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MODEL PREDICTIVE CONTROL IN SWITCHED RELUCTANCE MOTOR DRIVES: FINITE CONTROL SET, CONTINUOUS CONTROL SET, AND INTEGRATION WITH PHYSICS-INFORMED NEURAL NETWORKS

Zhu Xirong [1] (post-graduate student)
Scientific supervisor – PhD, Associate Professor Galina Demidova[1]
[1]ITMO University
35249412@qq.com

Abstract
This paper presents a comprehensive comparative analysis of model predictive control (MPC) techniques for switched reluctance motor (SRM) drives, with particular emphasis on finite control set MPC (FCS-MPC) and continuous control set MPC (CCS-MPC) methodologies. The working principles, mathematical formulations, and implementation aspects of both approaches are systematically examined. FCS-MPC leverages the discrete nature of power converters by directly applying optimal switching states, offering fast transient response and intuitive implementation at the cost of variable switching frequency. CCS-MPC computes continuous voltage references combined with PWM modulation, achieving fixed switching frequency and superior steady-state performance with reduced torque ripple. A fundamental challenge underlying both approaches is the accuracy of the nonlinear flux linkage model. Emerging opportunities for physics-informed neural network (PINN) integration are discussed, where governing equations are embedded into neural network architectures to learn physically consistent flux characteristics from limited experimental data while maintaining accuracy across the entire operating envelope. The integration of PINN-based modeling with predictive control offers a systematic framework for high-performance SRM drives requiring minimal experimental characterization.

Keywords
Switched Reluctance Motor, Finite Control Set Model Predictive Control, Continuous Control Set Model Predictive Control, Physics-Informed Neural Networks, MPC

УПРАВЛЕНИЕ С ПРОГНОЗИРОВАНИЕМ ВЕНТИЛЬНО-ИНДУКТОРНОГО ДВИГАТЕЛЯ: МЕТОДЫ С КОНЕЧНЫМ И НЕПРЕРЫВНЫМ МНОЖЕСТВОМ УПРАВЛЯЮЩИХ ВОЗДЕЙСТВИЙ И ИНТЕГРАЦИЯ С ФИЗИЧЕСКИ-ИНФОРМИРОВАННЫМИ НЕЙРОННЫМИ СЕТЯМИ

Чжу Сижун [1] (аспирант)
Научный руководитель – кандидат технических наук, доцент Демидова Г.Л.[1]
[1]Университет ИТМО
35249412@qq.com

Аннотация
В работе представлен комплексный сравнительный анализ методов предиктивного управления для приводов на базе вентильно-индукторного двигателя (ВИД) с применением алгоритмов с конечным набором управляющих воздействий (КНУВ) и с непрерывным набором управляющих воздействий (НУВ). Рассмотрены принципы функционирования, математические модели и особенности практической реализации обеих стратегий. Метод КНУВ непосредственно использует дискретную природу силового преобразователя, осуществляя выбор оптимального коммутационного состояния на каждом шаге дискретизации на основе минимизации целевой функции, включающей ошибку слежения по моменту, ограничение тока и коммутационные потери. Данный подход обеспечивает высокое быстродействие и естественный учет ограничений, однако характеризуется переменной частотой коммутации. Метод НУВ формирует непрерывные управляющие напряжения посредством решения задачи оптимизации с последующей широтно-импульсной модуляцией, что обеспечивает фиксированную частоту переключений и улучшенные показатели в установившемся режиме при сниженной пульсации электромагнитного момента. Ключевой проблемой для обоих подходов является точность

нелинейной модели потокосцепления. Для решения данной задачи предлагается интеграция физически-информированных нейронных сетей (ФИНС), в которых электромагнитные уравнения и энергетические соотношения включаются в функционал потерь при обучении. Такой подход позволяет формировать физически согласованную модель потокосцепления на основе ограниченного объема экспериментальных данных при сохранении высокой точности во всем рабочем диапазоне. Показано, что интеграция ФИНС с алгоритмами предиктивного управления повышает точность регулирования момента, устойчивость к параметрическим отклонениям и снижает требования к экспериментальной идентификации двигателя.
Ключевые слова
Вентильно-индукторный двигатель, предиктивное управление, КНУВ, НУВ, физически-информированные нейронные сети, ФИНС, потокосцепление, электропривод

Accurately modeling the nonlinear flux linkage characteristics of Switched Reluctance Motors represents a fundamental challenge in developing high-performance control systems[1]. Although SRMs offer inherent advantages including robust construction, magnet-free design, and fault-tolerant capability—making them attractive for electric vehicles, aerospace systems, and industrial automation[2]—their doubly salient structure produces highly nonlinear electromagnetic characteristics that complicate controller design[3]. Conventional approaches to SRM control, from basic hysteresis control to sophisticated torque sharing functions[4], have traditionally relied on extensive lookup tables derived from finite element analysis or experimental measurements[5]. These methods suffer from two critical limitations: the prohibitive cost of comprehensive experimental characterization across the entire operating envelope[6], and the inherent degradation of controller performance when actual motor parameters deviate from fixed pre-characterized representations due to manufacturing tolerances or thermal effects. This paper presents a comprehensive comparative analysis of model predictive control techniques for SRM drives, with particular emphasis on finite control set MPC and continuous control set MPC methodologies. The working principles, mathematical formulations, and implementation aspects of both approaches are systematically examined. Furthermore, this paper proposes integrating Physics-Informed Neural Networks with MPC to address the modeling bottleneck. By embedding governing electromagnetic equations directly into the neural network architecture during training, the proposed approach learns physically consistent flux characteristics from limited measurements while maintaining predictive accuracy across the entire operating envelope, offering superior tracking performance under parameter uncertainty compared to conventional lookup table-based implementations.

The control problem for an SRM drive involves tracking a reference torque while minimizing copper losses and torque ripple, subject to physical constraints including maximum current and available DC bus voltage. Traditional approaches construct extensive lookup tables through experimental characterization, then employ these tables within hysteresis controllers or model-based algorithms. However, this methodology presents a fundamental dilemma: comprehensive characterization requires prohibitive experimental effort, while sparse characterization risks inaccurate prediction in unmeasured regions, leading to degraded control performance—particularly problematic for model-based methods like MPC that depend heavily on prediction accuracy. This work examines two principal MPC categories for SRM control. Finite Control Set MPC exploits the discrete nature of the power converter by evaluating all possible switching states at each sampling instant, predicting resulting flux and torque trajectories, and directly applying the optimal switching combination that minimizes a cost function comprising torque tracking error, current magnitude, and switching effort. This approach achieves fast transient response and intuitive constraint handling at the cost of variable switching frequency. Alternatively, Continuous Control Set MPC computes continuous voltage references through optimization algorithms and subsequently employs PWM techniques to generate switching signals, achieving fixed switching frequency and superior steady-state performance with reduced torque ripple [7].A fundamental challenge underlying both approaches is the accuracy of the nonlinear flux linkage model. This work proposes that Physics-Informed Neural Networks learn this function from limited experimental data while respecting embedded physical constraints. The PINN architecture accepts current and rotor position as inputs and outputs flux linkage, with training loss comprising both data-fitting terms and physics-based regularization derived from electromagnetic principles and energy conservation. This approach ensures physically consistent predictions even in sparsely measured regions, dramatically reducing experimental characterization requirements. The differentiable nature of the PINN model subsequently facilitates seamless integration with both MPC frameworks—enabling efficient gradient-based optimization in CCS-MPC implementations and accurate trajectory prediction in FCS-MPC.Simulation studies comparing PINN-enhanced MPC with conventional lookup table-based implementations reveal several important findings. First, the PINN-based approach achieves comparable modeling accuracy with significantly fewer experimental characterization points, as physics-based regularization effectively interpolates behavior in unmeasured regions from electromagnetic first principles. Second, under parameter variations simulating thermal effects or manufacturing tolerances, the PINN-enhanced controller demonstrates superior torque tracking performance, with RMS tracking error substantially reduced compared to fixed lookup table implementations—critically important as MPC performance degrades significantly with model mismatch. Third, the differentiable PINN model enables more efficient gradient-based optimization in CCS-MPC, reducing computation time compared to numerical differentiation through lookup tables with interpolation.

This paper has presented a comprehensive framework integrating Physics-Informed Neural Networks with Model Predictive Control for Switched Reluctance Motor drives. The key contribution lies in demonstrating that PINNs can learn accurate flux linkage characteristics from limited experimental data by embedding electromagnetic governing equations into the network architecture, effectively addressing the modeling bottleneck that has historically limited MPC performance in SRM applications. Both FCS-MPC and CCS-MPC implementations leveraging PINN models have been systematically analyzed, with simulation results confirming superior tracking accuracy and robustness to parameter variations compared to conventional lookup table-based approaches. Future research directions include experimental validation on physical SRM test benches, extension of the PINN framework to incorporate thermal and mechanical dynamics for comprehensive multiphysics modeling, and development of real-time implementation strategies that leverage model reduction techniques to satisfy computational constraints of embedded hardware platforms.

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/ Galina Demidova

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