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A Comprehensive Review of Current Progress in Finite Control Set Model Predictive Control: Tackling Issues and Strategies for Enhancing Performance in Electric Vehicle Applications

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ABSTRACT
Model Predictive Control (MPC) has become increasingly prominent as an effective and broadly embraced control strategy for electric drives and power converters in recent times, owing to its uncomplicated approach., flexibility, rapid dynamic response, and parameter robustness. MPC is mainly categorized in two parts: Continuous Control Set (CCS) MPC and Finite Control Set (FCS) MPC. This article aims to present a comprehensive overview of FCS-MPC approaches widely employed in electric vehicle applications and to elucidate the challenges like parameter robustness, variable switching frequency and computational burden associated with FCS-MPC as these parameters have great influence in dynamic performance of electric vehicle. So, the paper also explores the many solutions proposed by researchers to reduce parameter sensitivity, fixed switching frequency and reduce computational load. This publication will provide researchers with insights for their future work in this field.

Keywords - *Finite Control Set MPC, Robustness, Computational burden, Switching frequency*

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I. INTRODUCTION

Before the origination of internal combustion engines (ICE), electric vehicles (EV) were the means of transportation worldwide. The EVs have been in use since 1918. Since then, because of the rapid development and viability of Internal Combustion Engines [ICE], the use of electric vehicles on public roads was substantially reduced [1].

In the past ten years, many greenhouse gas releases have produced environmental difficulties, this has led nations to focus more on reducing energy consumption and lowering emissions [2]. According to regular reports on greenhouse gas emissions from the United Nations, these gases are the principal factors that affect climate change. Without intervention, scientists project that the Earth's average surface temperature is projected to rise by more than 3 degrees Celsius within this century [3]. Between 30 and 50 percent of carbon dioxide (CO2) emissions from roads originate from automobile engines, making them one of the largest contributors to greenhouse gases [4]. Besides greenhouse gas emissions other key factors like depletion of petroleum reservoir and the daily rise in fuel cost, geopolitical and war-like issues create an uncertainty in the supply of fuel. According to statistics, transportation industries are responsible for two-thirds of the growth in petroleum use, which is severely harmful to the long-term viability of human society [5]. As a result, the process of eliminating carbon from transportation systems will lead to the complete termination of carbon dioxide emissions in this sector [6]. Zero-emission automobiles may present a viable resolution to these issues [3], [6]–[8]. Consequently, numerous developed countries are encouraging the use of electric vehicles (EVs) to decrease atmospheric pollution, CO2 emissions, and additional gases that cause the greenhouse effect [3]. It is anticipated that the portion of electric vehicles in automobile industry is projected to increase from 2% in 2016 to 22% by 2030, marking a substantial shift in the industry [3]. The rapid advancements in power electronics drives and electric machinery have led to the extensive proliferation of electric vehicle (EV) technologies and applications in recent years [9].

EVs have so many advantages over ICE vehicles which makes it popular among the automobile industry. Electric vehicles have the capability to deliver power from their energy reserves while idle and can be synchronized with the electrical grid for comprehensive energy administration[10]. An electric vehicle's primary system is composed of five key elements: an electric motor, a controller, a power converter, a battery stack, and a charging unit.[7]. Electric motor is an essential part of EVs and the advancement of transportation electrification may be influenced by innovations in electric motor technology. Significant enhancements in traction dynamic performance have been achieved through technological advancements. These improvements stem from research and development efforts in three key areas: Semiconductor based power electronic switching devices, digital signal processors, and advanced intelligent control systems [11]. AC motors have number of advantages, including less maintenance, smaller in size, high efficiency, robust and less costly.

Some authors have studied the EV market from 2010 to 2020 and concluded that Induction Motor (IM), Switched Reluctance Motor (SRM) and Permanent Magnet Synchronous Motor(PMSM) [2], [3] are installed as a traction motor in EV. Induction Motors due to their simple construction, reliability, robustness, cost effectiveness and adaptability have been effectively applied in EV applications [12]. Despite several advantages the Induction Motor has low overload capacity, poor power factor, low efficiency particularly at low speed, high rotor losses produce more heat and noise. Another popular motor gained increasing attention in EV industry is Switched Reluctance Motor (SRM) due to their simplicity, robustness, no winding and Permanent Magnet on the rotor, fault tolerant and less maintenance. Even if a number of benefits, SRM face challenges in broad use of EVs. Significant challenges associated with SRMs include the generation of acoustic noise and vibrations, which lead to pulsating torque production and torque fluctuations. These issues negatively impact the vehicle's drivability and the comfort experienced by passengers [3]. Concurrently, the adoption of SRM was also constrained by complex control systems and power conversion devices. Combined with their exceptional torque-speed characteristics and excellent dynamic performance, PMSMs are considered optimal for electric vehicle applications and are generally favored over the other AC motor drives, like IM and SRM. Because of their exceptional performance attributes, PMSM is the most preferred choice as a Propulsion motor for EV application. These motors owing to great efficiency, substantial power output, and high torque density, extensive constant power speed range, compactness, less maintenance, less weight, ease of design, noiseless operation and reliability making them ideal for modern EVs [1]–[3], [5], [7], [11]. Furthermore, PMSM delivers swifter and precise torque regulation, improving the vehicle's drivability.

Research into control strategies for electric vehicles (EVs) is essential for enhancing energy efficiency, maintaining system reliability, boosting fuel economy, and minimizing emissions. The regulation of a power electronic converter which modulates the characteristics of PMSM as per the EV requirements i.e. controlling the speed and torque of a PMSM during accelerating, decelerating, braking and climbing is very crucial. The electric vehicle's speed and torque characteristics are noted to undergo continuous variations during the entire ride [10]. Meanwhile, the dynamic performance of electric vehicles (EVs) plays a vital role in various aspects, including customer satisfaction, safety considerations, competitive edge, and battery longevity and management. As a result, the control method employed for the PMSM must demonstrate superior dynamic performance to effectively manage variable inputs. These factors can be extensively evaluated using advanced control techniques like Model Predictive Control (MPC), Direct Torque Control (DTC), and Field Oriented Control (FOC) [5], [7], [9], [13]–[17]. In comparison with FOC and DTC, MPC offers tremendous merits like readily comprehensible, online optimization, simplified design, incorporation of diverse constraints and nonlinearities, minimal distortion of current, reduced losses in switching and robustness makes it more suitable to electric drive application [8], [15]–[21].

Over the past several decades, model predictive control (MPC) has garnered increased interest in scholars and industry professionals owing to simplicity, intuitive nature, swift dynamic responsiveness, capability to manage nonlinear constraints, and capacity for controlling multiple variables simultaneously [20], [22]–[26]. Furthermore, MPC is versatile and not limited to specific machine types. It can be implemented across various AC machines, including IM, PMSM, SRM, and Brushless DC(BLDC) motors [15], [17]. For electric vehicle (EV) applications, precise and seamless torque regulation, along with rapid motor responsiveness, are crucial factors. Model Predictive Control (MPC) offers benefits like straightforward implementation, quick dynamic reactions, and the capacity to manage non-linear systems, making it well-suited for these requirements. Therefore, Model Predictive Control (MPC) is ideally suited for PMSM characterized by strong coupling and nonlinearity [25].

The flow of remaining portion of the article is organized like: Component II provides a thorough classification of MPC, fundamental principles of FCS-MPC and its algorithmic approach. Current challenges and various solutions proposed by FCS-MPC from researchers are summarized in Component III, while in Component IV discusses in brief the effectiveness of FCS-MPC for EVs and future scope for the researchers and finally conclusions are summarized in Component v.

II. MODEL PREDICTIVE CONTROL (MPC)

Model Predictive Control (MPC), a well-established nonlinear control methodology in process industries, for instance petrochemicals, is now arising as a promising control approach in the realms of electric drives and power electronics [17]. The advancement of fast and robust processors has made nonlinear control an appealing field for researchers pertaining to power electronics and drives [15]–[17]. Electric vehicle applications benefit significantly from Model Predictive Control (MPC) due to its superior dynamic reaction, simplified design process, and capacity to manage nonlinear systems. These characteristics make MPC an optimal control strategy for electric vehicles. The MPC concept is predicated on calculating the future response of the system under control to determine its optimal operational conditions. The predictive algorithm's application consists of three key stages: assessing hidden variables, anticipating the system's upcoming actions, and enhancing outcomes through a pre-established cost function [7]. MPC typically determines control actions by optimizing a cost function that represents the system's intended performance. This function evaluates the discrepancy between the predicted system output and a reference value. System model calculations generate these output predictions. During each sampling interval, the MPC controller computes a sequence of control actions that optimize the specified cost function. However, the system's implementation encompasses solely the inaugural component of this sequential arrangement.

2.1 Classification of MPC

According to control sets of voltage vector the MPC encompasses two distinct categories: (1) Continuous Control Set MPC (CCS-MPC) and (2) Finite Control Set MPC (FCS-MPC) [15], [17], [23]–[40]. Detailed classification is mentioned in Figure 1. The continuous reference voltage vector in CCS-MPC can be derived through analytical or numerical methods. Subsequently, Pulse Width Modulation (PWM) techniques are exerted to transform this continuous vector into appropriate gate signals. The modulator can be anyone that is valid for power converter. That’s why this referred as CCS-MPC. The main benefits of CCS-MPC are fixed switching frequency. CCS-MPC is again classified into two parts: (1) Generalized Predictive Control (GPC) (2) Deadbeat Predictive Control (DBPC).

CCS-MPC offers many advantages i.e. fixed switching frequency, accuracy in prediction of dynamic behavior, reduction in harmonics, more versatile, smaller torque ripple and lower computational burden [23], [38], [40], [41]. However, CCS-MPC generates a continuous reference voltage vector needs a modulator to produce switching pulses for semiconductor switches, which delays the response. Besides this CCS-MPC has complex algorithm and needs large memory to save total switching states in look up table optimized offline [17], [27].

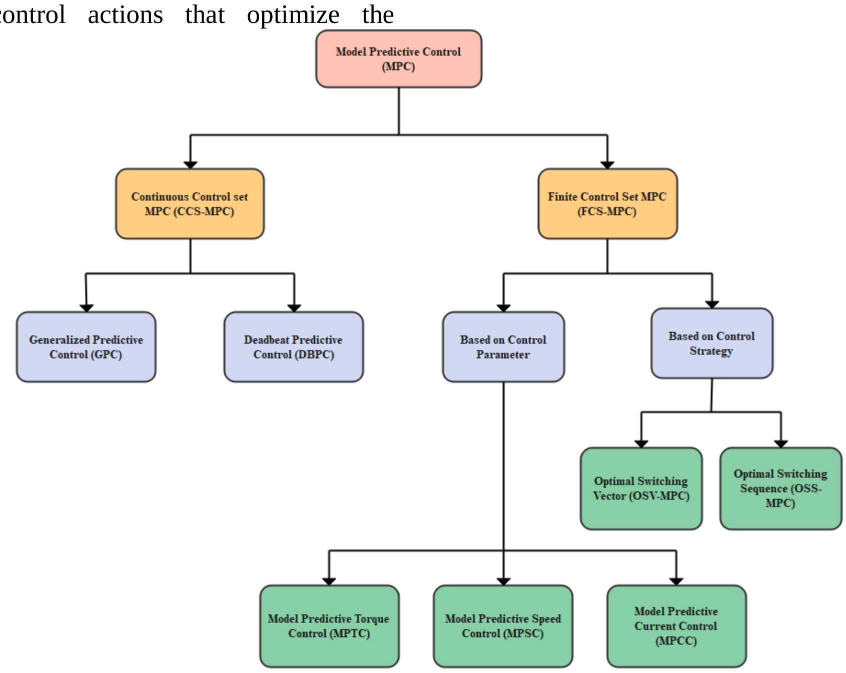

Figure 1: Classification of MPC control strategy

Unlike conventional CCS-MPC techniques, which typically exclude cost functions, power electronics systems characterized by nonlinearities and constraints integrate cost function optimization into their control mechanisms. The optimization challenge in Model Predictive Control for power converters can be simplified due to the finite set of possible switching states. This simplification allows for the prediction of system behavior to be limited exclusively to these feasible switching configurations. [37]. Cost function is then determined for every potential state of switching and switching function that minimizes a predetermined cost function is ultimately selected for implementation at the subsequent sampling moment. This method is referred to as Finite Control Set Model Predictive Control (FCS-MPC) due to the finite number of switching states (additionally known as Direct MPC [42], [43]). A discrete model is employed to forecast system behavior for all possible actuation sequences within the prediction horizon

2.2 Formulas for applying FCS-MPC to PMSM

The model implemented for the PMSM aims to anticipate the id and iq values for the upcoming sampling moment. The equations are written by:

$$i_d^p(k+1) = \left(\left(1-\left(\frac{Rs*Ts}{L}\right)\right)*i_d(k)\right) + \left(T_s*\omega*i_q(k)\right) + \left(v_d(k)*\frac{T_s}{L}\right) \qquad (1)$$

$$i_q^p(k+1) = \left(\left(1-\left(\frac{Rs*Ts}{L}\right)\right)*i_q(k)\right) - \left(T_s*\omega*i_d(k)\right) - \left(T_s*\omega*\Phi_m\right) + \left(v_q(k)*\frac{T_s}{L}\right) \qquad (2)$$

The next step involves minimizing the cost function, which is represented by a squared error formula as shown below:

Cost function

$$\theta = (i_d^* - i_d)^2 + \left(i_q^* - i_q\right)^2 + (T^* - T_e)^2 + SW_{min} + C_{max} \qquad (3)$$

The electromagnetic torque of the PMSM below base speed is given by:

$$Te = 1.5*p*\Phi_m*i_q \qquad (4)$$

The PMSM's electromagnetic torque within field weakening domain (constant power) is given by:

$$Te = 1.5*p*\Phi_m*i_q + \left(L_d - L_q\right)*i_q \qquad (5)$$

Where i_d and i_q are d and q axis current respectively, Rs represents stator winding resistance in ohm, L stands for stator winding inductance in mH, T_s defines sampling time in ms, ω describes PMSM's rotor speed in rad/s, $v_d(k)$ specifies d axis stator voltage at sampling instant k, $v_q(k)$ is the q axis stator voltage at sampling instant k, $i_d^p(k+1)$ is the future predicted value of d-axis current at sampling instant $(k+1)$, $i_q^p(k+1)$ is the future predicted value of q-axis current at sampling instant $(k+1)$, Φ_m = Permanent Magnet flux of the rotor in weber. T^* is the torque reference in Nm, SW_{min} is additional constraints added to minimize cot function, C_{max} is the constraints to limit maximum allowable d-q current.

2.3 Principle of FCS-MPC

The FCS-MPC principle has three simple steps:

(1) Present states are predicted through measured current and voltage, a process referred to as delay compensation.

(2) The possible states over subsequent sampling interval for various switching states are predicted utilizing a discrete-time prediction model.

(3) The converter is assigned the ideal switching configurations, which are determined by minimizing the cost function.

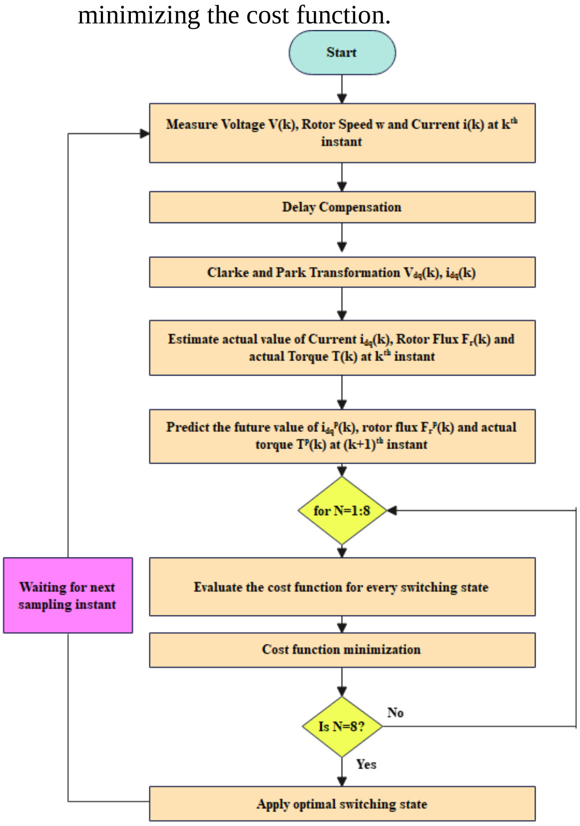

Figure 2: Flowchart for implementation of FCS-MPC

The Figure 2 depicts a comprehensive flowchart elucidating the procedural implementation of FCS-MPC methodology, where N denotes the quantity of available switching states for voltage source inverters with two levels.

FCS-MPC displayed in Figure 5 offers simplicity, flexibility and easily adoption to power electronics circuits. Power electronics converters and drives find FCS-MPC to be an attractive choice due to quick dynamic response, the elimination of delays through the absence of modulators, the ability to incorporate non-linearities and constraints into the cost function, and the potential for real-time optimization.[23], [36], [39], [44], [45]. Although FCS-MPC and CCS-MPC may offer similar performance, FCS-MPC requires more computational resources [46]. FCS-MPC as demonstrated in Fig. 3 can be divided into two further categories according to duration for which optimal voltage vector is applied: Optimal Switching Vector MPC (OSV-MPC) and Optimal Switching Sequence MPC (OSS-MPC) [35], [40]. OSV-MPC applies a single output voltage vector throughout the entire sampling interval and it can be continuing for a next sampling interval also. This results in a fluctuating switching frequency. To address this issue, OSS-MPC employs a control set that includes a restricted number of potential switching sequences for each switching period [40]. OSS-MPC considers the instant of the switching state which acts as a modulator in optimization problem. One notable MPC method, OSV-MPC, is widely employed and leverages all accessible switching vectors as potential control actions on the converter system [35]. In literature authors have compared MPC strategies which are mentioned in the Table 2 below [40].

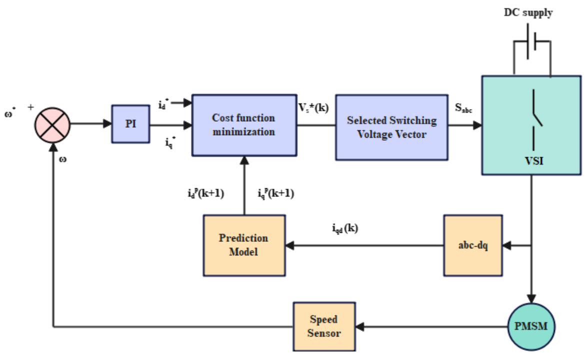

Figure 3: Schematic representation of FCS-MPC

FCS-MPC is categorized as Model Predictive Torque (and flux) Control (MPTC) [17], [24]–[26], [30], [32], Model Predictive Speed Control (MPSC) [17], [24], [25], [32], Model Predictive Current Control (MPCC) [17], [24]–[26], [30], [32] and Model Predictive Flux Control (MPFC) [24], [25] based on various control parameters and with the aim of enhancing control effectiveness. The schematics of MPTC, MPCC and MPSC put on show in Figure 4, Figure 5 and Figure 6 respectively. In contrast to traditional inner current PI controllers, MPTC and MPCC employ nonlinear predictive controllers, theoretically enabling unlimited inner current control bandwidth. Similarly, MPSC replaces the outer speed PI controller with a nonlinear controller and integrates the speed control loop into the cost function [17].

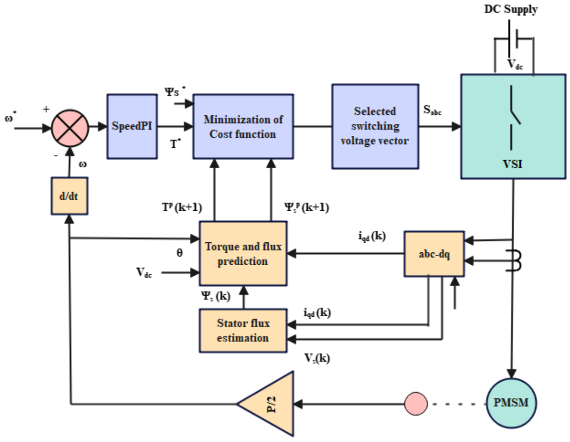

Figure 4: Model Predictive Torque Control (MPTC)

To implement MPTC there are three steps: Estimate the torque or flux from measured current or voltage measurement, predict the future value of torque and flux and design the cost function [16]. The MPCC technique utilizes a cost function based on current error to substitute for the internal current PI regulators in the FOC framework [16], [17], consequently, it is also known as predictive field oriented control (PFOC). In contrast, MPSC replaces the outer speed PI controller with a nonlinear controller and incorporates the speed control loop into the cost function. The MPSC methodology integrates speed and current control into a unified cost function, allowing for concurrent management of velocity and electrical variables without necessitating an external PI controller [17].

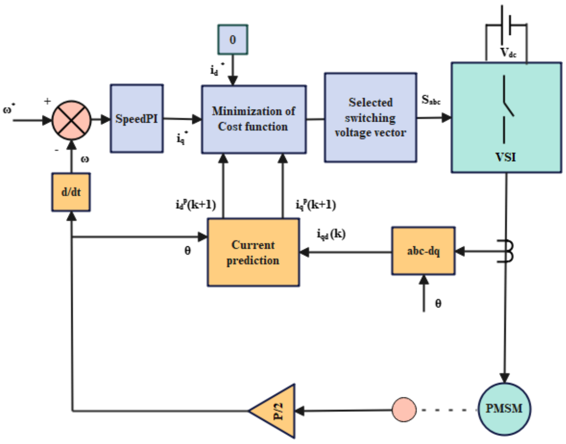

Figure 5: Model Predictive Current Control (MPCC)

Although numerous researchers have advanced FCS-MPC using diverse approaches, critical challenges remain that require urgent resolution in the near future for MPC implementation, e.g., robustness, variable switching frequency and computational burden. In FCS-MPC switching voltage vector needs to be calculated in each sampling period for each predictions.

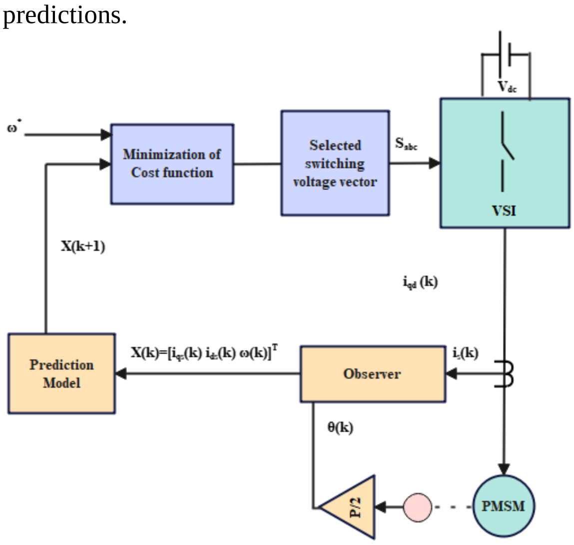

Figure 6: Model Predictive Speed Control (MPSC)

The Longer the prediction horizon, larger the computational burden [23] in each sampling time is a limiting factor for high sampling frequencies applications [20].The modulator ensures a fixed switching frequency, wherein the sampling frequency and switching frequency are identical [20]. Without modulation switching voltage vector persists for a longer time in each sampling interval leads to variable switching frequency, exhibits large torque and current ripple [23], [38].

III. ADDRESSING THE CRITICAL CHALLENGES OF FCS-MPC AND THEIR PRESENT REMEDIES

The integration of FCS-MPC into electric vehicle systems demands specific performance criteria: diminished switching frequency, superior efficiency, reduced acoustic noise, minimized torque ripple, decreased total harmonic distortion (THD), durability and rapid dynamic response. A review of the literature reveals that several factors significantly impact the dynamic performance of electric vehicles. These factors include parameter estimation in sensorless control, discrepancies in model parameters, fluctuating switching frequencies and computational duration. Several researchers have suggested resolutions for the aforementioned challenges, enhancing the suitability of FCS-MPC for electric vehicle applications.

3.1 Robustness or Model Parameter Mismatch

Although FCS-MPC demonstrates resilience to parameter fluctuations, its predictive outcomes are influenced by the parameters of the machine model. Consequently, discrepancies in these parameters can result in diminished control effectiveness. To enhance the progress and effective implementation of FCS-MPC in electric vehicle applications, scientists have developed approaches aimed at improving its resilience to parameter variations. Recently, various novel strategies have emerged, establishing a new category of predictive controllers that operate independently of models [29], [48], does not use actual machine model is gaining increasing attention. A visual representation summarizing the diverse approaches is provided in the Table 2 below.

3.2 Variable Switching Frequency

The implementation of the modulator enables CCS-MPC to attain a steady switching frequency while simultaneously delivering superior dynamic and steady-state performance [29]. The modulator maintains a consistent switching frequency, which corresponds to the sampling frequency. Conversely, in FCS-MPC systems without a modulator, the applied switching voltage vector can remain constant for multiple sampling intervals, resulting in a non-uniform switching frequency. Variable switching frequency can lead to increased torque and current ripple, acoustic noise, Electromagnetic interference, control complexity, filtering challenges which negatively impacts the smoothness of operation and ride comfort in electric vehicles. To address these issues researchers have proposed several solutions briefly mentioned in the Table 3 below.

Table 1: Suggested remedies by researachers to improve robustness

Suggested Remedies by Researchers for Robustness Improvement	Literature Survey
❖ Luenberger Observer	[15], [29], [50]
❖ Combination of MPC with delay estimator	[51]
❖ Model free MPC (MFPC)	[21], [24], [26], [29], [48], [50]
• Completely MFPC, Prediction Correction Based MFPC	[29]
• Ultra Local Model Based MFPC	[26], [29]
• Autoregressive with Exogenous Input Model, Autoregressive Moving Average Structure, Look UP Table (LUT) store information of Current Variation	[26]
• Model Free Terminal Sliding Mode Controller	[8]
❖ Unconstrained MPC with integral terms added into cost function	[21], [50]
❖ Speed loop cascaded with external torque loop	[21]
❖ MPC combined with Sliding Mode Control (SMC)	[9], [24]–[26], [29], [52]–[54]
❖ Equivalent input disturbance, Extended state observer, Frequency-Domain disturbance observer, Generalized proportional integral observer, Intelligent disturbance observer, Nonlinear disturbance observer, Uncertainty and disturbance estimator, Unknown input observer	[24]
❖ Kalmen filter, Moving horizon estimation	[25], [50]
❖ Disturbance Observer	[24]–[26], [29], [50]
❖ improved stator flux observer, electromagnetic torque observer, PCC with disturbance estimation and current compensation, Hyperbolic Tangent Sliding Mode Approach, Discrete Time Parameters developed Popov's Hyperstability Criterion, Discrete Time Parameters developed Adaptive System Reference, ADALINE Neural Network, Data Based Recursive Calculation	[25]
❖ Neuro-fuzzy control methods	[8], [55]
❖ Online parameter identification- Recursive Least Square (RLS), Extended Kalmen filter (EKF), Neural Network (NN)	[24]
❖ Model Reference Adaptive System (MRAS)	[24], [26]
❖ Two step MPC	[56]
❖ Bacterial Foraging Optimization Algorithm (BFOA)	[57]
❖ Modulated MPC	[58]
❖ Hybrid Parallel Observer (SMO and Adaptive Observer)	[59]
❖ Fast Two Vector based Model Free MPC	[49]
❖ Incremental Prediction Model MPC	[60]
❖ H∞-Synthesis Control, μ- Synthesis Control, Iterative Learning Control (ILC)	[26]
❖ H∞-Based Feedback Control with Fuzzy Adaptive Sliding Mode Observer	[61]
❖ Artificial Neural Network (ANN)	[62]
❖ Look UP Table based MPC(LUT-MPC) • LUT-Disturbance Observer MPC(LUT-DOB) • LUT based Parameter Estimation Method (LUT-PEM) • No Parameter MPC(NMPC)	[29]

Table 2: Suggested remedies by researchers for keeping the switching frequency consistent

Suggested Remedies by Researches to Fix Switching Frequency	Literature Survey
❖ Optimum switching instant	[15]
❖ Combined with Lyapunov	[15]
❖ Multiple voltage vector in one sampling interval	[16], [32]
❖ Duty cycle control	[15], [24]
❖ Modulated MPC (M2PC)	[20], [21], [23], [24]
❖ Fuzzy controller	[23], [55]
❖ Multi-step MPC	[21], [24], [63]–[65]
❖ Model Predictive Pulse Pattern Control (MP3C)	[21], [26]
❖ Discrete Space Vector Modulation (DSVM)	[15], [66]
❖ Vector evaluation table with magnitude and angle of output vector adjustment	[67]
❖ FCS-MPDTC with Lyapunov function in cost function	[68]
❖ Genetic Algorithm and Artificial Neural Network	[55]
❖ Multi Vector MPC- Auxiliary Voltage Vector MPC, Generalized Double Vector MPC, Three Vector MPC	[24]
❖ Model Predictive Flux Control with Vector Duty Ratio Modulation	[69]

3.3 Computational Complexity (Burden)

The complexity of FCS-MPC calculations is influenced by the chosen optimization algorithm. Nevertheless, FCS-MPC necessitates solving the optimization problem in real-time. Researchers have also developed methods for designing weighting factors using Artificial Intelligence, aiming to enhance control system performance. This process involves extensive computations, which presents a challenge for implementing the method on conventional control hardware platforms. Also, the extending the prediction horizon enhances system stability and performance, though it simultaneously increases the computational load. However, FCS- MPC has problems such as high current harmonics, significant torque ripple, and unfixed switching frequency [29]. To deal with these issues, scientists have developed enhanced control methods, which in turn increase the computational load on the microprocessor. The computational load increases when employing a greater number of voltage vectors, whether they are virtual or applying to multilevel inverters [26]. The computational load may pose a challenge for applications requiring high sampling rates, such as high-speed drives in electric vehicles. So, the solutions and related research achievements are summarized in the Table 4 below.

Table 3: Suggested remedies by researchers to reduce the computational burden

Suggested Remedies by Researchers to Reduce Computational Burden	Literature Survey
❖ Modified Discrete MPC	[27]
❖ Pulse Pattern Control	[27]
❖ Homotopy	[27]
❖ Branch and Bound	[20], [27], [40]
❖ Park and Clarke transformation	[27]
❖ Quadratically and linearly constrained quadratic programme (QLCQP)	[27]
❖ Alternating direction method of multipliers (ADMM)	[27]
❖ Transforming cost function into equivalent optimization problem	[40]
❖ Sphere Decoding Algorithm (SDA)	[20], [40], [64]
❖ Long Prediction Horizon FCS-MPC Based on K-Best Sphere Decoding	[70]

❖ Voltage vector elimination technique	[21]
❖ Extrapolation strategy	[20]
❖ Modulated MPC (M2PC)	[23]
❖ Fuzzy Controller	[26], [55]
❖ Candidate vector optimization, Duty Cycle MPC based on dead beat principle, only prediction of one zero voltage vector	[24]
❖ Discrete Space Vector Modulation (DSVM)	[26], [66]
❖ Virtual Vector based MPC	[26]
❖ Two step MPC	[56]
❖ Hybrid Parallel Observer (SMO and Adaptive Observer)	[59]
❖ Pre Selection Strategy based on Stator flux increment followed by Optimal Switching Sequence Method	[71]
❖ Multi Vector Based MPC	[26], [72]
❖ Lagrange Multiplier Aided Modulated MPC	[73]
❖ Look Up Table (LUT) with four voltage vector for prediction and cost function evaluation	[26]
❖ Reference Voltage Vector from Dead Beat Control scheme	[26]

IV. DISCUSSION

This article examines the current state of Finite Control Set Model Predictive Control (FCS-MPC) for Permanent Magnet Synchronous Motor (PMSM) drive systems. It highlights ongoing challenges and recent advancements in areas such as robust operation, computational efficiency, and switching frequency optimization.

4.1 Robustness

Various control techniques, including sensorless and fault-tolerant control, are increasingly combined with FCS-MPC to enhance performance. However, further research is needed to assess the robustness, computational demands, and overall performance of these hybrid control schemes. For instance, both sensorless control and FCS-MPC rely on system parameters, and incorporating sensorless control introduces additional parameters, potentially increasing computational complexity. While observer-based methods are used, they do not completely eliminate model inaccuracies. It's important to note that minimizing model deviations remains the primary objective in robust controller design. Consequently, researchers often combine improved predictive models with observers to address multi-parameter mismatch issues. Future research should also explore the combining predictive control with additional well-known control techniques. The Nonlinear Model Predictive Control (NPMPC) approach has drawn more attention, with its robust performance being validated. Ultra local model based Model-Free Predictive Control (MFPC) is advancing, though estimating uncertainties in these models remains challenging. Data-driven look-up table MFPC reduces online calculations but requires additional algorithms to address table stagnation issues. Fast Two-vector MFPC demonstrates superior performance compared to deadbeat control, offering improved dynamic and steady-state responses. While Bacterial Foraging Optimization Algorithm (BFOA) compensation helps mitigate distortion effects, it cannot completely eliminate them, particularly for resistance distortion at various speed ranges. Modulated MPC exhibits lawless speed performance and quicker dynamic responsiveness under various operating conditions compared to predictive and PI strategies. Hybrid parallel observers enhance sensorless control accuracy following parameter changes. Fuzzy and Artificial Intelligence (AI) based methods, while efficient and responsive, can be complex and costly. MPC and fuzzy-based approaches are highly model-dependent. Current research focuses on developing simplified MPCs with reduced computation load, lower parameter sensitivity, and rapid dynamics to enhance electrical drive performance. Model-free strategies have shown promise in achieving high-quality machine control without requiring precise models, offering opportunities to improve drive robustness by incorporating modern estimation techniques. AI techniques present a new avenue for research, as they work with basic models and instantaneous variables. This emerging field warrants further exploration in the future. Leuenberger observer improves robustness, but increases computational burden; long prediction horizon makes the control performance worse. Multiple voltage vector in one sampling interval keeps switching frequency constant, but increases computation burden. Cascaded free MPC is complex as it includes many cost function's components, Multi objective MPC creates stability issue and sequential MPC decreases efficiency, limits controllability of torque and flux which degrades the performance.

4.2 Variable Switching Frequency

Compared to FCS-MPC, a Lyapunov-based FCS-MPDTC for the PMSM can achieve a constant switching frequency, reduced sampling frequency, and minimized torque ripple. While DSVM expands the quantity of voltage vectors, resulting in a higher computational load, it maintains similar performance regarding switching frequency, dynamic torque responsiveness, stator current THD, and torque and flux ripple. Utilizing multiple-step prediction has decreased the inverter-generated load current distortion, but its complexity and implementation challenges in brief sampling intervals remain areas for future study. Additionally, for larger rating motor drives, combining optimized pulse patterns with predictive control could further diminish load current distortion while operating at low switching frequencies. Some studies have examined Multistep MPC methods for steady-state performance, but their dynamic performance has not been evaluated. A voltage modulator-equipped neuro-fuzzy controller can deliver swift torque and flux responses in milliseconds at low velocities, while sustaining a steady switching frequency. Simplified two-step FCS-MPC offers a balance between switching frequency and steady-state response. Modulated MPC is suggested to maintain a constant switching frequency. Multi-objective MPC delivers quick dynamic response but is affected by variable switching frequency. A dual-vector dimensionless model predictive control for PMSM drives, utilizing fuzzy decision-making, maintains a constant switching frequency and exhibits excellent steady-state performance. Model Predictive Pulse Pattern Control decreases switching frequency by 40%, but there is still room for research when compared to FOC SVM. These considerations should prove valuable for future researchers in their studies, potentially enhancing the effectiveness of FCS-MPC controlled PMSM drives in EV applications.

4.3 Computational Burden

The computational load is reduced through the use of a hybrid parallel observer. FCS-MPC, being parameter-dependent, requires parameter adjustments, which increases the computational burden. While the incorporation of multi-vectors enhances steady-state performance, it also inevitably raises the complexity and computational demands of FCS-MPC. Additional study is required to investigate the integration of FCS-MPC with other methods for improved performance. A popular approach to minimize unnecessary resource usage while maintaining control effectiveness is to integrate event-triggered control with FCS-MPC. The implementation of event-triggered control substantially decreases computational expenses, enabling the development of more advanced solutions. While modulated MPC exhibits favorable harmonic characteristics and retains the benefits of FCS-MPC, it significantly increases the computational load. Multi Objective MPC adds to the computational complexity, leading some researchers to deem it impractical for multilevel inverter implementation. This issue requires additional research. MFPC techniques, such as current difference and ultra-local model approaches, may demand greater computational resources. In recent years, reinforcement learning (RL) is a promising approach for data-driven control method for PMSM drives, offering the benefit of reduced computational requirements. The use of observers in sensorless control also contributes to increased computational complexity. While multi-vectors improve steady-state performance, they also increase the complexity and processing needs of FCS-MPC. Further investigation is needed regarding the integration of FCS-MPC with other methods to improve overall performance. To optimize resource utilization while maintaining control effectiveness, a popular approach involves combining event-triggered control with FCS-MPC. Event-triggered control substantially decreases computational expenses, enabling the development of more advanced solutions. While modulated MPC exhibits favourable harmonic characteristics and maintains the advantages of FCS-MPC, it significantly increases computational demands. Multi Objective MPC adds to this complexity, leading some researchers to consider it impractical for multilevel inverter implementation, an issue requiring further investigation. MFPC techniques, such as current difference and ultra-local model approaches, may necessitate increased computational resources. The use of observers in sensorless control also contributes to increased computational complexity. To mitigate the computational demands of DSVM-based MPC, various voltage vector pre-selection strategies have been introduced. To identify the optimal voltage vector, a two-step optimization approach is utilized, building upon the reference voltage vector derived from deadbeat control. Although these optimizations aim to enhance system performance, the overall computational load remains substantial. Consequently, there is a need to decrease the computational requirements of DSVM while preserving its benefits. Two Voltage Vector-MPCC still requires iterative evaluation, resulting in a significant computational burden. Scientists have conducted various studies aimed at decreasing computational complexity and enhancing accuracy by employing rapid and intelligent prediction techniques based on MPC. As digital platforms advance and computing power increases, multi-step FCS-MPC is poised to become a future research trend. However, its widespread adoption has been hindered by high computational complexity. The integration of SDA in FCS-MPC allows microprocessors to efficiently solve for multi-step MPC in real-time, while maintaining well-known steady-state and dynamic responses. This represents a future research direction for multi-step MPC. The substantial computational load has undoubtedly presented significant challenges for digital chips. As a result, an increasing number of scholars are focusing on decreasing complexity and minimizing the cost of online computing.

V. CONCLUSION

The article provides a quick overview of the present scenario, trends and advantages of electric vehicle over conventional vehicle. Among the IM, SRM and PSMSM for EV, PMSM is most favorable motor due to superior efficiency, torque, and power density, compact, less maintenance, ease of control and noiseless operation. Recently among the different advanced control techniques Model Predictive Control (MPC) is obtaining popularity due to simple structure, flexible, fast torque response which helps in acceleration, deceleration and faster braking, torque ripple minimization, efficiency can be designed as per EV requirements. MPC can also be combined with other controllers for improving steady state and dynamic performance.

Additionally, this study examined the categorization of different MPC techniques for PMSM drive systems as proposed by researchers, as per literature survey FCS-MPC has gotten a lot more attention than CCS-MPC on account of absence of modulator so no intrinsic delays, inclusion of secondary terms into cost function, exploitation of the discrete character of the converter with a restricted number of switching states, faster response and simplicity.

Some researchers also demonstrated the issues regarding implementing the FCS-MPC-based control of PMSM improves robustness and flexible switching frequency and computational burden. Solutions proposed by researchers in literature of above-mentioned issues are summarized in this article. The comprehensive examination of robustness, variable switching frequency and computational burden provides researchers with insights for future investigations. Still there is scope of improvements found from the literature for above said issues. New developments and improvements in the solutions of mentioned issues of FCS-MPC emerges as an intelligent and competitive control for EV industry.

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