Analysis, Optimization, Control, and Learning of Cyber-Physical Systems

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The overarching goal of the Information and Decision Science (IDS) Lab is to enhance understanding of complex systems and establish a holistic, multifaceted approach using scalable data and informatics to developing rigorous mathematical models and decentralized control algorithms for making engineering complex systems able to realize how to improve their performance over time while interacting with their environment. The emphasis is on applications related to connected and automated vehicles (CAVs), sociotechnical systems, energy and sustainable systems, smart cities and connected communities.

Self-Learning Powertrain Control

My interest in developing control algorithms that could make systems able to learn their optimal operation started early on, while I was still at graduate school, when I read an article about the discrepancy between true fuel economy of a vehicle and the one posted on the window sticker. The article was discussing the implications of the driver's driving style on engine operation, and stated that the state-of-the-art control methods, by that time, consist of static controllers which cannot optimize engine operation for different driving styles but only for predetermined ones. This article provided inspiration that eventually led to forming the topic of my dissertation. In my dissertation [1], I developed the theoretical framework [2–5] and control algorithms [6–8] that can turn the engine of a vehicle into an autonomous intelligent system capable of learning its optimal operation in real time while the driver is driving the vehicle. I modeled the evolution of the state of the engine as a control Markov chain [9] and proved [10] that it eventually converges to a stationary probability distribution deemed characteristic of the driver's driving style. Through this approach, the engine progressively perceives the driver's driving style [11] and eventually learns to operate in a manner that optimizes specified performance criteria, e.g., fuel economy, emissions with respect to the driver's driving style. The framework also allows the engine to identify the driver, and thus it can adjust its operation to be optimal for any driver based on what it has learned in the past regarding her/his driving style. The outcome of my dissertation research eventually led to a US patent [12].

Moving to General Motors Research & Development as a Senior Researcher, I had the chance to continue working on self-learning control for advanced powertrain systems. I led several projects on autonomous intelligent propulsion systems and developed computational mathematical models and control algorithms towards making highly energy-efficient and eco-friendly vehicles. I was a member of the team that demonstrated successfully the implementation of self-learning control algorithms [13] in two demo vehicles, Saturn Aura and Opel Vectra.

Hybrid-Electric Vehicles

When I joined Oak Ridge National Laboratory (ORNL) as an Alvin M. Weinberg Fellow, although the focus of my fundamental research interests remained the same, the emphasis of the applications shifted from powertrain systems to vehicles, and then to CAVs. At ORNL, I had the chance to work across different technical areas including stochastic optimal control [14–16], optimal design and power management control and routing of hybrid electric vehicles (HEVs) and plug-in HEVs

(PHEVs) [17–27], and driver's feedback systems [28–30]. The latter eventually led to a technology [31] that was licensed in SanTed Project Management LLC. I also contributed to the solution of problems that included smart buildings aimed at optimizing energy system parameters to (1) improve sustainability, (2) facilitate cost-effective energy generation, and (3) allocate demand optimally to different energy sources, e.g., solar, renewable, etc [32–34]. On the fundamental research front, I established the theoretical framework for the analysis and stochastic control of complex systems consisting of interactive subsystems [35]. In particular, I developed a duality framework and showed that the Pareto control policy minimizes the long-run expected average cost criterion of the system while also presented a geometric interpretation of the solution and conditions for its existence. I provided theoretical results showing that the Pareto control policy provides an equilibrium operating point among the subsystems, and if the system operates at this equilibrium, then the long-run expected average cost per unit time is minimized. This result implies that the Pareto control policy can be of value when we seek to derive the optimal control policy for complex systems online. Later on, and in my role as the Deputy Director of the Urban Dynamics Institute at ORNL, I developed several initiatives with the goal to investigate how we can use scalable data and informatics to enhance understanding of the environmental implications of CAVs and improve transportation sustainability and accessibility. I contributed towards the development of a decentralized optimal control framework whose closed-form solution exists under certain conditions, and which, based on Hamiltonian analysis, yields for each vehicle the optimal acceleration/deceleration, in terms of fuel consumption. The solution allows the vehicles to cross merging roadways without creating congestion, and under the hard safety constraint of collision avoidance [36–40].

Emerging Mobility Systems

Emerging mobility systems are typical cyber-physical (CPS) systems where the cyber component (e.g., data and shared information through vehicle-to-vehicle and vehicle-to-infrastructure communication) can aim at optimally controlling the physical entities (e.g., CAVs, non-CAVs). A mobility system encompasses the interactions of three heterogeneous dimensions: (1) transportation systems and modes, e.g., CAVs, shared mobility, and public transit integrated with advanced control algorithms, (2) social behavior of drivers, operators (for autonomous vehicles), and travelers (or pedestrians) interacting with these systems, and (3) information management of data available and shared information. The constellation of these three dimensions constitutes a sociotechnical system that should be analyzed holistically. The CPS nature of emerging mobility systems is associated not only with technological and information management dimensions but also with human adoption (social dimension). My students and I, in conjunction with my collaborators, have made contributions on the technological dimension of mobility systems by developing control algorithms for optimal coordination of CAVs [41–72] and identifying potential research paths with connected autonomous systems [73]. However, I came to realize that current methods analyze, design, and optimize a mobility system without considering the social dimension resulting in systems that might not be acceptable by the drivers, travelers, and the public. In particular, one key research question that still remains unanswered is "how can we develop an energy-efficient mobility system that can be widely acceptable by drivers, travelers, and the public?" To address this question, my students and I are taking the following research steps that combine the three aforementioned dimensions [74–76]: (1) explore how advanced control technologies in conjunction with Big Data from vehicles and infrastructure can improve the efficiency of transportation systems and modes, e.g., eliminate stop-and-go driving, reduce congestion; (2) investigate public attitudes toward emerging transportation systems and identify the human behavioral and emotional responses to systems such as CAVs and shared mobility, and (3) address the negative rebound effects of improving the efficiency of transportation systems by exploring whether household activities and travel demand might increase if the efficiency of the transportation systems improves. Step 1 will identify the new congestion patterns of optimized transportation systems and modes. Step 2 will examine public reaction, adoption, and use of a potential energy-efficient mobility system, which will determine the urban planning, public policy, and governance frameworks to enable the system-wide optimal outcomes. Step 3 will determine the new levels of travel demand and, eventually, the impact on vehicle miles traveled. The expected outcome of my group's research in this area will aim at identifying a mobility system which is not only energy efficient but also acceptable by the drivers, travelers, and the public.

Team Decision Proplems

Team theory is a mathematical formalism for decentralized stochastic control problems in which a "team," consisting of a number of members, cooperates to achieve a common objective. It was developed to provide a rigorous mathematical framework of cooperating members in which all members have the same objective yet different information. The underlying structure to model a team decision problem consists of (1) a number of $K \in \mathbb{N}$ members of the team; (2) the decisions of each member; (3) the information available to each member, which is different; (4) an objective, which is the same for all members; and (5) the existence, or not, of communication between team members. Team theory can be applied effectively in applications that include informationally decentralized systems such as emerging mobility systems [73], and in particular, optimal coordination of connected and automated vehicles at traffic scenarios [55, 63, 68, 77–79], networked control systems [80, 81], mobility markets [75], smart power grids [82, 83], power systems [84], cooperative cyber-physical networks [85–87], social media platforms [88], cooperation of robots [89–91], and internet of things [92–94].

Team theory was established with the seminal work of Marschak [95], Radner [96], and Marschak and Radner [97] on *static team* problems, and with Witsenhausen [98,99] on *dynamic team* problems. In static team problems [100, 101], the information received by the team members is not affected by the decisions of other team members [102], while, in dynamic team problems, the information of at least one team member is affected by the decisions of other members in the team [102]. If there is a prescribed order in which team members make decisions, then such a problem is called a *sequential* team problem. If, however, the team members make decisions in an order that depends on the realization of the team's uncertainty and decisions of other members, then such a problem is called a *non-sequential* team problem. Formulating a well-posed non-sequential team problem is more challenging as we need to ensure that the problem is causal and deadlock free [103–105].

We have addressed sequential dynamic team decision problems with nonclassical information structures [106–108]. In the most recent effort [109], we provided structural results and a classical dynamic programming decomposition of sequential dynamic team decision problems. We first addressed the problem from the point of view of a manager who seeks to derive the optimal strategy of a team in a centralized process. Then, we addressed the problem from the point of view of each team member, and showed that their optimal strategies are the same as the ones derived by the manager. Our key contributions are (1) the structural results for the team from the point of view of a manager that yield an information state which does not depend of the control strategy of the team, and (2) the structural results for each team member that yield an information state which does not depend on their control strategy. These results allowed us to formulate two dynamic programming decompositions: (a) one for the team where the manager's optimization problem is over the space of the team's decisions, and (b) one for each team member where the optimization problem is over the space of the decision of each member. Finally, we showed that the control strategy of each team member is the same as the one derived by the manager. Therefore, each team member can derive their strategy, which is optimal for the team, without the manager's intervention.

A potential direction for future research should explore the intersection of learning and control for team decision problems with nonclassical information structures. For example, cyber-physical systems, e.g., emerging mobility systems [73], in most instances, represent systems of systems with informationally decentralized structure. In such systems, however, there is typically a large volume of data with a dynamic nature which is added to the system gradually and not altogether in advance. Therefore, neither traditional supervised (or unsupervised) learning nor typical model-based control approaches can effectively facilitate feasible solutions with performance guarantees. These challenges could be circumvented at the intersection of learning and control. Given that the control strategies presented here are separated, a similar separation could be established between learning and control, and thus, combine the online and offline advantages of both traditional supervised (or unsupervised) learning and typical model-based control approaches.

Multi-Agent and Swarm System

There are two application areas that we have identified to study and control emergent behavior in multi-agent systems. The first is flocking, which is characterized by the unstructured aggregate motion of many agents. Flocking has the hallmark trait of emergence; namely, the agents are able to achieve and maintain an organized structure at the system-level while make observations and decisions using only local information. During a recent review on optimal flocking [91], it became clear that a majority of flocking research focuses on implementations of Reynolds flocking rules. To advance this area of research, we are particularly interested in how flocking emerges in swarms of constraint-driven agents, i.e., energy-minimizers subject to local interaction constraints [110, 111]. A critical aspect of this research is the development of self-relaxing constraints [112], which enable agents to re-plan their trajectories when new information renders their current state infeasible. Our hypothesis is that by designing the interaction rules of constraint-driven agents, we can draw rigorous guarantees on the system-level behavior. We expect that the tools used to design and analyze emergent flocking will apply to a range of multi-agent and swarm systems. The second application area we have identified in multi-agent systems is achieving formations using only local rules and information. Formation control and flocking share many similarities, both involve many agents moving through a shared space subject to local interaction rules. The fundamental difference between the two is an exercise in optimal decision making. That is, given the agent's current local information, which goal ought the agent assign itself to maximize the partially-observable system-level objective. We have proposed an approach that combines a heuristic banning mechanism with an energy-optimal local assignment [113,114], which hints at several interesting results. Perhaps the most compelling is that the system's global energy consumption is not necessarily monotonic with the quantity of information shared between agents. This leads to our second research hypothesis, that information in decentralized systems can be classified as high or low quality, and this is a function of the system and agent-level objectives. In fact, the optimal decisions of a system made up of selfish agents can often be counter-intuitive. The expected outcome of this effort is a theoretical framework for the design and analysis of emergent behavior in robotic swarm systems. This framework will be directly applicable to optimal swarming and formation tasks, and its analysis tools will apply to a variety of other complex systems.

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