944, and MSE values remained generally low. This consistent success strongly confirms that the LRNN architecture is a highly suitable and effective choice for the forward modeling task. The high level of accuracy achieved in each training trial supports the robustness and reliability of the single-layer RNN model and demonstrates that it can produce consistent results for this problem. The high agreement between the output and target values is visually confirmed.

4.1.1 Inverse Model Training Results

In the inverse model, since the relationship is more complex, in addition to the force data, "time-shifted" versions of the force were provided as a look-ahead to the input of the model. This allows the dynamic training, reflecting the impact of current and future force values. This improved input structure allows the network to predict the future behavior of the SMA actuator while taking into account its dynamic hysteresis properties. Although the two- or single-layer inverse LRNN model training results are not as successful as the forward model, they have achieved an acceptable level of success for similar data sets, especially when compared with PID controller.

The model training results still seem to be successful, although not as high as the forward model. It made successful predictions for inputs similar to the training data with a high R-value (0.99891) and low MSE (626.14). As in the forward model,

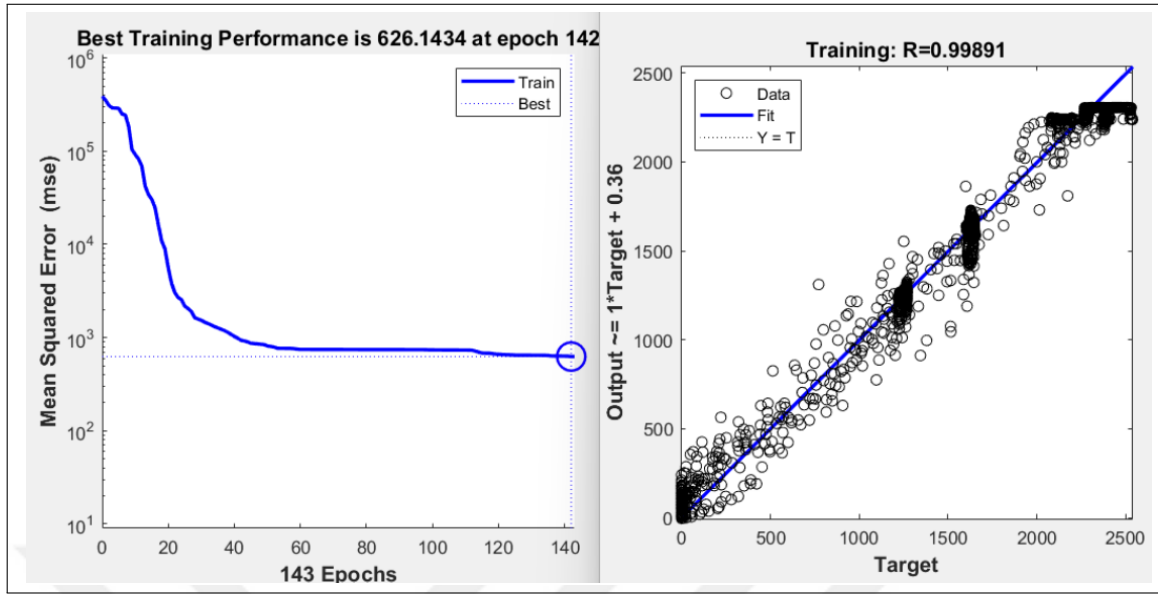


Figure 4.4 Training Success of the Inverse LRNN Model Trained with Dataset 1. It shows high R-value (0.99891) and MSE (626.1434) values.

the inverse model was able to make high-accuracy predictions with different data sets. In Figure 4.4, the voltage output prediction for Test 1 (training data) is very close to the real values, as expected. It also seems successful in output prediction with the Test 2 data set, which is close to the training data, and although Test 3 and Test 4 are clearly separated from the training data, it was able to give satisfactory results for these datasets. This also reveals the adaptability of the inverse model to different operating conditions.

Although the MSE value is higher compared to the forward model results, this is due to the nature of inverse modeling, and when evaluated together with the high R-value, it is understood that the error level is still within acceptable limits and the model can successfully produce precise predictions.

Figure 4.4 shows the training performance and regression plot for the inverse model trained with Dataset 1. The model achieved a high R-value of 0.99891 and an MSE of 626.1434.

Although the MSE value is higher compared to the forward model results, this

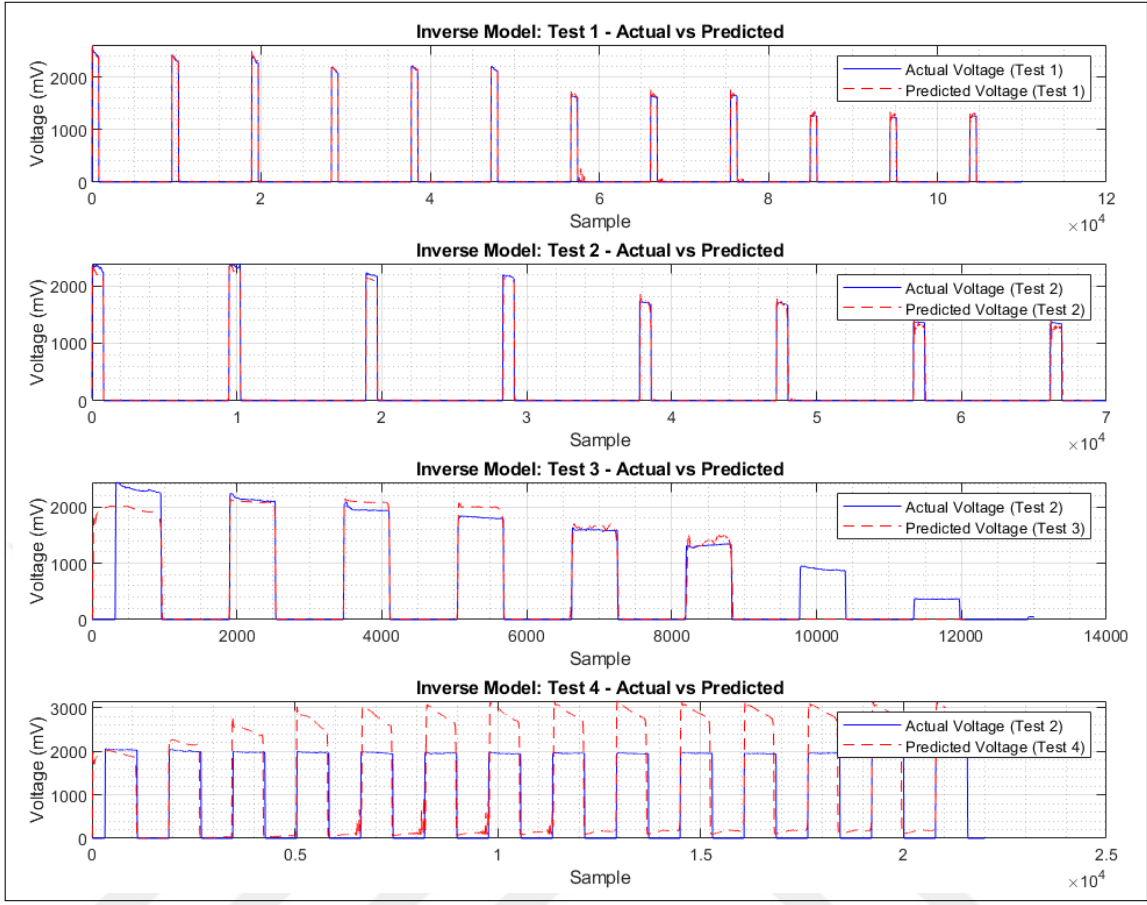


Figure 4.5 The graph displays the voltage predictions generated by the inverse model trained on Dataset 1 for both its training dataset and other datasets.

is due to the nature of inverse modeling, and when evaluated together with the high R-value, it is understood that the error level is still within acceptable limits and the model can successfully produce precise predictions.

4.1.2 Inverse Model - Forward Model Connection Simulation Results

To evaluate the success of the developed control strategy, simulations were conducted in the MATLAB Simulink environment using inverse and forward LRNN models. The desired force value was given as input to the inverse model, and the voltage estimated by this model was applied to the forward model. The force estimate obtained from the simulation was compared with the initial desired force, and the performance of the control strategy in the virtual environment was analyzed. The figures illustrate

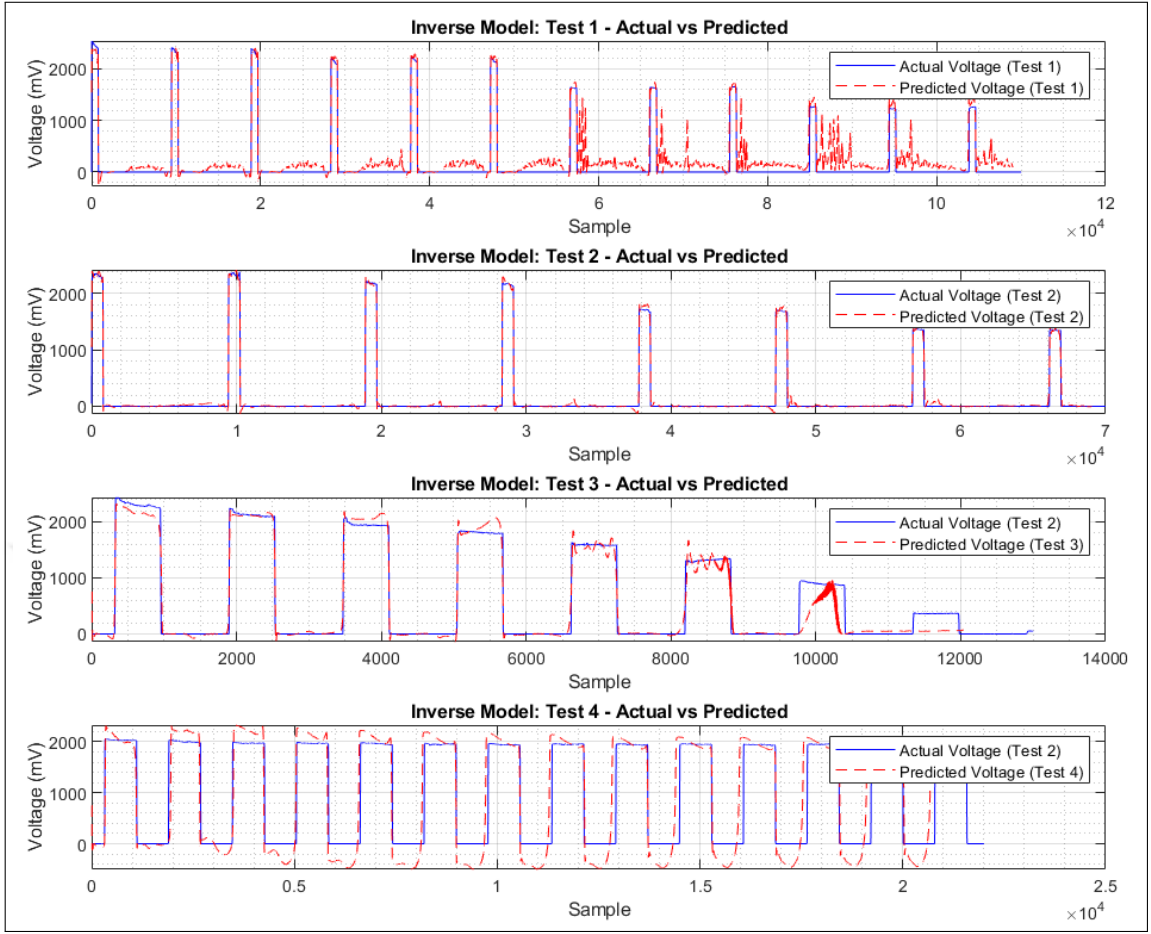


Figure 4.6 The graph displays the voltage predictions generated by the inverse model trained on Dataset 3 for both its training dataset and other datasets.

this process: the desired force, intended as input to the inverse model, was provided as input, and the model output determined the voltage levels required to produce this force. These estimated voltage values were then input into the forward model, and the resulting forces that this voltage level would generate were estimated. This allowed for the evaluation of whether the system yielded reliable results under appropriate conditions. In the figures, one of the models trained with Dataset 1, which demonstrated high success in both the forward and inverse modeling tasks, was used. It was tested sequentially with different datasets. The first graph shows the desired input force, the second graph displays the estimated voltage levels required by the inverse model for this force, and the third graph shows and compares the estimated force generated by the forward model in response to these voltage levels.

In this simulation scenario, the desired force (F_{desired}) was given as input to the inverse LRNN model as a control signal. The inverse model produces the estimated voltage (V_{estimate}) value that should be applied to the SMA actuator to achieve this desired force. This estimated voltage value is then applied as input to the forward LRNN model to simulate the behavior of the system. The forward model, in turn, predicts the expected force output (F_{estimate}) from the system in response to this estimated voltage.

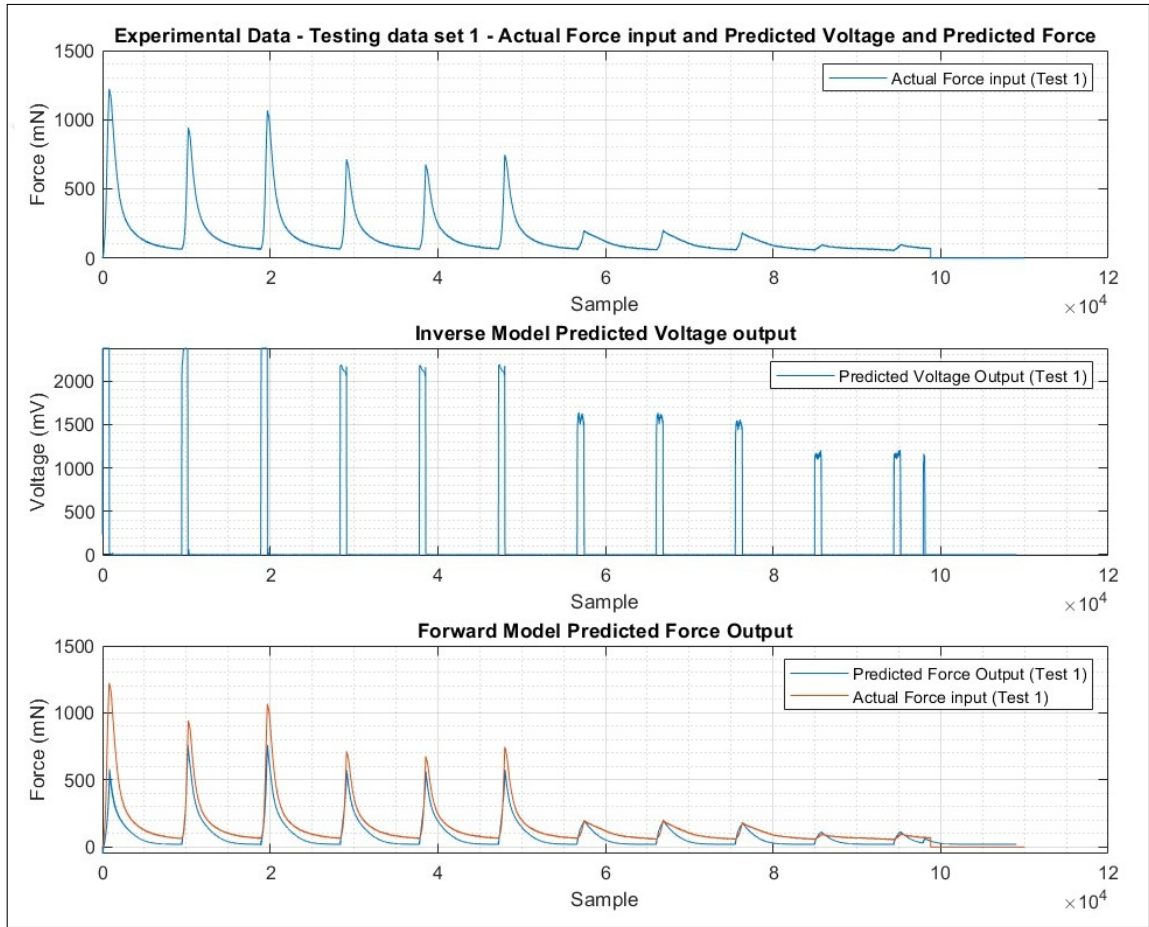


Figure 4.7 In this simulation, one of the successful forward and inverse models trained with Dataset 1 was used and tested. The desired force input was given to the inverse model, and the voltage generated by the model was applied as input to the forward model, and thus, the expected force output was compared with the desired force input.

The performance metrics for achieving a desired force trajectory in this study are included in Tables 4.2 and 4.3. The results obtained in this paper demonstrate the feasibility of a system capable of predicting the necessary excitation to enable an SMA actuator to produce the desired force within certain operational limits, such as a specific frequency and amplitude range.

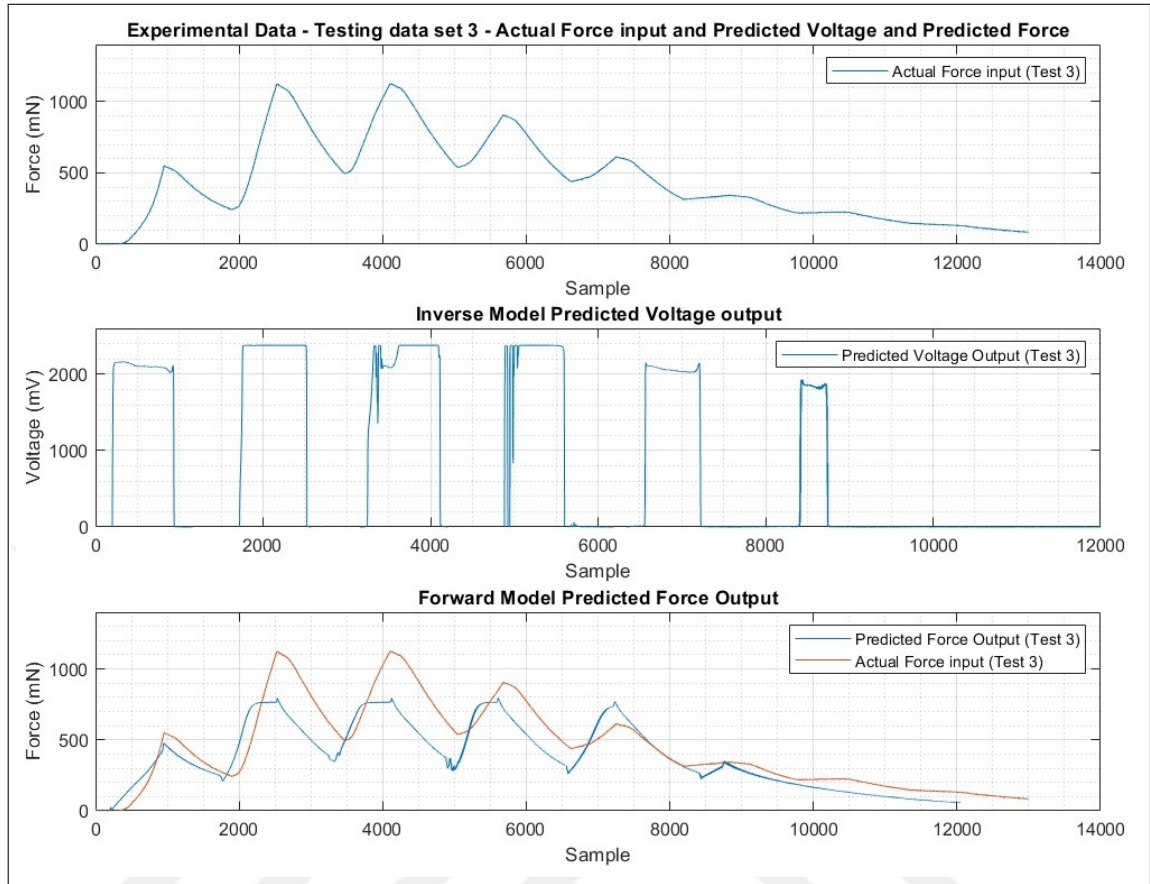


Figure 4.8 This scenario was tested using dataset 3. The desired force input was given to the inverse model, and the voltage generated by the model was applied as input to the forward model, and thus, the expected force output was compared with the desired force input.

Due to a significantly delayed response, the differential gain makes pid controller unstable. K_d is set to 0 to avoid total loss of control. Strong inherent hysteresis makes conventional PID tuning impossible. P and I values are chosen such that the overall system does not break, and some observable response could be achieved.

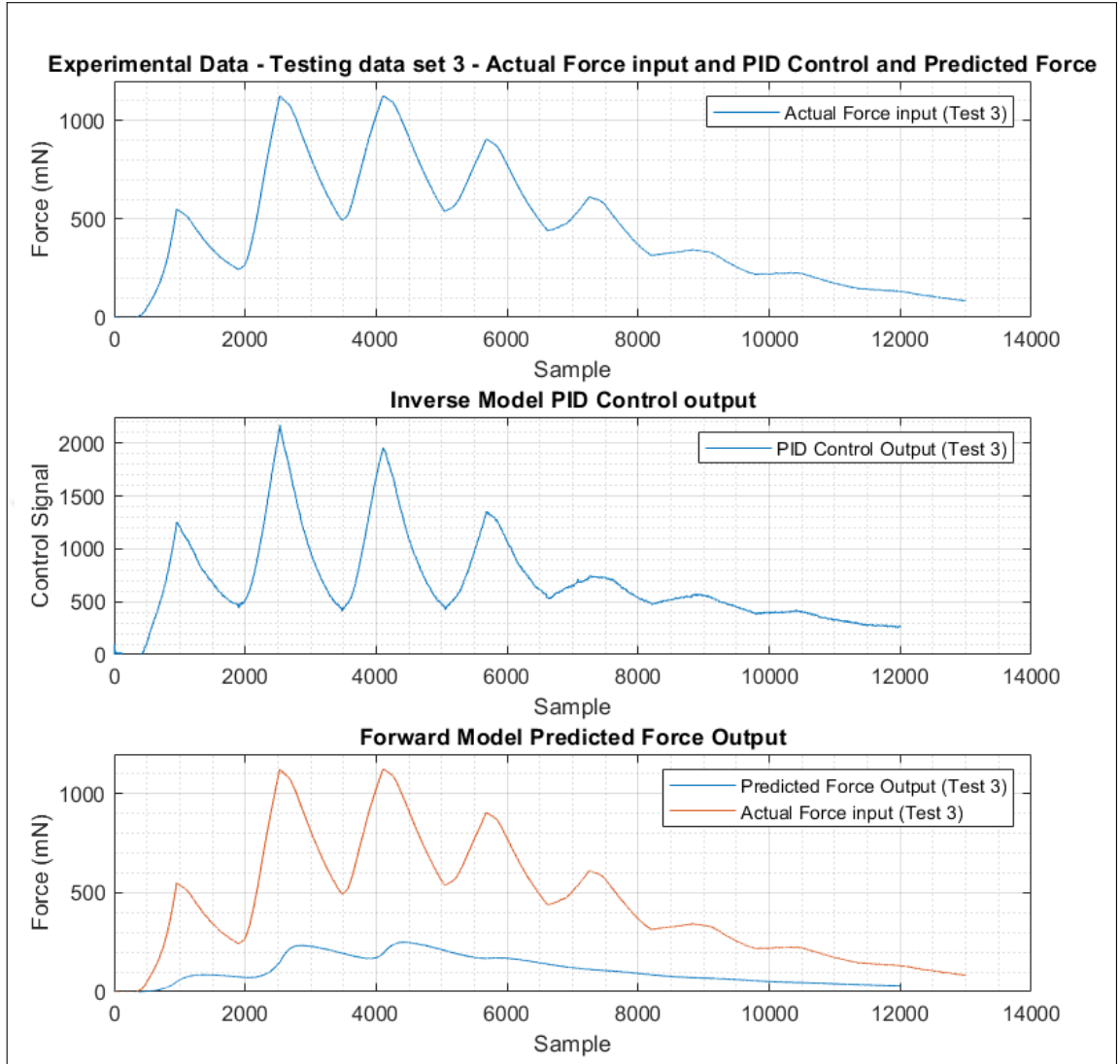


Figure 4.9 The same scenario shown in figure 4.8 was tested using dataset 3 with PID control. The desired force input was given to the PID controller model, and the control signal generated by this model was applied as input to the forward model; thus, the expected force output was compared with the desired force input.

Table 4.2
Forward RNN Model Performance with PID Comparison (RMSE).

Data Set	Train 1	Train 2	Train 3	Train 4	PID
Test 1	8.96	25.20	190.00	127.00	265.0
Test 2	18.00	9.89	152.00	135.00	145.0
Test 3	76.20	140.00	4.06	320.00	49.4
Test 4	137.00	229.00	191.00	14.80	80.2

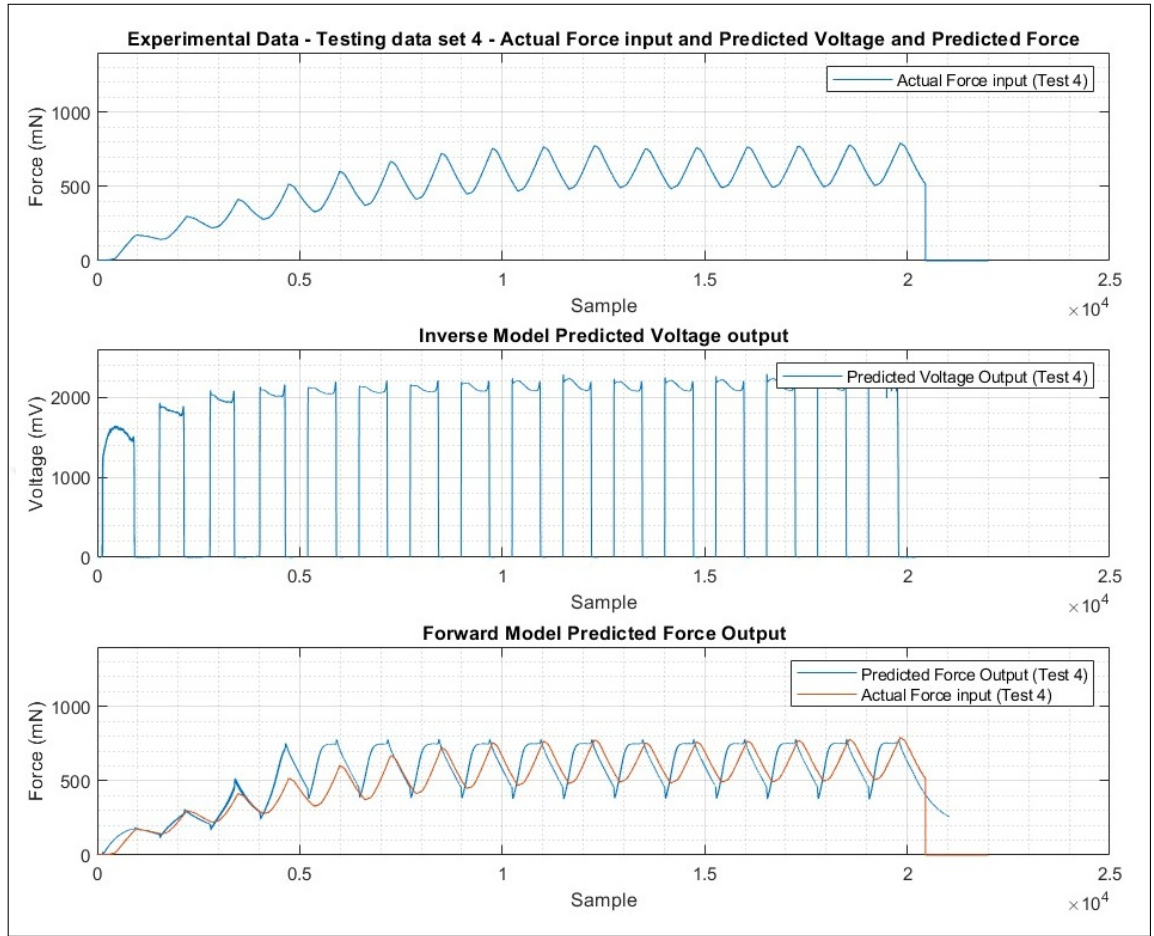


Figure 4.10 This scenario was tested using dataset 4. The desired force input was given to the inverse model, and the voltage generated by the model was applied as input to the forward model, and thus, the expected force output was compared with the desired force input.

Table 4.3
Forward RNN Model Performance with PID Comparison (R^2).

Data Set	Train 1	Train 2	Train 3	Train 4	PID
Test 1	0.997	0.976	0.0004	0.856	0.0706
Test 2	0.988	0.996	0.0815	0.830	0.198
Test 3	0.951	0.705	0.999	0.571	0.566
Test 4	0.752	0.254	0.0946	0.998	0.887

5. DISCUSSION

This study originated from the motivation to address the long-standing limitations of conventional prosthetic systems, particularly their lack of agility and natural motion in high degrees of freedom (DOF) applications. Shape Memory Alloys (SMAs) were identified early as promising candidates for biomimetic actuation due to their muscle-like contraction capabilities, silent operation, and lightweight structure. However, their inherent nonlinear behavior, thermal hysteresis, and sensitivity to external conditions introduced significant challenges, particularly in force control and real-time actuation.

Developmental Challenges and Experimental System Design

Early stages of the research were marked by difficulties in collecting clean, interpretable data due to noise, actuator heating delays, and system hysteresis. This led to the design and implementation of a compact, practical testbed capable of real-time voltage, current, and force data acquisition. Multiple PWM profiles and test scenarios were applied to understand the dynamics of SMA springs under varying thermal and electrical conditions.

Limitations of Conventional Modeling Approaches

Initial attempts to model the actuator behavior using polynomial fitting and both linear and nonlinear regression yielded only localized accuracy. These classical approaches were unable to generalize across broader operating conditions or account for the system's dynamic nonlinearity. While piecewise fitting improved local performance, it remained insufficient for practical, real-time applications.

Shift to Machine Learning-Based Approaches

Driven by the limitations of traditional modeling, the research pivoted to machine learning techniques. Inspired by previous work in neural modeling of dynamic systems, NARX and Recurrent Neural Networks (RNNs) were selected due to their ability to capture time-dependent behavior. NARX models incorporated time-delayed input-output structures, while RNNs leveraged internal memory through recursive connections.

The study culminated in the development of highly accurate Layer Recurrent Neural Network (LRNN) models. The forward LRNN successfully predicted force output from voltage input with a regression coefficient of $R = 0.9996$, while the inverse model, enhanced through time-shifted inputs, determined the required voltage for a desired force trajectory with $R = 0.99989$. These results mark a significant improvement over traditional methods.

Contribution to Literature and Practical Applications

The LRNN architecture offers a data-driven, scalable control strategy that adapts to different actuator configurations without requiring hand-crafted physical models or excessive tuning. Unlike the control schemes commonly employed in advanced prosthetics—which often remain confined to labs due to their complexity and cost—this architecture offers a more deployable and accessible solution.

These results directly contribute to the literature on intelligent control of nonlinear actuators, demonstrating the viability of integrating SMAs into practical prosthetic and robotic systems. Moreover, the control strategy’s modularity and adaptability open avenues for future implementation in multi-actuator systems, including multi-finger prosthetic hands or exoskeletal devices.

Limitations and Future Work

While the LRNN models performed robustly under controlled scenarios, certain limitations remain. The inverse model’s reliability may decrease under unmodeled

variations such as extreme ambient temperatures, long-term fatigue, or mechanical coupling in multi-actuator systems. Additionally, training time and the quality of collected data remain critical for real-time deployment.

Future research will focus on extending the model to more diverse actuator geometries, real-world environmental conditions, and multi-degree-of-freedom control scenarios. Incorporating additional sensors (e.g., thermal or strain gauges) and exploring hybrid modeling techniques that blend physical insights with data-driven architectures may further improve performance and reliability.



6. CONCLUSION

This thesis presents a robust and data-driven approach for modeling and controlling Shape Memory Alloy (SMA) actuators using Layer Recurrent Neural Networks (LRNNs). By successfully training both forward and inverse models, the study demonstrates high-precision force estimation and voltage control capabilities, achieving regression coefficients exceeding 0.999.

Compared to traditional modeling techniques, the LRNN-based framework offers a scalable and adaptable solution, particularly well-suited for prosthetic applications where real-time performance and nonlinear dynamics are critical. The proposed approach eliminates the need for complex analytical modeling or manual parameter tuning, thus enhancing its practicality and deployment potential.

Despite the promising results, the inverse model's performance may degrade under unmodeled conditions such as temperature fluctuations, long-term material fatigue, or actuator coupling in multi-DOF systems. Addressing these limitations is crucial for broader generalization and real-world implementation.

Overall, this work provides a significant contribution to the intelligent control of nonlinear actuators. It lays a strong foundation for the integration of SMA-based actuation systems in responsive, biomimetic prosthetic and robotic platforms, enabling more natural and efficient human-machine interaction.

7. APPENDIX

The MATLAB code for forward and inverse models are presented here.

7.1 Forward Model MATLAB Code

```

1 clear all;
2 load('Data024_10son110soffcesitli.mat', 'Data1'); % set2
3 Data10s=Data1;
4 V2= Data10s(:,2);
5 C2= Data10s(:,3);
6 R2= V2./C2*1000;
7 F2= Data10s(:,4); % digipot= Data(:,5); sps= Data(:,6);
8 load('Data024_8son112soffcesitli.mat', 'Data1'); % set1
9 Data=Data1;
10
11 % Symbolic
12 Data=Data1;
13 tend=length(Data(:,1));
14 tp= Data(:,1);
15 V= Data(:,2);
16 C= Data(:,3);
17 R= V./C*1000;
18 F= Data(:,4); % digipot= Data(:,5); sps= Data(:,6);
19
20 figure();
21 %subplot (2,1,1);
22 plot(V );
23 hold on;
24 %plot(tp);
25 ylim([0 max(V)*1.1]);
26 xlim([0 tend]);

```

```

27 xlim([0 75000]);
28 ylabel('Voltage (mV)');
29 xlabel('sample');
30 title('Voltage input ');
31 legend('V input');
32 grid on;
33 grid minor;
34
35 figure();
36 %subplot (2,1,2);
37 plot(F);
38 ylim([min(F)*0.9 max(F)*1.1]);
39 xlim([0 tend]);
40 xlim([0 75000]);
41 ylabel('Force (mN)');
42 xlabel('sample');
43 title('Force output data ');
44 legend('F output');
45 grid on;
46 grid minor;
47
48 n1=120;
49 n2=2*n1;
50 n3=3*n1;
51 n4=4*n1;
52 n5=5*n1;
53 n6=6*n1;
54 n7=7*n1;
55 n8=8*n1;
56
57 V2set=V2;
58 F2set=F2;
59 V2sets=smoothdata(V2set, "movmean",20);
60 F2sets=smoothdata(F2set, "movmean",20);

```

```

61 V2sets=V2sets(1:75000);
62 F2sets=F2sets(1:75000);
63
64 V1set=V;
65 F1set=F;
66 V1sets=smoothdata(V1set, "movmean",20);
67 F1sets=smoothdata(F1set, "movmean",20);
68 V1sets=V1sets(1:75000);
69 F1sets=F1sets(1:75000);
70
71 a1=F1sets(n8:end);
72 a2=F1sets(n7:end-n1);
73 a3=F1sets(n6:end-n2);
74 a4=F1sets(n5:end-n3);
75 a5=F1sets(n4:end-n4);
76 a6=F1sets(n3:end-n5);
77 a7=F1sets(n2:end-n6);
78 a8=F1sets(n1:end-n7);
79 a9=F1sets(1:end-n8+1);
80
81 % V1sets= V1sets(1:end-n8+1);
82 % F1sets= horzcat (F1sets(1:end-n8+1),F1sets(n1:end-n7),F1sets(n2:end-n6),
      F1sets(n3:end-n5), F1sets(n4:end-n4), F1sets(n5:end-n3),
      F1sets(n6:end-n2), F1sets(n7:end-n1), F1sets(n8:end));
83 % V2sets= V2sets(1:end-n8+1);
84 % F2sets= horzcat (F2sets(1:end-n8+1), F2sets(n1:end-n7),F2sets(n2:end-n6),
      F2sets(n3:end-n5), F2sets(n4:end-n4), F2sets(n5:end-n3),
      F2sets(n6:end-n2), F2sets(n7:end-n1), F2sets(n8:end));
85
86 figure ();
87 plot (V1sets);
88 hold on;
89 plot (F1sets);
90 xlabel('Time');

```

```

91 ylabel('Data');
92 legend('V input','F output','F(n+50) input','F(n+100) input','F(n+150)
    input','F(n+200) input','F(n+250) input','F(n+300) input','F(n+350)
    input','F(n+400) input','V(n) output');
93 %xlim([index2s-4000, index2s]);
94 title('Forward Model Four level input ');
95 grid on;
96 grid minor;
97
98 figure ();
99 subplot (2,1,1)
100 plot (V1sets);
101 hold on;
102 plot (F1sets);
103 xlabel('Time');
104 ylabel('Data');
105 legend('set 1');
106 title('Forward LRNN network input sets');
107 subplot (2,1,2)
108 plot (V2sets);
109 hold on
110 plot (F2sets);
111 xlabel('Time');
112 ylabel('Data');
113 legend('set 2');
114
115 % Forward RNN model
116
117 p1set = tonndata(V1sets, false, false); % V1 Input
118 t1set = tonndata(F1sets, false, false); % F1 Output
119 p2set = tonndata(V2sets, false, false); % V2 Input
120 t2set = tonndata(F2sets, false, false); % F2 Output
121
122 delay=5;

```

```

123 hiddensize=10;
124 % inverse RNN model -- layrecnet(layerDelays,hiddenSizes,trainFcn)
125 %lrn_net1 = layrecnet(delay,[ hiddensize hiddensize ]); % hidden layer size
    will be greater
126 lrn_net = layrecnet(delay,[ hiddensize ]);
127 lrn_net.trainFcn = 'trainbr';
128 lrn_net.trainParam.show = 5;
129 lrn_net.trainParam.epochs = 200;
130 lrn_net= train(lrn_net,p1set,t1set);
131 RNNy1set = lrn_net(p1set); % testing with training data
132 RNNy2set = lrn_net(p2set); % testing with testing data
133
134 figure;
135 subplot (2,1,1);
136 plot(cell2mat(t1set)'); % plot (p cell structure to matrix)
137 hold on;
138 plot(cell2mat(RNNy1set)');
139 legend('Actual Force','Predicted Force set1');
140 xlabel('Time');
141 ylabel('Data');
142 %xlim([18000 28000]);
143 title('Forward RNN network four level input');
144 grid on;
145 grid minor;
146 subplot (2,1,2);
147 plot(cell2mat(t2set)'); % plot (p cell structure to matrix)
148 hold on;
149 plot(cell2mat(RNNy2set)');
150 legend('Actual Force','Predicted Force set2 ');
151 xlabel('Time');
152 ylabel('Data');
153 %xlim([18000 28000]);
154 grid on;
155 grid minor;

```

```

156
157 figure;
158 plot(cell2mat(t2set)')-cell2mat(RNNy2set)'); % plot (p cell structure to
    matris)
159 hold on;
160 plot(cell2mat(t2set)');
161 plot(cell2mat(RNNy2set)');
162 legend('Error: Actual-Predicted Force','Actual Force','Predicted Force');
163 xlabel('Time');
164 ylabel('Data');
165 title('Forward RNN network Actual-Predicted Force output and error ');
166 grid on;
167 grid minor;
168
169 %save('RNN_Forward_4level_02.mat', 'lrn_net');
170 %load RNN_Inversetwolevelinputset345.mat;
171 gensim(lrn_net);
172 m=(1:1:200000);
173 F1all= horzcat (Fsmoothyeni(1:end-n5+1),
    Fsmoothyeni(n1:end-n4),Fsmoothyeni(n2:end-n3),
    Fsmoothyeni(n3:end-n2),Fsmoothyeni(n4:end-n1),Fsmoothyeni(n5:end));
174 siminF1 = timeseries (F1all,m(1:length(F1all)));

```

Listing 7.1
Code for Forward Model

```

1 clear all;
2 load('Data024_10son110soffcesitli.mat', 'Data1');
3 Data10s=Data1;

```

```

4 V2= Data10s(:,2);
5 C2= Data10s(:,3);
6 R2= V2./C2*1000;
7 F2= Data10s(:,4); % digipot= Data(:,5); sps= Data(:,6);
8
9 load('Data024_8son112soffcesitli.mat', 'Data1');
10
11 % Symbolic
12 Data=Data1;
13 tend=length(Data(:,1));
14 tp= Data(:,1);
15 V= Data(:,2);
16 C= Data(:,3);
17 R= V./C*1000;
18 F= Data(:,4); % digipot= Data(:,5); sps= Data(:,6);
19
20 figure();
21 subplot (2,1,1);
22 plot(V );
23 hold on;
24 plot(tp);
25 ylim([0 max(V)*1.1]);
26 xlim([0 tend]);
27 xlim([0 100000]);
28 ylabel('Voltage (mV)');
29 xlabel('sample');
30 title('TEST01 - Voltage, Force- n ');
31 grid on;
32 grid minor;
33
34 subplot (2,1,2);
35 plot(F);
36 ylim([min(F)*0.9 max(F)*1.1]);
37 xlim([0 tend]);

```

```

38 xlim([0 100000]);
39 ylabel('Force (mN)');
40 xlabel('sample');
41 grid on;
42 grid minor;
43
44 n1=120;
45 n2=2*n1;
46 n3=3*n1;
47 n4=4*n1;
48 n5=5*n1;
49 n6=6*n1;
50 n7=7*n1;
51 n8=8*n1;
52
53 V2set=V2;
54 F2set=F2;
55 V2sets=smoothdata(V2set, "movmean",20);
56 F2sets=smoothdata(F2set, "movmean",20);
57
58 V1set=V;
59 F1set=F;
60 V1sets=smoothdata(V1set, "movmean",20);
61 F1sets=smoothdata(F1set, "movmean",20);
62
63 a1=F1sets(n8:end);
64 a2=F1sets(n7:end-n1);
65 a3=F1sets(n6:end-n2);
66 a4=F1sets(n5:end-n3);
67 a5=F1sets(n4:end-n4);
68 a6=F1sets(n3:end-n5);
69 a7=F1sets(n2:end-n6);
70 a8=F1sets(n1:end-n7);
71 a9=F1sets(1:end-n8+1);

```

```

72
73 V1sets= V1sets(1:end-n8+1);
74 F1sets= horzcat (F1sets(1:end-n8+1),F1sets(n1:end-n7),F1sets(n2:end-n6),
    F1sets(n3:end-n5), F1sets(n4:end-n4), F1sets(n5:end-n3),
    F1sets(n6:end-n2), F1sets(n7:end-n1), F1sets(n8:end));
75 V2sets= V2sets(1:end-n8+1);
76 F2sets= horzcat (F2sets(1:end-n8+1), F2sets(n1:end-n7),F2sets(n2:end-n6),
    F2sets(n3:end-n5), F2sets(n4:end-n4), F2sets(n5:end-n3),
    F2sets(n6:end-n2), F2sets(n7:end-n1), F2sets(n8:end));
77
78 figure ();
79 plot (V1sets);
80 hold on;
81 plot (F1sets);
82 xlabel('Time');
83 ylabel('Data');
84 legend('F(n) input','F(n+50) input','F(n+100) input','F(n+150)
    input','F(n+200) input','F(n+250) input','F(n+300) input','F(n+350)
    input','F(n+400) input','V(n) output');
85 %xlim([index2s-4000, index2s]);
86 title('Inverse Model Two level input (look ahead sample = 8)');
87 grid on;
88 grid minor;
89
90 %figure force n and force
91 figureForceNextInputs
92
93 figure ();
94 subplot (2,1,1)
95 plot (V1sets);
96 hold on;
97 plot (F1sets);
98 xlabel('Time');
99 ylabel('Data');

```

```

100 legend('set 1');
101 title('Inverse RNN network input sets');
102 subplot (2,1,2)
103 plot (V2sets);
104 hold on
105 plot (F2sets);
106 xlabel('Time');
107 ylabel('Data');
108 legend('set 2');
109
110 % Inverse RNN model
111 shft=2;
112 a=[(zeros(shft,1))'']';
113 Vi1set=[a;V1sets(1:end-shft)];
114 Vi2set=[a;V2sets(1:end-shft)];
115
116 figure ();
117 plot (F1sets);
118 hold on;
119 plot (Vi1set);
120 xlabel('Time');
121 ylabel('Data');
122 legend('F input','F input+1','F input+2','F input +3','F input +4','F input
      +5','F input +6','F input +7','F input +8','V output');
123 %xlim([index2s-4000, index2s]);
124 title('Two level input, shifted ');
125 grid on;
126 grid minor;
127
128 pilset = tonndata(F1sets, false, false); % V1 Input
129 ti1set = tonndata(Vi1set, false, false); % F1 Output
130 pi2set = tonndata(F2sets, false, false); % V2 Input
131 ti2set = tonndata(Vi2set, false, false); % F2 Output
132

```

```

133 delay=5;
134 hiddensize=10;
135 % inverse RNN model -- layrecnet(layerDelays,hiddenSizes,trainFcn)
136 %lrn_net1 = layrecnet(delay,[ hiddensize hiddensize ]); % hidden layer size
    will be greater
137 lrn_net1 = layrecnet(delay,[ hiddensize ]);
138 lrn_net1.trainFcn = 'trainbr';
139 lrn_net1.trainParam.show = 5;
140 lrn_net1.trainParam.epochs = 200;
141 lrn_net1= train(lrn_net1,pi2set,ti2set);
142 RNNiy1set = lrn_net1(pi1set); % testing with testing data
143 RNNiy2set = lrn_net1(pi2set); % testing with training data
144
145
146 figure;
147 subplot (2,1,1);
148 plot(cell2mat(ti1set)'); % plot (p cell structure to matrix)
149 hold on;
150 plot(cell2mat(RNNiy1set)');
151 legend('Actual Voltage','Predicted Voltage set1');
152 xlabel('Time');
153 ylabel('Data');
154 %xlim([18000 28000]);
155 title('Inverse RNN network four level input');
156 grid on;
157 grid minor;
158
159 subplot (2,1,2);
160 plot(cell2mat(ti2set)'); % plot (p cell structure to matrix)
161 hold on;
162 plot(cell2mat(RNNiy2set)');
163 legend('Actual Voltage','Predicted Voltage set2 ');
164 xlabel('Time');
165 ylabel('Data');

```

```

166 %xlim([18000 28000]);
167 grid on;
168 grid minor;
169
170 figure;
171
172 plot(cell2mat(ti2set)'-cell2mat(RNNiy2set)'); % plot (p cell structure to
    matris)
173 hold on;
174 plot(cell2mat(ti2set)');
175 plot(cell2mat(RNNiy2set)');
176 legend('Error: Actual-Predicted Voltage','Actual Voltage','Predicted
    Voltage');
177 xlabel('Time');
178 ylabel('Data');
179 title('Inverse RNN network Actual-Predicted Voltage output and error ');
180 grid on;
181 grid minor;
182
183 %save('RNN_Inverse_4level_02.mat', 'lrn_net1');
184 %load RNN_Inversetwolevelinputset345.mat;
185
186 gensim(lrn_net1);
187 m=(1:1:200000);
188 F1all= horzcat (Fsmootheryeni(1:end-n5+1),
    Fsmootheryeni(n1:end-n4),Fsmootheryeni(n2:end-n3),
    Fsmootheryeni(n3:end-n2),Fsmootheryeni(n4:end-n1),Fsmootheryeni(n5:end));
189
190 siminF1 = timeseries (F1all,m(1:length(F1all)));

```

Listing 7.2

Code for Inverse Model

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