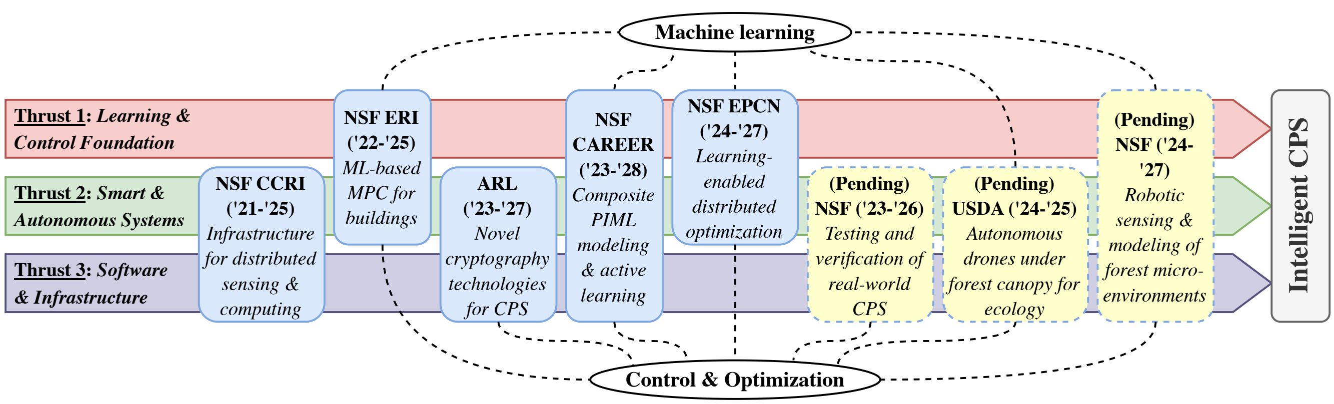
Research Statement

Learning and Control Foundation, Applications, and Tools for Intelligent Cyber Physical Systems

My research develops the **learning and control foundation, applications, and tools for intelligent *cyber-physical systems* (CPS)**. New concepts emerging from machine learning (ML) are challenging but also creating new opportunities for CPS research. An intelligent CPS deeply integrates ML for decision and control to achieve high performance, adaptability, safety, and autonomy. By **merging ML, control, optimization, and computing**, I focus on the creation of methods, algorithms, software, and engineering solutions to enable autonomous operation of intelligent CPS in a wide range of applications. Ultimately, my research aims to *fundamentally* enhance the design, implementation, performance, and application of intelligent CPS. My research program is established along the following thrusts:

1. **Learning and Control Foundation of Intelligent CPS:** The bedrock of my research is a theoretical and algorithmic foundation of learning and control for intelligent CPS. It is focused on integrating knowledge of the physical laws governing a CPS into ML, known as *physics-informed machine learning*, to yield interpretable, robust, accurate, and physically consistent models that enhance the performance and safety of learning-based CPS. It also includes integration of ML and optimization for learning-enabled distributed optimization, distributed learning and control of heterogeneous multi-agent systems, and real-time learning-based control in complex environments. My research is advancing these frontiers for intelligent CPS, supported by my NSF CAREER award, my NSF ERI grant, my NSF EPCN grant, and several currently pursued NSF and USDA proposals.
2. **Smart and Autonomous Systems:** My research creates data-driven models, learning-based control and optimization algorithms, implementations, and testbeds for smart and connected buildings, autonomous rovers and drones for environmental and ecological applications, mobile robotic sensor networks, and autonomous race cars, among other applications. As ensuring the security of smart and autonomous systems has become vital in many critical applications, my research is combining novel cryptography technologies with control, optimization, and learning for securing these systems. This research thrust is supported by my NSF CAREER, NSF ERI, NSF CCRI, and ARL grants, and several currently pursued proposals.
3. **Software and Infrastructures for Intelligent CPS:** To facilitate and accelerate the research, implementation, and deployment of intelligent CPS, this thrust focuses on building software tools and infrastructures for intelligent CPS. My research has developed open-source software, is developing a large-scale research infrastructure (NSF CCRI), and will create cyber-infrastructures for ML and control (NSF CAREER), secure autonomous military systems (ARL), verified embedded systems (pending), and autonomous forest ecological modeling and monitoring (pending).

My research program is summarized in the following diagram and the remainder of this document.



1 Selected Past Research

1.1 Learning-Enabled Control and Optimization

The core **foundation of my research program** is built at the **intersection of learning, control, and optimization**. My past research has focused on establishing fundamental understanding of synergistic integration of ML with control and optimization, and on solving practical challenges of learning-enabled control and optimization. My approaches do not seek to *replace* control and optimization with ML but rather *seamlessly integrate* ML into current and novel control and optimization methods, while exploiting useful features of ML and developing computation methods and algorithms to address challenges arising from such integration.

I have merged ML and control in **learning-based control methods** that incorporates control-oriented data-driven models of complex physical systems using a variety of ML techniques, including neural networks and Gaussian processes

[C2, C5, C12–C14, C16–C19, C22, C24, W2]. My approaches apply data-driven models for model predictive control (MPC) with probabilistic guarantees on safety and constraint satisfaction through chance constraints, exploiting the predictive uncertainty of the models. A *major drawback* of many existing data-driven modeling approaches is that they primarily use nominal or randomly excited operation data for learning dynamical models, which, due to excitation deficiency, results in model inaccuracy and sample inefficiency, and consequently unsafe control and increased experiment cost. To overcome this challenge, I have developed **active learning methods** that seek the excitation that generates the most informative training data for learning physical systems, which could substantially reduce the experiment time and enhance the model accuracy [C18]. I have extended these methods to create **simultaneous active learning and control** approaches for online learning and continuous improvement of data-driven models for real-time control while maintaining constraints and reducing the overall learning and control cost [C12, C13, C18], as opposed to popular approaches that often learn and update models offline and in batches. My methods have been validated for building energy control [C18, C19, C22, C24] and for autonomous robots and race cars [C3, C5, C12–C14].

A *notable barrier to practical learning-based control methods* is their computational complexity, due to their typically highly complex and non-convex ML models. I have tackled the **computational challenges of learning-based control** by developing efficient centralized and distributed optimization algorithms combining successive convexification, linearized Gaussian process approximation, and variants of the alternating direction method of multipliers (ADMM). They were applied in learning-based MPC [C12–C14, C16, C17] and robot networks [C4, C7, C10, C11, J7, J9], and were shown to accelerate solving complex learning-based MPC problems by up to tenfold over standard algorithms [C16, C17].

In search of safer, more accurate, more data-efficient, and more physically consistent ML methods, I have investigated **physics-informed machine learning** (PIML) that integrates ML and physics for learning complex physical systems, such as building energy systems [P1]. I developed a novel causal deep operator network (Causal-DeepONet) method for learning dynamical systems from data, which has higher and more consistent accuracy and data efficiency than other neural network models for multi-step prediction and control purposes, by exploiting the inherent temporal causality of these systems [C2]. My paper [C3] proposes a PIML method for motion prediction of autonomous vehicles, that incorporates physical priors of a car's dynamics with ML to enhance the prediction accuracy and physical consistency over state-of-the-art methods. My work has resulted in a collaborative *review paper and well-attended tutorial session on PIML for learning and control of dynamical systems* at the flagship conference ACC 2023 [C6].

While numerous distributed optimization methods have been successfully developed, they often assume perfect communication, whereas real-world applications often use wireless networks, possibly in large sparse areas, which present critical communication challenges. I proposed a novel approach for **learning-enabled communication-efficient distributed optimization** with ADMM by leveraging ML for online learning of the agents' proximal operators [C21, P2]. Such integration of ML within a distributed optimization framework enables substantial reduction of communication overhead and increased robustness to communication uncertainty. I have extended this approach to develop new learning-enabled adaptive quantization methods, which were shown to reduce transmission time by up to 98% compared with the vanilla ADMM [C15, J3], and to develop optimal joint communication and optimization decision policies [J2].

1.2 Learning, Control, and Computing for Smart and Autonomous Systems

My research has leveraged the foundation established by the previous thrust to advance smart and autonomous systems in various application domains. The capabilities of **environmental sensing and monitoring** systems have been substantially enhanced by advances in IoT, computing, ML, and robotics. I deployed ML to create algorithms for accurate microalgal density estimation from images taken by a low-cost camera for monitoring microalgae in a closed cultivation system [J4, J6, J8]. I developed efficient distributed algorithms for optimal adaptive sampling and collision-free coordination of mobile robotic sensor networks (MRSN) [C11] with nonholonomic dynamics [J9], and a novel multi-step adaptive sampling and control algorithm for MRSN that significantly improves sampling efficiency and control performance in complex environments with obstacles [J7].

Leveraging ML and distributed optimization, I developed adaptive learning and control for **autonomous racing** on multi-friction surfaces [C5], physics-constrained **motion prediction for autonomous driving** with enhanced accuracy and physical consistency [C3], real-time distributed collision-free and connectivity-preserving **trajectory planning for multi-robot systems** [C4, C7, C10, J5], and **distributed online learning and control of robotic vehicles** [C12–C14]. To tackle the **computation burden of safety-critical autonomous systems**, which often employ complex algorithms such as vision-based navigation, I created a novel *anytime computation* framework for real-time adaptation of computation time vs. accuracy to ensure safety and desired performance [C28, J10].

Ensuring the **security of smart and autonomous systems** has become vital as they are increasingly ubiquitous in many critical applications. Sponsored by the US Army Research Lab, I have developed a secure consensus protocol for distributed multi-agent systems using *fully homomorphic encryption* [C8, J1], future-proof secure communication in multi-robot systems using *post-quantum cryptography* (PQC), and a face-based security system using PQC [C9].

My ***award-winning paper*** at the conference ICCPS [C18] developed a **framework for optimal data-driven modeling and control of buildings**, from active learning to ML-based modeling and MPC [C18, C22, C24, W2], to overcome the difficulty and high engineering cost of accurate building modeling and advanced building control implementation. My methods were shown to obtain highly accurate models in substantially reduced experiment time, which were used for learning-based MPC with probabilistic guarantees and computationally efficient solving algorithms [C16, C17]. They were practically demonstrated in a real-world commercial building management system [C19, C20]. More recently, my research has developed novel physics-informed ML methods for learning building energy models from real data of the NAU campus buildings with improved model accuracy and data efficiency [C2, P1].

2 Future Research

Informed by and building on my past research, my current and future research will move forward the thrusts of my research program, as outlined on the first page. Besides my current grants, I will continue pursuing funding to support my research program from diverse sponsors in multiple suitable tracks, including *fundamental research* (NSF), *applied research* (DOE, DOD, USDA, etc.), and *translational/commercialized research* (NSF TIP, SBIR, STTR, etc.).

2.1 Learning and Control Foundation of Intelligent CPS

I will develop a foundation of learning and control for intelligent CPS along three major directions, whose **overarching themes** are (1) to uncover the black-box nature of ML to deeply integrate physics and other domain knowledge for safer, more effective, and more efficient ML, and (2) to solve practical challenges of ML in real-world CPS such as performance and safety guarantees, and computation and communication efficiency.

1. **Physics-informed learning of complex CPS:** While ML has shown tremendous success in many domains, it remains a grand challenge to incorporate physical principles into ML, known as *physics-informed machine learning* (PIML), to yield interpretable, robust, accurate, and physically consistent models that enhance the performance and safety of learning-based CPS. State-of-the-art PIML often fails to exploit *intrinsic structures*, *causality*, *composability*, and *heterogeneity* of real-world systems. My research will address these **fundamental gaps** by creating a ***hierarchically composable PIML*** framework for composing models and physical properties in a hierarchical structure to systematically combine heterogeneous data-driven and physical model components for modeling complex systems. I will develop ***physics-informed active learning***, which incorporates physics into active learning to obtain the most informative data consistent with physics for improving the sample efficiency and accuracy of learning. My **long-term goal** is to advance the frontiers of PIML for CPS by developing, validating, and deploying PIML methods and software for effective, efficient, and scalable data-driven learning, optimization, and control of real-world complex CPS. This direction is supported by my NSF CAREER award and NSF ERI grant, and more funding from the NSF that I am pursuing.
2. **Learning-enabled control:** I will develop control approaches, such as MPC, that adopt PIML models for optimal and adaptive control, and novel computation algorithms for solving these control problems effectively and efficiently. As many intelligent CPS are safety-critical, I will investigate methods for guaranteeing safety and performance of the resulting closed-loop system, e.g., using chance constraints or robust control techniques. These methods will have broad applications in control of complex CPS like smart buildings and autonomous robots. This direction is supported by my NSF ERI and CAREER grants, and currently pursued NSF and USDA funding.
3. **Learning-enabled distributed optimization and computation:** This direction will develop novel methods and algorithms that deeply integrate ML with optimization and computation for large-scale hierarchical and distributed control systems. My **key approach** is to *sample and learn*, in an online fashion, ML models of suitable entities in a system, then use the predictive power of the models to *infer* their behaviors within an optimization framework, *adapt* communication and computation, and *discover and exploit* their correlation relationships, in order to avoid unnecessary edge communication and computation and enhance efficiency and effectiveness of learning, communication, and computation. The ultimate goal is to scale learning, control, and optimization for large-scale CPS. This research direction will be supported by my NSF EPCN grant and further extramural funding that I will pursue.

2.2 Smart and Autonomous Systems

My fundamental research has always been inspired by and validated in practical CPS applications, as demonstrated in my past research from smart buildings to environmental monitoring, autonomous racing, and multi-robot systems. My future research will continue to be motivated by and aim at solving practical and challenging problems of smart and autonomous systems, some of which are described below.

Multi-robot sensing, learning, and monitoring: Building on my current research in environmental sensing and monitoring and in multi-robot systems, I will develop models and algorithms for autonomous sensing and monitoring of natural and built environments, exploiting advances in ML, control, optimization, and robotics. I will be pursuing two major directions. One is ***multi-scale planning and control of heterogeneous robots for distributed active learning*** of large-scale and long-term spatio-temporal phenomena in complex environments, with an application in modeling forest micro-environments (my CCRI grant and a pending NSF proposal). My approach will include incorporating domain insights into ML to enhance active learning and combining ML, control, and optimization for more effective and efficient deployment and coordination of heterogeneous robots. The other is ***autonomous drones in GPS-denied and cluttered environments***, e.g., under a forest canopy with applications in ecological modeling and monitoring, where sensor fusion, SLAM, real-time planning and control, and reactive control will be integrated. Supporting this direction are a pending USDA proposal, a company I co-founded, and planned SBIR/STTR proposals.

Smart and connected buildings and energy resources: My past research has shown the benefits of data-driven learning and control for enhanced energy efficiency in buildings. Going forward, I will develop learning-enabled approaches for smart buildings and distributed energy resources (DERs), focusing on interdisciplinary approaches that combine ML, control, and optimization to address challenges such as the high cost and difficulty of modeling, and the multi-scale and complexity of buildings and building-DER-grid integration. Established on my existing work, this direction is supported by my NSF ERI and CAREER grants, and future NSF and DOE funding that I am pursuing.

Secure CPS: As security has become vital in many critical smart and autonomous systems, I will grow my current research in secure CPS [C8, C9, J1], supported by my DEVCOM ARL grant, in several directions. With my cybersecurity collaborators, I will integrate novel cryptography methods that exploit the uniqueness of physical systems, e.g., differential-sensor-based physically unclonable functions, in critical autonomous systems, such as robots and medical devices. I will investigate enhancing cryptography and its computational efficiency with ML to secure low-computation and low-power edge CPS. Additionally, I will continue my research in securing distributed control systems with modern cryptography, e.g., fully homomorphic encryption and other post-quantum cryptography methods. Funding will be sought from the NSF and other relevant agencies, for example DOD and DHS.

2.3 Software and Infrastructures for Intelligent CPS

I believe that the impacts of my fundamental and applied research will be substantially strengthened and broadened if developed into tools that can be used by others. An important focus of my future research is to build **software and research infrastructures for modeling, design, analysis, simulation, implementation, and testing of intelligent CPS**, which will benefit researchers in CPS, autonomous systems, scientific machine learning, and other computational sciences. In the next 3–5 years, I will build a large-scale research platform for multi-agent networks spanning five sites in three states (NSF CCRI grant) and a comprehensive cyber-infrastructure for physics-informed learning and control (NSF CAREER award).

My future research will always prioritize, besides the core theoretical and applied research, development of software tools, implementations, testbeds, living labs, and real-world applications. These developments will be funded either independently, like my CCRI project, or as a crucial component of my research, like most of my grants. Importantly, these efforts will provide ***excellent and inclusive opportunities to involve students***, especially undergraduate and underrepresented students, in research. This thrust is aligned with the NSF's priorities in developing inter-disciplinary research tools and infrastructures and broadening participation in STEM, from which I will seek funding for my efforts.

References

References are numbered as in the list of publications in the accompanying Curriculum Vitae.