



République Algérienne Démocratique et Populaire
Ministère de l'Enseignement Supérieur et de la Recherche Scientifique
École Nationale Supérieure des Technologies Avancées
Department of Electric Engineering

Final Year Project to Obtain the Diploma of

Master in Electrical Engineering

-Field-

Electric Engineering

-Specialty-

Electric traction

-Subject-

An Introduction to Predictive Control

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Presented publicly the 30 / 06 / 2025

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2024/2025

Dedication

With all humility, I begin by praising God,
the Eternal Source of light and guidance,
for granting me the strength, patience, and clarity
to reach this milestone.

I wholeheartedly dedicate this work to my mother,
who, though absent at this stage of my life, remains ever present in my heart.
Fate may have separated us, but her love continues to guide me.

To my father,
for his unwavering support, faith in me, and words of encouragement when I lacked the strength to move forward.

To my sisters, Sara, Rahma, and Soundous,
whose moral support and genuine joy have always meant so much to me.

To my brother,
for his valuable guidance and advice throughout this journey.

To my cherished friends,
whose presence, encouragement, and shared memories
helped shape this incredible Six-year journey.

To all my classmates of the 2025 cohort,
whose shared efforts, perseverance, and camaraderie have made this experience truly memorable.

A special dedication to my exceptional project partner,
Kerchich Lotfi,
whose intelligence, kindness, and dedication
turned every challenge into an opportunity and every moment of collaboration into a pleasure.

Thank you all.

Meriem Isra

Acknowledgements

I, Merime Isra Bazzine, would like to express our heartfelt appreciation to all those who made this project possible.

First and foremost, I extend my deepest gratitude to my academic advisors, Dr. Ali Benachour, and to Mr. Abdelfettah Hoggui for their insightful guidance, generous support, and continuous encouragement throughout the entire duration of this final project.

I sincerely thank the entire teaching and administrative staff of the Department of Electrical Engineering at the École Nationale Supérieure des Technologies Avancées (National Higher School of Advanced Technologies, formerly ESSA), whose professionalism and dedication have shaped our academic journey and supported our growth throughout these formative years.

Finally, I thank all individuals—directly or indirectly—who contributed to the success of this endeavor.

Abstracts

الملخص

يركز هذا المشروع على دراسة وتطبيق تقنيات التحكم التنبؤي في أنظمة الدفع الكهربائي. ويستعرض كيف يمكن لاستراتيجيات التحكم المتقدمة أن تُحسِّن من أداء وكفاءة واستجابة الأنظمة مثل المركبات الكهربائية والمحركات الصناعية والروبوتات. من خلال تحليل مختلف أساليب التحكم التنبؤي، لا سيما التحكم التنبؤي النموذجي (MPC)، يبرز المشروع كيفية التنبؤ بسلوك النظام في المستقبل واستخدامه لاتخاذ قرارات تحكم مثلى.

الكلمات المفتاحية: التحكم التنبؤي النموذجي، FCS-MPC، CCS-MPC.

Abstract

This project focuses on the study and application of predictive control techniques in electric drives. It explores how advanced control strategies can improve the performance, efficiency, and responsiveness of systems such as electric vehicles, industrial motors, and robotics. By analyzing different predictive methods, particularly Model Predictive Control (MPC), the project highlights how future system behavior can be predicted and used to make optimal control decisions.

Keywords: Model Predictive Contol,FSC-MPC,CCS-MPC.

Résumé

Ce projet porte sur l'étude et l'application des techniques de commande prédictive dans les entraînements électriques. Il explore comment les stratégies de commande avancées peuvent améliorer les performances, l'efficacité et la réactivité des systèmes tels que les véhicules électriques, les moteurs industriels et la robotique. En analysant différentes méthodes prédictives, en particulier la commande prédictive basée sur un modèle (MPC), le projet met en évidence la manière dont le comportement futur du système peut être anticipé et utilisé pour prendre des décisions de commande optimales.

Mots-clés : Commande prédictive basée sur un modèle, FCS-MPC, CCS-MPC.

Table of Contents

Table of Contents **4**

List of Figures **5**

List of Tables **6**

General Introduction **7**

1 Fundamentals of Predictive Control **8**
1.1 Introduction . . . 9
1.2 Advantages and Limitations of MPC . . . 9
1.2.1 Advantages . . . 9
1.2.2 Limitations . . . 10
1.3 Operating Principle of Model Predictive Control . . . 10
1.3.1 Dynamic System Model . . . 10
1.3.2 Cost Function (Objective Function) . . . 11
1.3.3 Prediction and Control Horizons . . . 11
1.3.4 Receding Horizon Principle . . . 11
1.4 Industrial Applications of MPC . . . 12
1.4.1 Petrochemical and Refining Industry . . . 12
1.4.2 Power Generation . . . 12
1.4.3 Automotive and Aerospace . . . 12
1.4.4 Metallurgy . . . 12
1.4.5 Other Applications . . . 13

2 Model predictive control in Electric Drives **14**
2.1 Introduction . . . 15
2.2 Predictive control methods . . . 15
2.2.1 Hysteresis-based predictive control . . . 16
2.2.2 Trajectory Based Pridictive Control . . . 17
2.2.3 Deadbeat Based Predictive Control . . . 18
2.3 Finite Control Set MPC (FCS-MPC) . . . 19
2.3.1 Advantages of FCS-MPC: . . . 20
2.4 Continuous Control Set MPC (CCS-MPC) . . . 20
2.5 Conclusion . . . 21

General Conclusion **23**
2.6 General Conclusion . . . 23

List of Figures

2.1 Predictive control methods 15
2.2 Predictive current control, boundary circle, and space vector [14] 16
2.3 Hysteresis-based predictive control [4] 17
2.4 DSPC: Trajectories in the e/a-state plane 17
2.5 Predictive dead-beat current control: (a)-Deadbeat Block Diagram, (b)-Current Controller Operation [11]. 19

List of Tables

2.1 Comparison between FCS-MPC and CCS-MPC 21

General Introduction

Predictive control, also known as Model Predictive Control (MPC), is an advanced control technique that has revolutionized the way complex dynamic systems are managed across various industries [1]. Unlike traditional control methods, such as the PID controller (Proportional-Integral-Derivative), MPC uses a dynamic model of the process to anticipate its future behavior over a defined time horizon [1, 7]. This ability to predict and optimize control actions based on future forecasts is what distinguishes MPC and gives it remarkable robustness and efficiency.

The fundamental idea behind predictive control was first introduced by Jacques Richalet in 1978, followed by the contributions of Charles R. Cutler and David W. Clarke, who helped generalize and promote its industrial adoption [1–3]. Since then, MPC has become a cornerstone in process control, especially in industries such as oil refineries, chemical processing, agri-food, metallurgy, and aerospace, where systems often exhibit significant delays, inverse responses, and numerous disturbances [1].

The power of MPC lies in its ability to explicitly handle constraints on both controlled and manipulated variables, which is crucial for the safety and operational efficiency of real-world systems [1, 8]. At each time step, the MPC controller solves an *online optimization problem* to determine the optimal sequence of control actions that will minimize a predefined cost function while respecting system constraints [1, 9]. Only the first action of this sequence is applied to the system, and the process is repeated at the next time step, following the principle of the receding horizon.

This document aims to provide a comprehensive introduction to predictive control by exploring its fundamental principles, advantages, challenges, and applications. We will cover key concepts such as system modeling, cost function formulation, constraint handling, and the underlying optimization algorithms. The objective is to present an overview that serves as a solid foundation for a deeper understanding of this essential control technique, drawing upon influential academic references in the field.

Chapter 1

Fundamentals of Predictive Control

1.1 Introduction

Model Predictive Control (MPC) is an advanced control strategy that has gained considerable recognition in the field of control systems engineering, particularly for the management of complex and multivariable processes. Its main appeal lies in its ability to anticipate a system's future behavior and to optimize control actions accordingly, while respecting a set of operational constraints. This approach contrasts sharply with traditional controllers, such as PID regulators, which mainly react to current and past errors without explicitly predicting the future [1].

The origins of MPC date back to the 1970s, with pioneering contributions from researchers such as Jacques Richalet, who developed the concept of Heuristic Predictive Control (HPC) [1]. Subsequently, methods like Dynamic Matrix Control (DMC) by Cutler and Ramaker [2], and Generalized Predictive Control (GPC) by Clarke, Mohtadi, and Tuffs [3], consolidated the theoretical and practical foundations of MPC, paving the way for its widespread adoption in industry. Today, MPC is a mature technology, widely implemented across various sectors such as petrochemicals, energy, automotive, and aerospace, where it enhances the efficiency, safety, and profitability of operations [10].

This chapter aims to explore the fundamentals of Model Predictive Control. We begin with a discussion on the inherent advantages and limitations of this technique. Then, we explain the operating principle of MPC, including how a dynamic model is used to predict system behavior, how a cost function is minimized under constraints, and how the receding horizon concept is applied. Finally, we present an overview of typical industrial applications of MPC, illustrating its versatility and real-world impact. The objective is to provide a deep understanding of the key concepts underlying MPC, supported by relevant academic and industrial references.

1.2 Advantages and Limitations of MPC

Model Predictive Control (MPC) offers numerous advantages that justify its widespread adoption in industry, but it also presents certain limitations that must be considered.

1.2.1 Advantages

The main advantages of MPC include:

- **Explicit Constraint Handling:** One of MPC's major strengths is its ability to directly integrate constraints on process variables (inputs, outputs, states) into the optimization problem. This allows the system to operate near its performance limits without violating safety or quality constraints, which is crucial for optimizing industrial operations [1, 11].
- **Multivariable Optimization:** MPC is inherently designed to manage multiple-input multiple-output (MIMO) systems. It can coordinate the actions of several manipulators to simultaneously achieve multiple control objectives, even in the presence of complex interactions among variables [1].
- **Anticipation of Disturbances and Delays:** Thanks to its predictive model, MPC can anticipate the impact of measurable disturbances and process delays. This enables it to take corrective action before disturbances significantly affect system outputs, thereby improving control quality and reducing variability [1].

- **Improved Economic Performance:** By allowing systems to operate closer to their performance limits and optimizing operating trajectories, MPC can generate significant economic gains. This includes reduced energy consumption, better use of raw materials, increased production, and improved product quality [1].
- **Flexibility and Adaptability:** The MPC framework is flexible enough to accommodate different types of models (linear, nonlinear) and various cost functions, making it applicable to a wide range of processes. Moreover, MPC extensions such as Adaptive MPC can handle changes in process dynamics [6].

1.2.2 Limitations

Despite its many advantages, MPC has some drawbacks:

- **Implementation Complexity:** Designing and implementing an MPC controller is generally more complex than a PID regulator. It requires a strong understanding of system modeling, optimization theory, and numerical algorithms [7].
- **Requirement for Accurate Modeling:** The performance of MPC heavily depends on the accuracy of the dynamic model used. An inaccurate model can lead to poor predictions and, consequently, suboptimal or even unstable control performance. Model identification and maintenance can be demanding tasks [10].
- **Computational Load:** Solving the optimization problem at each time step can be computationally intensive, especially for large-scale systems or nonlinear models. This poses challenges for applications requiring fast sampling times or limited computing resources [7].
- **Stability and Robustness:** Although MPC is generally robust, ensuring stability and robustness in the presence of uncertainties (model errors, unmeasured disturbances) can be complex and requires advanced design and analysis techniques [9].
- **Initial Cost:** The initial cost of developing and deploying an MPC solution can be high due to software complexity and the need for qualified personnel. However, these costs are often offset by long-term operational gains [8].

1.3 Operating Principle of Model Predictive Control

Model Predictive Control (MPC) operates on a fundamental principle of online optimization, where control actions are computed by solving an optimization problem at each time step. This iterative process relies on four key elements: a dynamic model of the system, a cost function, a prediction and control horizon, and the receding horizon principle [1, 7].

1.3.1 Dynamic System Model

At the core of every MPC controller lies a dynamic model of the process to be controlled. This model is used to predict the future behavior of the system's output variables based on future control actions and anticipated disturbances. The model can take various forms, including linear models (e.g., transfer functions, state-space representations, impulse responses) or nonlinear ones, depending on the complexity and characteristics of the system [1, 10].

For a discrete linear system, the model can be represented by the state-space equations:

$$x(k+1) = Ax(k) + Bu(k) + Ed(k) \tag{1.1}$$

$$y(k) = Cx(k) \tag{1.2}$$

where $x(k)$ is the system state, $u(k)$ is the control input, $d(k)$ is the measurable disturbance, and $y(k)$ is the system output at time k. The matrices A, B, C, and E are derived from the process dynamics. The accuracy of these predictions is crucial for MPC performance, highlighting the importance of a well-identified and validated model [10].

1.3.2 Cost Function (Objective Function)

The cost function, also known as the objective function, quantifies the desired performance of the system over the prediction horizon. It is formulated to minimize the deviation between predicted outputs and desired reference trajectories while penalizing excessive changes in control actions. A typical quadratic cost function is given by:

$$J = \sum_{i=1}^{N_p} \|y(k+i|k) - r(k+i)\|_Q^2 + \sum_{i=0}^{N_u-1} \|\Delta u(k+i)\|_R^2 \tag{1.3}$$

where N_p is the prediction horizon, N_u is the control horizon, $y(k+i|k)$ is the predicted output at time $k+i$ based on data at time k, $r(k+i)$ is the reference trajectory, $\Delta u(k+i)$ is the control input increment, and Q, R are weighting matrices used to balance the importance of output errors and control effort [1, 7].

1.3.3 Prediction and Control Horizons

MPC uses two primary time horizons:

- **Prediction Horizon** (N_p): This is the number of future time steps over which the system's behavior is predicted. It must be long enough to capture the relevant dynamics of the process.
- **Control Horizon** (N_u): This is the number of future time steps over which the control actions are optimized. Typically, $N_u \leq N_p$. Beyond N_u, control inputs are often assumed to remain constant or zero [1, 7].

1.3.4 Receding Horizon Principle

The receding horizon principle is what makes MPC an online control strategy. At each time step:

1. The controller measures the current state of the system.
2. It uses the dynamic model to predict future outputs over the prediction horizon.
3. It solves the optimization problem to find the optimal sequence of control actions over the control horizon that minimizes the cost function while satisfying constraints.
4. Only the first control input from the optimal sequence is applied to the system.

5. At the next time step, the process is repeated with new measurements, and both horizons move forward by one step.

This is why it is called a *receding* or *moving* horizon [1,7]. This iterative process ensures that the controller continuously adapts to new information and disturbances, thereby maintaining robust and optimal performance in real time.

1.4 Industrial Applications of MPC

Model Predictive Control (MPC) has found a wide range of applications across various industries due to its ability to handle complex, multivariable, and constrained systems. Its deployment has led to significant improvements in operational efficiency, safety, product quality, and profitability. The sectors where MPC is most widely used include petrochemicals, refining, power generation, automotive, aerospace, and metallurgy [1, 9].

1.4.1 Petrochemical and Refining Industry

Historically, the petrochemical and refining industries were the first and largest users of MPC. The processes in these industries are characterized by slow dynamics, complex interactions among variables, significant delays, and a large number of operational constraints (temperatures, pressures, flow rates, purity levels). MPC is used to optimize the operation of distillation units, chemical reactors, catalytic crackers, and other key processes. It enables the maximization of valuable product yields, minimization of energy consumption, and compliance with quality specifications, while ensuring operational safety [9].

1.4.2 Power Generation

In the energy sector, MPC is applied to optimize electricity production and distribution, smart grid management, and control of power plants (thermal, nuclear, and renewable). It helps improve turbine efficiency, manage fluctuations in demand and supply, and integrate renewable energy sources in a more stable and predictable manner. MPC is also used in building HVAC (Heating, Ventilation, and Air Conditioning) systems to optimize energy consumption while maintaining occupant comfort [9].

1.4.3 Automotive and Aerospace

MPC is playing an increasing role in the automotive industry for autonomous vehicle control, engine management (fuel efficiency optimization and emission reduction), and vehicle dynamics control (stability, handling). In aerospace, it is used for aircraft flight control, trajectory management, and propulsion system control, where precision and robustness are critical [1, 9].

1.4.4 Metallurgy

In the metallurgical industry, MPC is applied for the control of furnaces, rolling mills, and other high-temperature processes. It helps optimize the quality of finished products, reduce energy consumption, and improve productivity by managing complex dynamics and thermal/mechanical constraints [1].

1.4.5 Other Applications

Beyond these major sectors, MPC is also used in areas such as water management, wastewater treatment, biotechnology, robotics, and even medicine (e.g., blood glucose control in diabetics). Its flexibility and ability to handle complex systems with constraints make it a valuable tool for optimization and automation across a broad range of applications [9].

In conclusion, the versatility of MPC and its ability to deliver significant operational gains have led to its widespread adoption in numerous industries. As processes become more complex and performance and sustainability demands increase, the role of MPC as an advanced control technology will continue to grow.

Conclusion

In this chapter, we explored the fundamental principles and operational framework of Model Predictive Control (MPC). At its core, MPC relies on a predictive model of the system, which enables it to anticipate future behavior and compute optimal control actions by minimizing a cost function over a defined prediction horizon. We examined how the dynamic system model, cost function formulation, prediction and control horizons, and the receding horizon strategy collectively form the backbone of MPC.

Furthermore, the chapter highlighted the extensive applicability of MPC in various industrial sectors, demonstrating its robustness and effectiveness in managing complex, multivariable, and constrained systems. From petrochemicals and energy to automotive, aerospace, and metallurgy, MPC continues to be a preferred control strategy due to its ability to improve efficiency, product quality, and operational safety.

As processes become increasingly complex and demand tighter constraints and higher performance, MPC stands out as a versatile and forward-looking solution. The foundational understanding provided in this chapter sets the stage for deeper investigations into advanced MPC strategies and their implementation in real-world scenarios in the following chapters.

Chapter 2

Model predictive control in Electric Drives

2.1 Introduction

Electric drives are fundamental systems in numerous industrial applications, ranging from robots to electric vehicles, as well as pumps and fans. The performance of these drives, in terms of precision, dynamics, and efficiency, is crucial for the proper functioning of the systems they power. Traditionally, the control of electric drives has been dominated by techniques based on Field-Oriented Control (FOC) or Direct Torque Control (DTC), which have proven their effectiveness [1]. However, with increasing demands for performance, robustness, and constraint management, Model Predictive Control (MPC) has emerged as a promising and increasingly adopted alternative [2].

MPC offers a unified approach for controlling electric drives, allowing for the natural integration of nonlinearities, operational constraints (current, voltage, speed limits), and multiple objectives (speed, torque regulation, loss minimization) within a single optimization framework. Its ability to anticipate the future behavior of the system and select optimal control actions makes it a powerful tool for improving the dynamics and precision of electric drives [3].

This chapter will focus on the application of MPC to electric drives. We will detail the operating principle of MPC applied to electric drives, highlighting key elements such as the modeling of electric machines and power converters, the formulation of the cost function, and constraint management. We will also explore the different types of MPC used in this field, including Finite Control Set MPC (FCS-MPC) and Continuous Control Set MPC (CCS-MPC). The objective is to provide a comprehensive understanding of how MPC is used to optimize the performance of electric drives.

2.2 Predictive control methods

Predictive control is a broad category of controllers that have recently been applied to power converters. Figure 2.1classifies different predictive control methods [2].

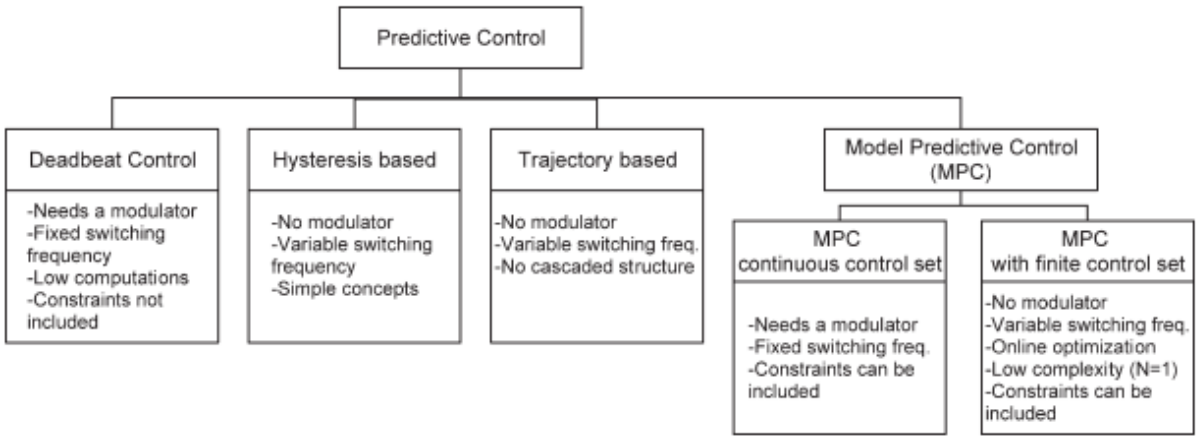


Figure 2.1: Predictive control methods

The key feature of predictive control is using a system model to predict future behavior and determine the best action based on an optimization criterion.

Different types of predictive control follow different criteria:

- Hysteresis-based control keeps the variable within set boundaries.

- Trajectory-based control ensures variables follow a predefined path.
- Deadbeat control aims to eliminate error in the next sampling instant.
- Model Predictive Control (MPC) minimizes a cost function for optimal performance.

Deadbeat control and MPC with continuous control sets require a modulator, leading to a fixed switching frequency. Other methods generate switching signals directly, resulting in a variable switching frequency.

A key advantage of predictive control is its intuitive nature. Some implementations, like deadbeat control and finite control set MPC (FS-MPC) with a short prediction horizon, are simple. However, more complex variations, especially robust deadbeat control and advanced MPC, can be difficult to implement.

Predictive control eliminates the need for a cascaded structure, enabling fast responses, such as in speed control with trajectory-based predictive control. It can also account for system nonlinearities without requiring model linearization and can include constraints in the controller design, these features are easily implemented in MPC but are challenging in deadbeat control.

2.2.1 Hysteresis-based predictive control

Hysteresis-based predictive control keeps system variables within a defined boundary. In predictive current control, switching instants are determined by error limits. For example, Figure 2.2 illustrates a circular boundary controlled by the current reference vector i_s^*. When the current vector i_s touches the boundary, the next switching state is selected through prediction and optimization.

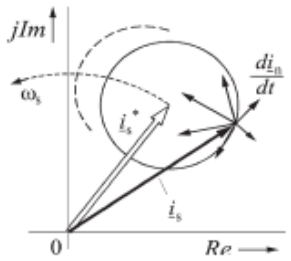


Figure 2.2: Predictive current control, boundary circle, and space vector [14]

The controller calculates possible current trajectories for different switching states and predicts the time required to reach the boundary again. The boundary moves dynamically based on the predicted current reference, as shown by the dotted circle in Figure 2.2. The optimal switching state is chosen to maximize on-time, effectively minimizing switching frequency.

The maximum switching frequency is limited by computation time. To handle higher frequencies, a double prediction method can be used, this method predicts the current trajectory before the boundary is reached, allowing for optimal selection of the future switching state.

For very high-power applications, switching frequency can be further reduced by using a rectangular error boundary instead of a circular one. Aligning this rectangle with the rotor flux vector in field-oriented predictive current control helps lower switching frequency more effectively [13].

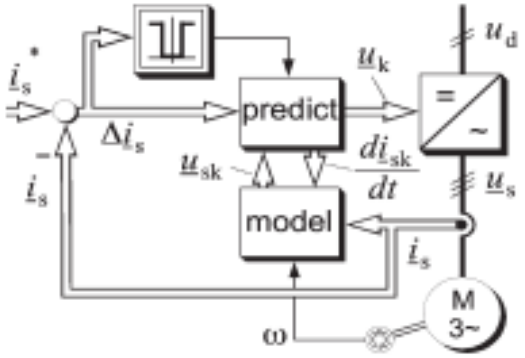


Figure 2.3: Hysteresis-based predictive control [4]

2.2.2 Trajectory Based Pridictive Control

Trajectory-based predictive control forces system variables to follow predefined paths.

Unlike cascade controllers, predictive control directly regulates system values. Most methods control stator currents, torque, or flux, while speed is managed by an external loop, however, DSPC (Direct Speed Control) directly controls the speed without a separate loop, calculating the switching events in a time-optimal manner.

DSPC classifies inverter switching states into three categories:

- Torque increasing
- Slowly torque decreasing
- Rapidly torque decreasing

By assuming constant inertia and torque derivatives over short intervals, DSPC maps system behavior into parabolic trajectories in a speed error vs. acceleration graph (figure2.4. The system state follows a predefined path, switching between torque increasing and decreasing states at optimal points to minimize speed error.

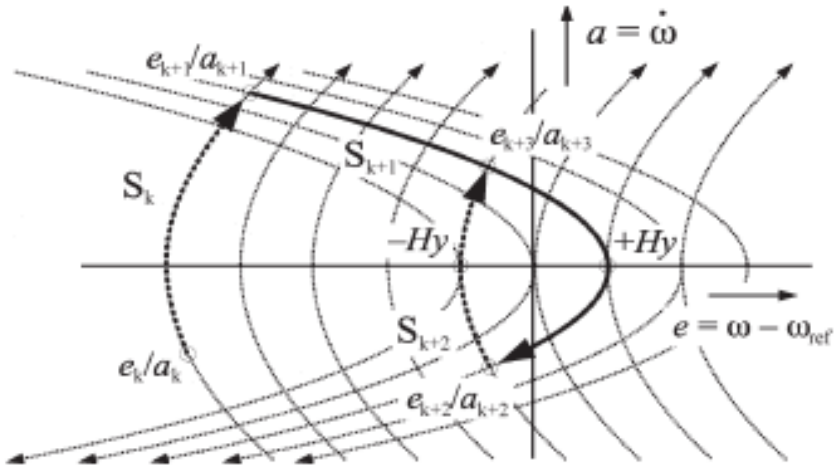


Figure 2.4: DSPC: Trajectories in the e/a-state plane

In steady-state operation, speed error oscillates within a hysteresis band ($-Hy$ to $+Hy$), maintaining an acceptable switching frequency. While the ideal steady-state point is zero error, switching constraints prevent this, necessitating the hysteresis approach.

DSPC exemplifies predictive control's core principle: using system knowledge to precalculate optimal switching states rather than linearizing nonlinear dynamics for traditional PI control. This allows direct speed control without a cascaded structure.

2.2.3 Deadbeat Based Predictive Control

The deadbeat controller is a well-known predictive control method that calculates the required reference voltage each sampling period to reach the desired value in the next instant.

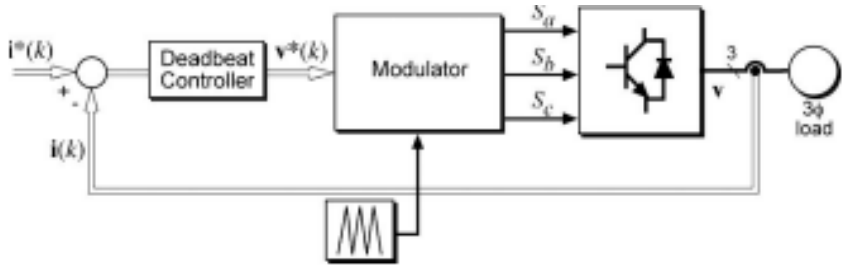
This voltage is then applied using a modulator, deadbeat control has been widely used in applications requiring a fast dynamic response, such as three-phase inverters, rectifiers, active filters, power factor correction, uninterruptible power supplies, DC-DC converters, and torque control of induction machines.

However, deadbeat control has drawbacks. It is highly sensitive to model inaccuracies, delays, and unmodeled dynamics, which can degrade performance or even lead to instability, additionally, incorporating nonlinearities and constraints into the system is challenging.

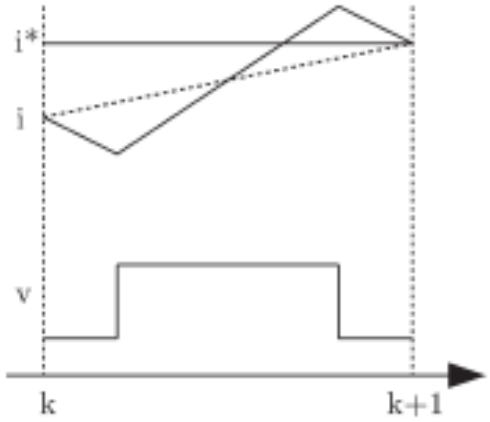
Several improvements have been proposed to address these issues:

- Compensating for calculation delays in the model.
- Enhancing robustness using adaptive self-tuning schemes, predictive internal models, and neural networks.
- Using disturbance observers for applications requiring unmeasured variables.
- Reducing switching frequency with modified algorithms.

These modifications improve stability and performance, making deadbeat control more reliable for real-world applications.



(a) Deadbeat current control [11]



(b) Illustration of deadbeat current controller operation [11]

Figure 2.5: Predictive dead-beat current control: (a)-Deadbeat Block Diagram, (b)-Current Controller Operation [11].

The figure 2.5 features an example of dead-beat current control applied to a 3-phase load, the usual PI controller is replaced by a dead beat controller which provides the voltage reference using the model of the system which is the basic voltage equation applied to a $R - L$ load in this particular case.

After being discretized ,for each sampling period the voltage reference $v^*[k]$ is applied to the converter through a modulator.

Then as Figure 2.5b shows it, the load current i at time (k) is different to the reference current i^* ,this error is used to calculate the new voltage reference $v^*[k]$ to minimize or ideally eliminate the error at time $(k + 1)$ [15].

2.3 Finite Control Set MPC (FCS-MPC)

FCS-MPC is one of the most popular forms of Model Predictive Control (MPC) in electric drives, particularly for controlling power converters. Its distinctive feature is that it considers a discrete and finite set of switching vectors that the converter can generate. For a three-phase two-level inverter, for example, there are eight possible voltage vectors [3].

The operating principle of FCS-MPC is as follows:

1. **Prediction:** At each time step, the system model is used to predict the future behavior of the controlled variables (e.g., currents, fluxes) for each available switching vector over a short prediction horizon (often a single time step).

2. **Cost function evaluation:** A cost function is then evaluated for each prediction, quantifying the deviation from references and the violation of constraints.

3. **Optimal selection:** The switching vector that minimizes the cost function is selected and applied directly to the converter for the next time step.

2.3.1 Advantages of FCS-MPC:

- *Simplicity of implementation:* There is no need for a separate pulse width modulator (PWM), as the MPC directly selects the switching states. This simplifies the control structure [3].
- *Direct constraint handling:* Constraints on voltages and currents can be easily integrated into the cost function.
- *Fast dynamics:* Direct control of switching states allows for very fast dynamic response.

Limitations of FCS-MPC

- *Variable switching frequency:* The switching frequency is not fixed and depends on the system state and the cost function, which can make filter design difficult and generate a broader harmonic spectrum [4].
- *Current and torque ripples:* Due to the discrete set of voltages, current and torque ripples can be larger than those obtained with PWM-based techniques [4].
- *Computational burden:* Although simple for a short horizon, the number of predictions to evaluate increases exponentially with the prediction horizon and the number of switching vectors, which can become a computational challenge for more complex systems.

2.4 Continuous Control Set MPC (CCS-MPC)

Unlike FCS-MPC, CCS-MPC considers that control actions (e.g., reference voltages) are continuous. The optimization problem is formulated to find the optimal continuous values of voltages to be applied to the system. These continuous voltages are then realized by a modulator (usually a PWM) that generates the switching signals for the converter [3].

Operating Principle of CCS-MPC

1. **Prediction:** The system model is used to predict the future behavior of the controlled variables over a prediction horizon, based on continuous reference voltages.

2. **Optimization:** An optimization problem is solved to find the optimal sequence of continuous reference voltages that minimizes the cost function while respecting constraints.

3. **Modulation:** The optimal reference voltages are then sent to a PWM modulator that generates the switching signals for the converter.

Advantages of CCS-MPC

- *Fixed switching frequency:* The use of a PWM modulator allows for a fixed switching frequency, which simplifies filter design and reduces harmonics [4].
- *Reduced ripples:* CCS-MPC can achieve lower current and torque ripples due to the flexibility offered by continuous modulation [4].
- *Lower computational burden:* For longer prediction horizons, CCS-MPC can be less computationally demanding than FCS-MPC, as it does not require evaluating every discrete combination of switching vectors.

Limitations of CCS-MPC

- *Requires a modulator:* A PWM modulator is necessary, which adds a layer of complexity to the control system.
- *Indirect constraint handling:* Constraints on switching states are not directly handled in the optimization problem, but rather by the modulator, which can make constraint management more complex.

Comparison and Choice

Table 2.1 summarizes the main differences between FCS-MPC and CCS-MPC.

Table 2.1: Comparison between FCS-MPC and CCS-MPC

Characteristic	**FCS-MPC**	**CCS-MPC**
Control set	Finite (discrete switching vectors)	Continuous (continuous reference voltages)
PWM modulator	Not required	Required
Switching frequency	Variable	Fixed
Ripples	Generally higher	Generally lower
Computational complexity	Can be high for long horizons	Lower for long horizons
Constraint handling	Direct	Indirect (via modulator)

The choice between FCS-MPC and CCS-MPC depends on the application's priorities. FCS-MPC is often preferred for its simplicity and fast dynamics in applications where ripples are acceptable. CCS-MPC is favored when low ripples and a fixed switching frequency are essential, at the cost of increased complexity due to the modulator.

Current research aims to combine the advantages of both approaches to develop hybrid and more performant MPC strategies in electric drives [3, 4].

2.5 Conclusion

Model Predictive Control (MPC) has emerged as a powerful and flexible control strategy for electric drives, offering advantages in performance, constraint handling, and dynamic response. This chapter has presented a detailed overview of various predictive control methods, highlighting their principles, implementation strategies, and specific roles in electric drive systems.

We began with an introduction to predictive control concepts, illustrating the core idea of using system models to predict future behavior and optimize control actions. Hysteresis-based control, trajectory-based control, and deadbeat predictive control were examined as foundational approaches, each with its unique strengths and challenges.

The focus then shifted to MPC, particularly its two main variants: Finite Control Set MPC (FCS-MPC) and Continuous Control Set MPC (CCS-MPC). FCS-MPC offers simplicity and fast response by directly selecting inverter switching states, though it suffers from variable switching frequency and potential torque ripples. On the other hand, CCS-MPC benefits from fixed switching frequency and smoother performance, at the expense of added complexity due to the modulation layer.

Ultimately, the choice between FCS-MPC and CCS-MPC depends on application-specific requirements such as desired dynamics, acceptable ripples, computational resources, and system constraints. Recent research aims to combine the strengths of both methods, leading to hybrid MPC strategies that further enhance the control of electric drives.

Model Predictive Control continues to be a promising field in power electronics and motor control, offering a structured and high-performance alternative to traditional control strategies in the pursuit of smarter, more efficient electric drive systems.

General Conclusion

2.6 General Conclusion

This part of the work has explored the fundamental concepts and practical implementations of predictive control techniques in electric drives. Starting from the motivation behind the evolution of control strategies, we introduced Model Predictive Control (MPC) as a modern, powerful alternative to classical methods like Field-Oriented Control (FOC) and Direct Torque Control (DTC). MPC's ability to incorporate system models, predict future behavior, and handle constraints in a unified optimization framework makes it highly suitable for modern drive applications.

We presented a classification of predictive control methods and highlighted their key features and operational principles. Techniques such as hysteresis-based control, trajectory-based predictive control, and deadbeat control were described in detail, each demonstrating how predictive strategies can directly influence performance, switching behavior, and dynamic response.

The focus then shifted to MPC, with a distinction made between Finite Control Set MPC (FCS-MPC) and Continuous Control Set MPC (CCS-MPC). While FCS-MPC is appreciated for its simple structure and fast dynamics, CCS-MPC offers reduced torque and current ripples and a fixed switching frequency—features desirable in applications requiring precision and smooth operation.

The comparative analysis underscored that the choice of predictive control method must align with the application's specific requirements, such as performance criteria, hardware limitations, and real-time constraints. Current research trends aim to merge the strengths of different strategies to develop hybrid and more intelligent control solutions.

In summary, predictive control—particularly MPC—offers a versatile and forward-looking approach to controlling electric drives. Its adaptability to system complexities, constraints, and performance goals makes it a central pillar in the future development of high-performance, energy-efficient motor control systems.

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