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Special Issue on Control and Systems Theory

In this ***special issue,*** *read about exciting new developments at the intersection of applied mathematics and control theory.*

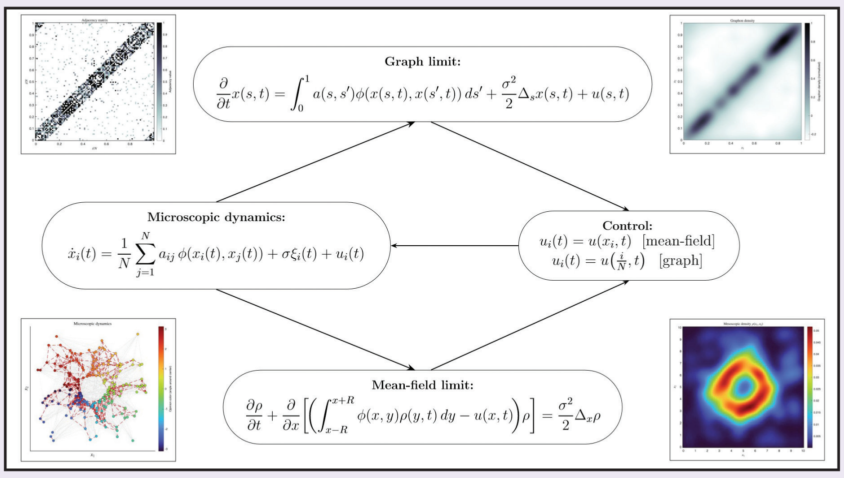

Figure 1. *The three scales of collective control. The microscopic level (left) tracks N individual agents. The graph limit (top) replaces the discrete network with a continuous graphon, yielding an integro-differential equation. The mean-field limit (bottom) replaces agents with a probability density satisfying a Fokker-Planck partial differential equation. Both continuum descriptions can be used to design a feedback control law $u(x,t)$ (right) that is then applied back to the agent-level system. Figure courtesy of the authors.*

The control of collective dynamics is an inherently multiscale challenge. In an article on page 5, Giacomo Albi, Dante Kalise, and Emmanuel Trélat discuss the design of strategies that account for individual behaviors while pursuing population-level goals.

Stackelberg Mean Field Games: A Framework for Policy Design in Complex Systems

By Gökçe Dayanıklı and Mathieu Laurière

Designing the "best" governmental policies is a highly challenging task, as policymakers must account for how individuals or institutions can respond to policy interventions. In aspects ranging from public health to finance, creating policies that remain optimal despite the response from the public presents a difficult problem. For example, the availability of a vaccine can impact how and when people socialize, which in turn can influence the spread of an infection. Similarly, a new capital requirement for banks may alter how banks manage risk and interact with their peers, while the implementation of a carbon tax may result in transitions to renewable energy, thus impacting supply variances and affecting electricity prices. In these cases, the agents (i.e., the banks, individuals, energy market participants, or other decision-makers) *adapt* to the policy environment. These emergent behaviors pose difficult challenges for mathematical modelers and policymakers and may trigger outcomes that differ from the policy's intended effects.

For this reason, establishing optimal policies has become a central interest for operations researchers, economists, and applied mathematicians. On the theoretical side, standard optimal control techniques typically assume that a policymaker steers a dynamical system whose evolution is fixed once a control is chosen. However, in many social, economic, and engineering settings, these dynamics are not static; they depend on how agents interact with one another and react to the implemented policies. On the computational side, agent-based modeling and simulation (ABM) can help policymakers visualize how agents might respond to policies according to heuristic rules. While ABM is invaluable for comparing different scenarios, it often faces a significant tradeoff between *realism* and *tractability*. Complex ABM can be difficult to calibrate, analyze, and optimize. Furthermore, because behavior in ABM is prescribed by fixed rules, it can be challenging to attribute specific causes to outcomes or to quantify exactly how a policy influences behavior.

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Hyperbolic Partial Differential Equations in Optimization and Control

By Michael Herty

Transport phenomena are ubiquitous in many physical, biological, and societal processes: applications range from fluid dynamics for air and spacecrafts, swarming dynamics of animal cohorts, data or product flows in large-scale computing or production systems [7], and description of emergent phenomena in collective dynamics [11]. Typically, these problems exhibit a temporal and spatial scale, a finite speed of information propagation, and highly nonlinear behavior. Mathematically, these phenomena allow for a unified description by general hyperbolic partial differential equations (PDEs). Some classical examples date back to 1757 when Leonhard Euler published *Principes généraux du mouvement des fluides* [5], known today as the Euler equations of fluid dynamics:

$$\partial_t \rho + \nabla_{\mathbf{x}} \cdot \rho\mathbf{u} = 0,$$
$$\partial_t(\rho\mathbf{u}) + \nabla_{\mathbf{x}} \cdot (\rho\mathbf{u}\otimes\mathbf{u}) + \nabla_{\mathbf{x}} p = 0,$$
$$\partial_t E + \nabla_{\mathbf{x}} \cdot (E+p)\,\mathbf{u} = 0. \tag{1}$$

The Euler equation (1) in conservative form solves for the density ρ, velocity $\mathbf{u}$, and total energy E as functions of space $\mathbf{x}$ and time t. The ideal pressure, $p=\rho e(\gamma-1)$, together with the ratio of the specific heats γ, and the internal energy e, is related to the total energy by $E=\rho e+\frac{1}{2}\rho\,||\,\mathbf{u}\,|^2$.

Since the Euler equations were published, tremendous progress has been made in both analytical and numerical aspects of hyperbolic PDEs, including results on well-posedness and the development of efficient, high-order methods on arbitrary grids. Due to its prominence within a wide range of applications, a strong demand for methods that emphasize optimization, optimal control, and controllability and stabilization, has emerged. Although researchers in different areas of expertise often approach these problems with a different focus and varying methods, all applied mathematicians share a substantial body of common knowledge and background on transport phenomena. Thus, the interdisciplinary nature of this research and analysis attracted many researchers interested in the novel fundamental theoretical results, as well as more recent results on corresponding numerical schemes.

Despite immense progress, the two approaches that drive both the theoretical and numerical developments of hyperbolic PDEs are still disjoint. On one hand, there is now an established theory for smooth solutions and multidimensional systems of conservation and balance laws; such solutions are known to exist given data with sufficiently small H^s norm or sufficiently small control horizon, respectively. Their construction is often conducted using the theory of characteristics or energy estimates in adapted weighted norms. The particularities of such solutions are also reflected by the tools used for controllability and stabilization. The second approach, which uses Lyapunov–type arguments, solves for the stabilization of linear and nonlinear hyperbolic balance laws in one

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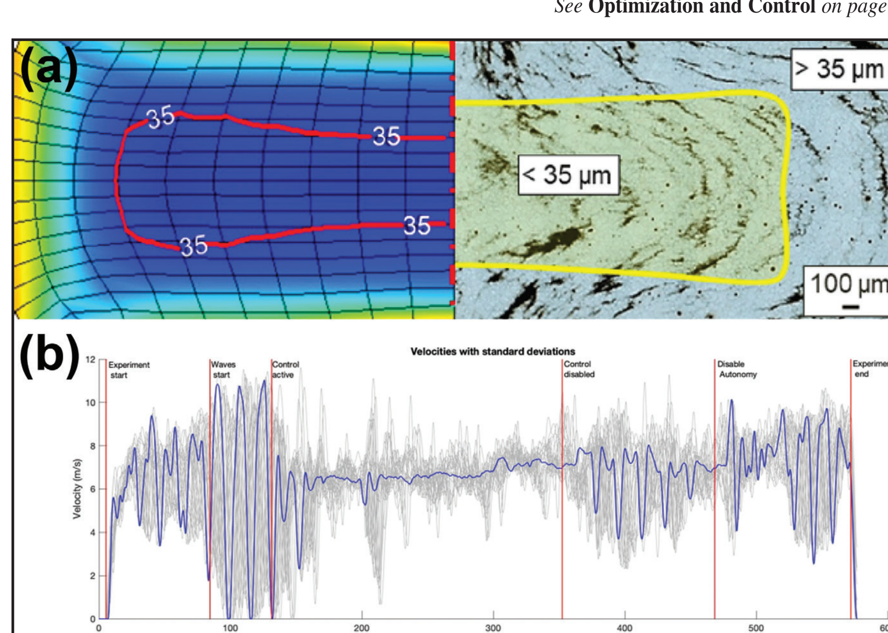

Figure 1. *Control concepts for hyperbolic systems are starting to enter new applications, including the process of metal forming and vehicular traffic flow.* **1a.** *Control of the boundary of crystallization during forming processes. On the right, a cross-sectional cut through the material and, on the left, the level set representation on a computational grid. The problem is modeled as stabilization problem for multidimensional (linear) hyperbolic systems.* **1b.** *Real-time control in a traffic flow field experiment on a ring road with a controlled vehicle. Shown are speed profiles of approximately 21 human driven cars (gray) as well as an automated car (blue). Figure 1a courtesy of the author, 1b courtesy of [11].*

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Applied Mathematics as Infrastructure for the Future of Artificial Intelligence

By Madhav Marathe and Erin Raymond

Recent breakthroughs in artificial intelligence (AI) have sparked extraordinary excitement, investment, and public attention. Much of the discussions surrounding these advancements are focused on data availability, computing scale, and the increase in sheer power these models hold. Yet as many SIAM members know well, these narratives tell only part of the story. Applied mathematics is central to the development of modern AI, from optimization and numerical linear algebra to probability, statistics, and dynamical systems, and it will be decisive in determining whether AI systems can be trusted, deployed, and sustained in the years ahead.

To address the rapid changes in AI, the SIAM AI Task Force developed "The Role of Applied Mathematics in a New Era of Artificial Intelligence,"[1] a white paper examining the role of applied mathematics in the future of AI — particularly in high-consequence domains where reliability, safety, and accountability are essential. The report advances a simple but consequential point: applied mathematics is not merely a supporting tool for AI, but a form of intellectual infrastructure that AI systems require to mature from impressive demonstrations into dependable components of science, engineering, and society.

From Impressive Predictions to Trustworthy Systems

Although many current AI systems excel at pattern recognition and prediction, often ranking remarkably high on benchmark tasks, real-world deployment demands far more than predictive accuracy — especially in regards to national security, healthcare, energy systems, agriculture, and scientific discovery. Decision-makers require AI systems that can quantify uncertainty, respect physical and operational constraints, support reasoning about cause and effect, and remain robust when conditions change or data are sparse.

Applied mathematics provides the frameworks that make these capabilities possible: uncertainty quantification allows models to communicate confidence and limitations rather than point estimates alone; optimization, model reduction, and multiscale analysis make large and complex systems computationally feasible while preserving essential structure; and verification and certification methods enable rigorous assessment of model behavior, performance, and safety. Together, these tools transform AI outputs from opaque predictions into inputs that can support accountable human judgment.

Shared Challenges Across Critical Domains

Across many different sectors, AI faces a common set of challenges that cannot be resolved by data and computation alone. In adversarial and high-consequence settings, AI systems must detect weak and noisy signals, reason under uncertainty, and support counterfactual analysis rather than retrospective pattern matching. In disciplines involving human health, AI must support individualized decisions that are explainable, auditable, and accountable. In tightly coupled physical infrastructures like energy systems, small errors can cascade into large failures; therefore, AI models must have stability, control, and robustness guarantees. To succeed in agriculture and environmental applications, AI tools must have the ability to extrapolate conditions beyond historical data to novel climates, extreme weather events, and ever-changing conditions, tasks that demand multiscale modeling and uncertainty propagation. In scientific discovery, speed alone is insufficient; AI-driven insights must be reproducible, interpretable, and consistent with physical laws. Across all of these domains, applied mathematics provides the unifying foundations that enable the uncertainty quantification, incorporation of constraints and domain knowledge, verification, and principled decision support that allow AI systems to become truly reliable, trustworthy tools.

Past Investments and Future Opportunity

The report emphasizes that past investments in applied mathematics have already delivered substantial returns. Research awarded with the 2024 Nobel Prize in physics[2] and the 2018[3] and 2021[4] Turing Awards—all projects focused on machine learning and computing—highlight that applied mathematics and formal methods lie at the heart of many foundational advances in AI. Recent work by researchers in the use of diffusion models for the earth system illustrated the benefit of using applied mathematics to improve AI systems, while advances in optimization, numerical methods, uncertainty quantification, and large-scale computation continue to make modern AI possible. At the same time, current deployments reveal the limits of existing theory when systems are scaled, coupled, or placed in high-stakes environments.

Looking forward, continued progress in AI will depend on the sustained investment in applied mathematics research. Key frontiers include mathematical foundations for foundation models, scalable uncertainty quantification, integration of symbolic and statistical reasoning, certification of learning-enabled systems, and mathematical tools for human-AI interaction and oversight. Without such advances, AI risks remaining brittle, opaque, and difficult to govern; with them, AI can mature into a trustworthy technology capable of supporting scientific discovery, economic competitiveness, and societal well-being.

A Call to the SIAM Community

For SIAM and its members, the message presented in "The Role of Applied Mathematics in a New Era of Artificial Intelligence" is both affirming and challenging. Applied mathematics has always been central to technological progress, and AI is no exception; however, realizing AI's promise *responsibly* will require continued leadership from the applied mathematics community through foundational research, interdisciplinary collaboration, education, and engagement with policymakers and the public.

The SIAM AI Task Force white paper offers one contribution to this effort. Its central conclusion is clear: the future of AI will not be determined by scale alone. It will be shaped by the mathematical foundations that enable understanding, control,

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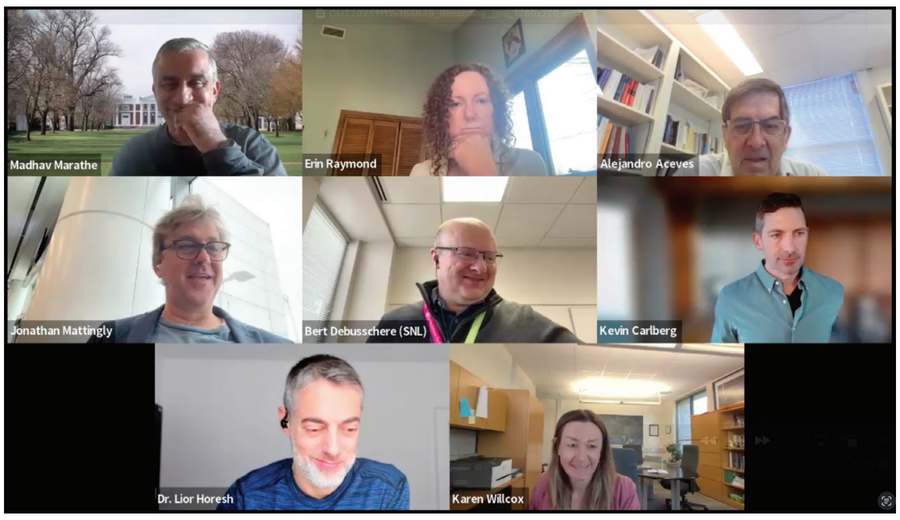

Members of the SIAM AI Task Force meet to begin writing "The Role of Applied Mathematics in a New Era of Artificial Intelligence." Top, from left to right: Madhav Marathe, Erin Raymond, and Alejandro Aceves. Middle, from left to right: Jonathon Mattingly, Bert Debusschere, and Kevin Carlberg. Bottom, from left to right: Lior Horesh and Karen Willcox.

[1] https://www.siam.org/media/b03hwuwe/siam-report-ai-task-force.pdf

[2] https://www.nobelprize.org/prizes/physics/2024/press-release/

[3] https://amturing.acm.org/award_winners/hinton_4791679.cfm

[4] https://amturing.acm.org/award_winners/dongarra_3406337.cfm

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Mean Field Games

Continued from page 1

To identify effective policies that anticipate emergent population behaviors in a tractable manner, we can employ the *Stackelberg equilibrium*, a fundamental concept in mathematical game theory. In a classical Stackelberg game, a leader initiates a strategy by setting an incentive, policy, or constraint. The follower then responds with their best strategy, namely, the behavior that optimizes their own objectives given the leader's incentive. Finally, the leader optimizes their own objective by accounting for the follower's optimal responses as a direct function of the initial incentive. This setting drew particular interest in contract theory literature, studied in a continuous-time framework via backward stochastic differential equations [12].

When there is more than one follower, we must also account for interactions among the followers. In this setting, we can assume that the followers respond to the leader's policy by playing a Nash equilibrium, where each follower chooses their best response (i.e., a strategy that optimizes their own objectives) given both the leader's policy and the behavior of the other followers. This creates a situation where, conditional on the leader's policy, no follower has an incentive to deviate from their strategy. In large populations, solving for a Nash equilibrium is challenging due to the increasing number of interactions, thus approximation methods such as mean field games (MFGs) can be employed. The full framework involving a leader and a large population of followers is typically referred to as a Stackelberg MFG [4, 8, 11].

Informally, the leader's problem is to choose a policy that optimizes their own objective, subject to the constraint that followers will find the equilibrium behavior for themselves. This "subject to" constraint is the crucial element of the framework; it transforms a standard, single-level optimization problem into a *nested* one, where the leader's decision must explicitly account for the internal optimization process of the followers. This hierarchy provides a robust abstraction for many policymaking scenarios, ensuring that the resulting interventions are resilient to the strategic adaptations of the population.

One prominent application of this framework is in the mitigation of epidemics [2]. In an MFG approach to disease control, the population is modeled as a large collection of agents whose health states (e.g., susceptible, exposed, infected, or recovered) change over time. Each individual manages their transition between health states; for instance, by controlling the intensity of their social interactions, an individual can minimize their personal risk or cost. A public health authority, as the leader, would influence this system through non-pharmaceutical interventions or incentives, aiming to steer collective behavior toward a socially optimal outcome — such as reducing the infection peak or preserving healthcare capacity. In this case, individuals (followers) naturally adjust their socialization habits in response to the spread of disease and the government's mandates, thus the optimal mitigation policies can be formulated as a Stackelberg MFG problem. Figure 1 presents a comparison of the spread of a disease under Stackelberg MFG policies to the free epidemic spread case — where the individuals do not adjust their socialization levels and the public health authority do not give any distancing guidelines. We can see that Stackelberg MFG policies give stricter guidelines to infected individuals which results in a decrease in the spread of the disease.

Another compelling application lies in systemic financial risk management and the stability of banking networks [7, 9]. In this setting, a central bank acts as the leader by announcing macroprudential policies (e.g., specific borrowing and lending rates or liquidity requirements). Related financial institutions then act as followers, adjusting their interbank lending strategies and risk-taking behaviors to maximize their individual profits, ultimately reaching a Nash equilibrium. The central bank's objective is to choose a policy that prevents a cascade of failures and ensures that the number of defaults remains below a critical threshold. Since the other banks' reactions to interest rates or capital buffers can shift the stability of the entire market, the central bank must solve a Stackelberg MFG to identify an intervention that is robust to the strategic shifts of the banking sector. This approach allows regulators to move beyond static stress tests and instead model the dynamic, reactive nature of the global financial system.

One other real-life-inspired application of the Stackelberg MFG is the modeling of electricity producers and their response to carbon reduction policies such as taxation [6]. The government, as the leader, selects carbon tax levels that optimize their own objectives, such as keeping maximum carbon emission levels at a specific level while ensuring the electricity demand is satisfied over the time horizon. The electricity producers in turn act as followers and decide on their nonrenewable and renewable energy resource investments to maximize their own objectives, such as maximizing their revenue while minimizing production-related costs. The producers interact with each other through the pricing of the electricity which is determined according to average supply and demand levels. Energy-market-related applications have been studied with MFGs and their extensions by many researchers [1, 3, 10].

New computational paths for solving these complex nested problems have emerged in recent years, moving beyond the limitations of traditional numerical methods. One generic approach involves reformulating the bilevel Stackelberg problem into a single-level mean field optimal control problem [9], which is then solved using a deep learning method. Another approach proposes a bilevel method based on a finite-dimensional approximation of the principal's decision space and a deep learning method to solve a forward-backward stochastic differential equation and fit the principal's loss function. This algorithm is then applied to a model for Renewable Energy Certificate markets [5].

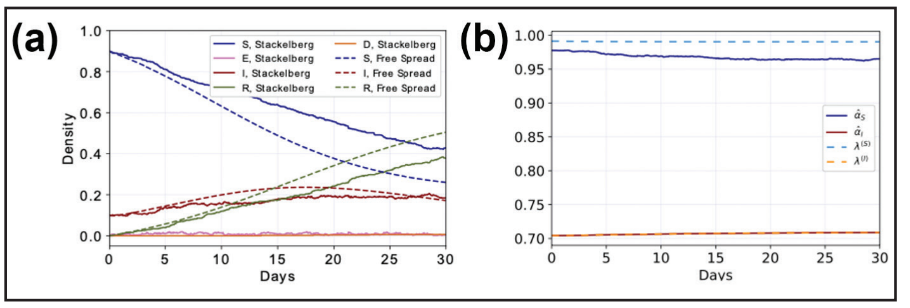

Figure 1. *Disease spread under Stackelberg mean field game (MFG) policies.* **1a.** *Comparison of the spread of disease under MFG policies as opposed to a free spread scenario.* **1b.** *Stackelberg MFG social distancing policies for susceptible individuals (blue, dashed) and infected individuals (orange, dashed), as well as Nash equilibrium social distancing response of susceptible individuals (blue, solid) and infected individuals (red, solid). Infected individuals are given stricter distancing guidelines than susceptible individuals, and susceptible individuals restrict socialization below the guidelines to protect themselves further. Figure adapted from [2].*

Stackelberg MFGs offer a rigorous mathematical foundation for understanding the interplay between top-down incentives and bottom-up strategic behavior. By treating the population's response using game theoretical ideas, we can design interventions that are more effective and robust.

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Artificial Intelligence

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and accountability. Treating applied mathematics as essential infrastructure, rather than an optional enhancement, is critical to the long-term success of AI.

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Optimization and Control

Continued from page 1

or more spatial dimensions and even on stratified domains (i.e., networks). Since most physically relevant equations are nonlinear, the classical tools of linear control theory rarely apply, leading to an emphasis on the development of new methods; strong results are available on the controllability and stabilization, particularly in the spatially one-dimensional (1D) setting [3, 10]. Recent developments investigate turnpike properties where the optimal control equals the optimal control of the associated static optimal problem over an extended time horizon — a phenomenon originally introduced by Nobel Prize winner Paul Anthony Samuelson in the context of financial markets and more recently used in the context of nonlinear balance laws. Numerical schemes that mirror analytical approaches for stabilization (and turnpike controls) have also been developed and their theoretical decay rates recovered. This is relevant for numerical schemes that are grid based—as opposed Lagrangian or characteristic methods—due to the presence of numerical dissipation.

Conversely, even for smooth initial data in the scalar nonlinear case, smooth solutions cease to exist beyond finite time. Thus, the formation of discontinuities requires a different set of analytical and numerical tools. Theoretically, progress has been made in the case of spatially 1D, nonlinear systems using the notion of weak entropic solutions, but due to the weak notion of solutions, results on controllability and stabilization in this setting are sparse compared to the smooth case [8]. The presence of discontinuities also required the development of a novel notion of analytical sensitivities for the solution with respect to control variates. Extensive work on alternative notions of differentiability began thirty years ago [4], since the evolution operator generated by the conservation law is generically non-differentiable in L^1, even in the scalar case. New concepts like shift-differentiability or tangent vectors have proven to be a suitable theoretical tool for the description of differentials.

Today, in the spatially 1D case, results on directional differentiability, and in the scalar case, on Fréchet differentiability, are available; these concepts also led to a theory for optimal control problems in the presence of (finitely many) discontinuities. Within this, calculus adjoint equations have posed additional challenges, being a PDE in a non-conservative form with possibly discontinuous coefficient. Even with the theoretical framework established, the development of suitable numerical schemes in multiple spatial dimensions and up to high-order for the optimal control problem is still under development. One reason for this limitation is that defining the differential requires the solution to have a particular structure of piecewise C^1 solutions with located, finitely many (typically non-intersecting) discontinuities. This structure is in general not obtained using classical discontinuous—Discontinuous Galerkin or Finite-Volume schemes—due to the presence of numerical dissipation and the Gibbs phenomena close to discontinuities. The latter requires additional care, as numerical error typically influences the results on the optimal control. Promising results for low-order, finite-volume schemes to control the dissipation in the spatially 1D setting exist, however, even in the case of 1D systems (and the multi-dimensional case), they are still an area of active research [9].

The aforementioned dichotomy requires a new set of adapted nonlinear tools making the control of hyperbolic PDEs an interesting and vibrant field of research. Furthermore, the field of optimization and control of nonlinear hyperbolic PDEs is rapidly expanding in many different directions. Significant theoretical and numerical contributions remain in optimization calculus and control, including problems involving optimization calculus in the presence of stratified geometries such as networks or manifolds; optimal control for multi-dimensional hyperbolic PDEs and control based on measure-valued solutions; and the controllability for general systems in the presence of shocks. The possibilities extend far further than the given list, and with the increase in understanding of the underlying concepts, the applications for control problems have increased significantly (see Figure 1, on page 1). The interaction with applications has proven to raise new and interesting control questions for the ubiquitous transport phenomena. The many unexplored areas—theoretical, numerical, or applied—most certainly merit the interest and attention of the mathematics community. In the future, we expect that the interdisciplinary fields of control and hyperbolic PDEs will lead to exciting and new results with a wide range of applications.

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From Individuals to Densities: The Many Scales of Collective Control

By Giacomo Albi, Dante Kalise, and Emmanuel Trélat

In 1987, computer graphics pioneer Craig Reynolds created his celebrated "boids" model [9] that demonstrated how simple local rules can generate the complex flocking patterns that we observe in nature. What Reynolds perhaps may not have anticipated was how his work would inspire a mathematical revolution that now spans traffic optimization, social dynamics, epidemic control, financial markets, and swarm robotics. Building on Reynolds' boids model, modern mathematicians now seek the ability to control collective dynamics for the use in a wide range of fields.

Controlling Collective Dynamics

The central challenge in controlling collective dynamics is inherently multiscale: how do we design strategies that account for individual behaviors while also achieving population-level goals? At the finest resolution, we track each agent explicitly, but at coarser scales, we describe the population through continuous densities or network-averaged fields. The mathematical journey from one extreme to the other is both conceptually rich and practically essential, as the choice of scale determines what computations are feasible at all.

As a running example throughout this article, we reference the Hegselmann-Krause model for opinion dynamics [4], in which N agents each hold an opinion $x_i(t) \in \mathbb{R}^d$ that evolves through interactions with their neighbors, random perturbations, and an externally applied control signal $u_i(t)$:

$$\dot{x}_i(t) = \frac{1}{N}\sum_{j=1}^{N} a_{ij}\phi(x_i(t), x_j(t)) + \sigma\xi_i(t) + u_i(t), \qquad i = 1, \dots, N. \tag{1}$$

Here, ϕ is an interaction kernel, $a_{ij} \geq 0$ encodes who influences whom, and $\sigma\xi_i(t)$ captures noise. A natural variant of this model incorporates *bounded confidence*: agent i only interacts with agents whose opinion lies within a radius R of its own. A typical control objective is consensus, where all agents are steered towards a target opinion x^* while simultaneously keeping the control effort small. This looks straightforward at small values of N, but the challenge grows quickly as the number of agents increases.

The Challenge of Scale

When N reaches into the thousands or millions—as is typical in crowd modeling, social networks, or swarm robotics—direct optimization of the agent-based system becomes computationally intractable. The optimization problem lives in $\mathbb{R}^{Nd}$, and its complexity scales exponentially with N: a system of 1,000 agents in two dimensions already poses a 2,000-dimensional problem, which standard numerical methods for optimal control simply cannot manage.

Beyond raw computation, two additional difficulties emerge. First, collective behavior often exhibits *emergent properties*—dramatic qualitative changes triggered by small perturbations in control signals—that are hard to anticipate from individual dynamics alone. The onset of consensus in an opinion model, the spontaneous formation of lanes in pedestrian flow, or the sudden polarization of a population can all arise from *microscopic* rules without any obvious macroscopic analog. The second difficulty stems from data collection. In practice, one rarely has access to the full state; sensors measure aggregate statistics rather than, e.g., the individual opinion of every single agent, and thus any realistic control architecture must operate from partial information.

These observations motivate a fundamental shift in perspective. Rather than tracking individuals, can we describe the distribution of agents and control that distribution instead? As N grows large, powerful mathematical limit theorems allow us to replace the high-dimensional discrete system with a tractable continuum description. Two distinct pathways can achieve this outcome, and each will preserve different structural features of the original problem. Understanding the relationship between these pathways is itself an active area of research.

The Graph Limit

The first pathway exploits the network structure encoded in the matrix a_{ij}. The graph limit procedure, formalized by Georgi Medvedev [5], assumes the existence of a continuous function $a : [0,1]^2 \to \mathbb{R}$, called a *graphon*, such that $a(i/N, j/N) = a_{ij}$. This assumption embeds the discrete interaction matrix into a smooth object on the unit square. As $N \to \infty$, the system (1) converges to the graph limit equation

$$\frac{\partial x}{\partial t} = \int_0^1 a(s,s')\phi(x(s,t), x(s',t))\,ds' + \frac{\sigma^2}{2}\Delta_s\, x(s,t) + u(s,t), \tag{2}$$

where the discrete label i has been replaced by a continuous label $s \in [0,1]$. The transformation is a systematic averaging: the Riemann sum over j becomes an integral over s' while the N-dimensional system collapses to a single nonlinear integro-differential equation in infinite dimensions. Without noise ($\sigma = 0$), (2) reduces further to a nonlocal ordinary differential equation, which is substantially easier to optimize over than the original agent-level formulation.

The graph limit is particularly natural when the network has identifiable macroscopic structure: spatial proximity graphs, hierarchical organizations, or graphs that approximate a smooth kernel. For opinion dynamics with spatially distributed agents, the graphon $a(s,s')$ can capture how the strength of influence decays with the distance between agent labels, carrying the essential geometry of the interaction network into the continuum formulation.

The Mean-field Limit

The second pathway takes a statistical mechanics perspective; rather than labeling agents by their position in a network, we ask how many agents occupy each opinion at time t. As $N \to \infty$, under mild conditions on the interaction kernel and the initial distribution, the empirical measure $\mu_N(t) = \frac{1}{N}\sum_j \delta_{x_j(t)}$ converges to a deterministic density $\rho(x,t)$. The controlled mean-field limit equation for the Hegselmann-Krause model takes the form of a controlled Fokker-Planck equation:

$$\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x}\left[\left(\int_{x-R}^{x+R}\phi(x,y)\rho(y,t)dy - u(x,t)\right)\rho\right] = \frac{\sigma^2}{2}\frac{\partial^2 \rho}{\partial x^2}, \tag{3}$$

where the control has become a function $u(x,t)$ of opinion and time, rather than a separate signal for each agent. The optimization problem now reads as follows: minimize the expected distance to consensus, integrated over the density and subject to the partial differential equation (PDE) in (3). The dimensionality has dropped from $N \cdot d$ to simply d plus time.

This formulation opens the door to the well-developed toolkit of PDE-constrained optimal control: adjoint methods, Pontryagin's maximum principle in infinite dimensions, and Hamilton-Jacobi-Bellman (HJB) equations. An important subtlety is that while the microscopic dynamics are linear in the original control problem, (3) involves a bilinear coupling between u and ρ, which introduces genuine nonlinearity and raises interesting questions about stabilizability and controllability of the resulting system [2, 3].

Connecting the Scales

The graph limit and the mean-field limit are not competing descriptions but complementary ones, related through a hierarchy of scales illustrated in Figure 1 (on page 1). In a precise sense, the mean-field equation (3) is more general; the solution to the graph limit equation (2) can be recovered from the mean-field density by a procedure known as the hydrodynamic limit, which extracts macroscopic flow fields from the kinetic distribution. For this reason, the mean-field level is often called the *mesoscopic scale* (intermediate between individual agents and bulk flow), while the graph limit corresponds to the *macroscopic scale* in the same sense as Euler equations in fluid dynamics [7].

Beyond First-order Models: Kinetic Equations

Many collective phenomena—including opinion polarization, bird flocking, and vehicle platooning—are more accurately described by second-order microscopic models, wherein the agent's state is represented by a *position-velocity pair* [6]. The mean-field limit of this second-order system yields a kinetic equation for the phase-space density $f(x,v,t)$ of agents at position x with velocity v, i.e., a controlled Fokker-Planck equation in the joint (x,v) space.

A particularly elegant route to these kinetic equations passes through *binary interactions* [8]. At the microscopic level, two agents with velocities v and v_* interact stochastically, exchanging momentum according to a rule that incorporates alignment, a control term, and noise. Designing the control at this binary level amounts to solving a small two-agent optimization problem with an explicit solution. One then applies a scaling limit that sends the interaction strength to zero while increasing the collision rate — a procedure analogous to the grazing collision limit in kinetic gas theory [10]. The resulting continuum equation is the controlled Fokker-Planck PDE, now derived from first principles of the microscopic interaction rule rather than postulated directly. This derivation provides a rigorous foundation that connects the binary level with the continuum, clarifying exactly how the macroscopic control term $U[f](x,v,t)$ inherits its structure from the microscopic design choices [1].

Closing the Loop: From Densities Back to Agents

A control law $u(x,t)$ that is derived at the continuum level must ultimately be translated into commands for actual agents. The simplest approach is direct substitution. If the control law was derived at the mean-field level, agent i receives the command

See **Collective Control** *on page 6*

Collective Control

Continued from page 5

$u_i(t) = u(x_i(t), t)$, which involves evaluating the continuum policy at the agent's current opinion. If the control was instead derived at the graph limit level, then the natural substitution is $u_i(t) = u(i\,/\,N, t)$, which involves evaluating the graphon-based policy at the agent's label rather than its state. This framework is computationally cheap and requires no inter-agent communication. Crucially, the resulting microscopic strategy is expressed in *feedback form*: each agent continuously observes its own state and adjusts accordingly, even though the mean-field optimization was originally posed as an open-loop problem over the density. This feedback structure is a valuable byproduct of the mean-field approach.

More sophisticated methods account for finite-size effects. Rather than applying the continuum law blindly, one can correct each agent's command by its deviation from the current population mean, thereby explicitly compensating for the unavoidable fluctuations when N is only moderately large. At the other end of the complexity spectrum, particle-filter methods maintain an approximate representation of the optimal density and adapt commands in real time as the empirical distribution evolves; these methods provide robust performance guarantees but at a significantly higher computational cost.

The approximation error between continuum-derived and optimal agent-level strategies is possible to rigorously quantify. Under standard regularity assumptions, the suboptimality of the mean-field control policy that is applied to the finite-agent system scales as $O(N^{-1/2})$, which is a direct consequence of the central limit theorem that governs the convergence of empirical measures. This scaling provides theoretical justification of the entire multiscale program: for large N, solving a PDE-constrained optimization problem and reading off individual commands is both computationally far cheaper than the N-agent problem and nearly optimal in performance. The mean-field approach thus provides a principled and quantifiably accurate shortcut through an otherwise intractable optimization landscape.

Open Problems and Outlook

The control of collective dynamics sits at the intersection of several rapidly developing fields, and many fundamental questions remain. On the theoretical side, the controllability of bilinear PDE systems such as (3) is not fully understood: standard results for linear systems do not transfer, and the nonlinear coupling between the density and the velocity field creates genuine obstructions. Questions also surround the metastability of equilibria in nonlocal Fokker-Planck equations and the related design of controls that steer the system away from undesired steady states and towards a target distribution, posing subtle challenges that extend well beyond classical stabilization theory.

On the computational side, solving the HJB equation that is associated with mean-field optimal control in high state dimensions remains a frontier problem. The value function lives on the space of probability measures—which is an infinite-dimensional object—and any tractable numerical method must introduce a finite-dimensional approximation. Tensor decomposition methods, deep learning approximations of the value function, and physics-informed neural networks are all active research directions, each with their own tradeoffs between accuracy, scalability, and generalizability.

Applications provide equally rich challenges. Social dynamics on real-world graphs, which are neither sparse nor graphon-convergent in any obvious sense, require new theoretical frameworks that can accommodate power-law degree distributions, community structure, and time-varying topology. Inverse optimal control in behavioral ecology—i.e., inferring the implicit objective that is being optimized by a flock of birds or school of fish from trajectory data—connects the forward problem discussed here to statistical inference and machine learning. At a very different scale, real-time feedback control of fusion reactor plasmas draws on the same mathematical infrastructure: a high-dimensional particle system whose continuum limit is a kinetic PDE, controlled under tight time constraints and subject to hard physical bounds.

What unites these problems is the same multiscale intuition that Craig Reynolds encoded in boids nearly four decades ago. Complexity at the individual level can organize into simplicity at the population level, and that simplicity is where tractable mathematics lives.

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[1] https://www.siam.org/get-involved/connect-with-a-community/activity-groups/control-and-systems-theory/

[2] https://www.siam.org/get-involved/connect-with-a-community/activity-groups/control-and-systems-theory/leadership/

Hamilton-Jacobi Equations, Finite Differences, and Neural Networks

By *Carlos Esteve-Yagüe, Richard Tsai, and Alex Massucco*

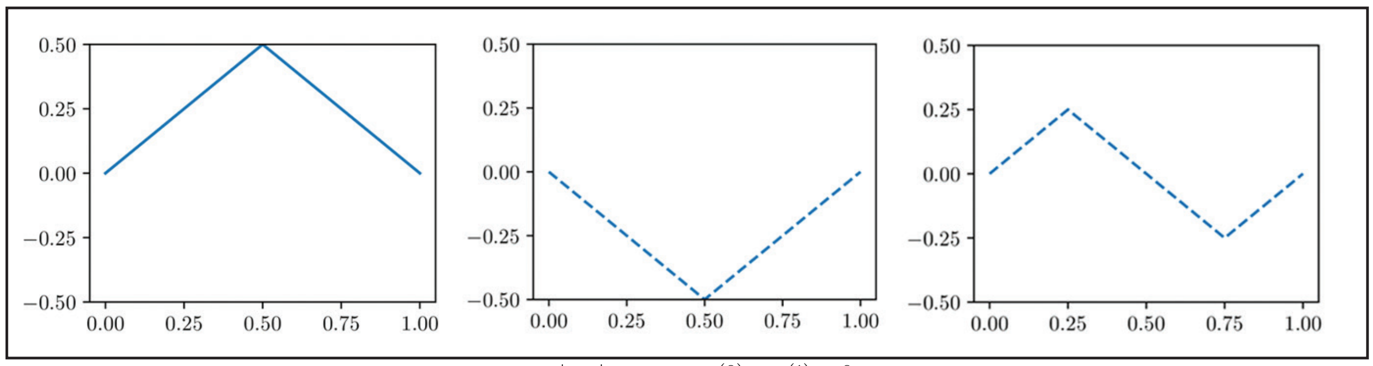

Figure 1. *Three weak solutions to the Eikonal equation* $|u_x| = 1$ *with* $u(0) = u(1) = 0$. *While multiple Lipschitz functions satisfy the equation almost everywhere (e.g., the dashed lines), only the solid profile is a viscosity solution. Standard residual minimization cannot distinguish between these candidates. Figure courtesy of the authors.*

When designing an automatic device, an important aspect is ensuring that it runs as efficiently as possible. In optimal control theory, the goal is to determine a control policy that will drive a controlled dynamical system to maximize a performance criterion. This framework has ubiquitous applications ranging from aerospace trajectory planning and autonomous robotics to financial portfolio optimization and chemical process control.

The foundations of optimal control theory were forged in the intellectual heat of the Cold War, during which a geopolitical divide mirrored an interesting mathematical duality. In the U.S., Richard Bellman and Rufus Isaacs at the RAND Corporation were tackling the complexities of military logistics and aerial pursuit. They established the dynamic programming principle (DPP) [2], which focuses on the global value function that satisfies a Hamilton-Jacobi-Bellman equation — a perspective that naturally yields closed-loop feedback policies. By generalizing Bellman's framework to differential games involving adversarial agents, Isaacs derived the Hamilton-Jacobi-Isaacs equation to solve zero-sum games in the 1960s. Simultaneously, Soviet mathematician L.S. Pontryagin and his school at the Steklov Institute addressed critical trajectory problems of the Space Race with Pontryagin's maximum principle. This approach provided the necessary conditions for optimality, offering a powerful variational tool for characterizing specific optimal trajectories [3].

The value function $u(x)$ of an optimal control problem provides a state-dependent feedback policy to optimally control the underlying system's dynamics (described by f), minimizing the sum of the running cost r along the way:

$$\alpha_*(x) = \arg\max_\alpha \{-f(x,\alpha)\cdot\nabla u(x) - r(x,\alpha)\}.$$

Under mild conditions on f and r, the value function is differentiable almost everywhere and satisfies a Hamilton-Jacobi (HJ) equation at the points of differentiability together with a Dirichlet boundary condition determined by the terminal cost. For deterministic problems, HJ equations are first-order partial differential equations (PDEs) of the general form

$$H(x,\nabla u) = 0, \quad \text{in } \Omega \subset \mathbb{R}^n,$$

where H is the Hamiltonian function. The domain Ω may include a time dimension as well.

However, HJ equations are typically nonlinear PDEs, and classical (C^1) solutions do not exist globally — even with smooth boundary data. Characteristic curves carry information from the boundary and thus inevitably intersect, leading to the formation of "kinks" or discontinuities in the gradient. In contrast, there are no unique continuous functions that satisfy the HJ equation at almost every point of the domain, along with the boundary condition. For example, the Eikonal equation $|u_x| = 1$ on the interval $[0,1]$ with zero boundary condition $u(0) = u(1) = 0$ admits infinitely many such solutions (see Figure 1). Yet only one of these solutions corresponds to the value function of the optimal control problem for the shortest path to the boundary; this solution is represented in the left plot in Figure 1.

In the 1980s, Michael G. Crandall and Pierre-Louis Lions introduced the notion of the viscosity solution, providing a definitive existence and uniqueness theory [5]. The viscosity solution unequivocally selects the physically meaningful solution (i.e., the value function) from potentially infinite weak candidates. The name "viscosity solution" arises from the characterization of the solution by means of the *vanishing viscosity method*, which selects the unique solution by taking the limit as $\varepsilon \to 0$ in the semilinear elliptic equation $H(x,\nabla u_\epsilon) = \epsilon\Delta u_\epsilon$. An analogous characterization of the viscosity solution regulates the solution's behavior at its nondifferentiable kinks by testing the equation against smooth functions that touch the graph from above and below. In a typical case, including the one-dimensional (1D) Eikonal equation, the viscosity solution must be locally concave at any extremal point — a consequence of the vanishing viscosity limit.

Classical Numerical Methods

For decades, the standard approach to computing viscosity solutions has relied on fixed grids. In this framework, the computational domain Ω is discretized into a Cartesian mesh, and the value function $u(x)$ is approximated by a function that is defined on the grid nodes. To ensure convergence to the correct viscosity solution, one must rely on the theory of Guy Barles and Panagiotis E. Souganidis, which guarantees that any finite difference discretization that satisfies *monotonicity, consistency, and stability* will converge to the unique viscosity solution [1].

However, classical monotone schemes are often limited to low-order accuracy. To achieve higher-order accuracy while handling discontinuities (kinks) robustly, essentially non-oscillatory (ENO) and weighted ENO (WENO) methods that are built on top of monotone schemes have become standard tools in this domain.

Prominent algorithms for boundary value problems include the fast marching methods and fast sweeping methods. Crucially, these methods work because they strictly adhere to the DPP. In plain English, the DPP states that *the optimal strategy from any point involves making the best immediate decision and then proceeding optimally from the resulting new state* [2]. The results are essentially one- or finite-pass (through the grid) algorithms, where the grid acts as the medium through which the "optimality information" propagates. For time-dependent problems with explicit time integration, the evolution is naturally one-pass.

The Curse of Dimensionality

While highly efficient in low dimensions (i.e., from one to three dimensions), grid-based methods become infeasible in higher dimensions d due to the increasing number of grid nodes, which grow exponentially with d.

This explosion is not merely due to the need to maintain resolution for the fine properties of the solution. The fundamental issue is that to propagate the causality that the DPP requires, grid nodes must exist *everywhere* in the domain to accumulate the running cost from the boundary to the interior in an orderly fashion as dictated by the system's characteristics. Even if the solution is primarily smooth and fine detail resolution is only necessary in a small region, the grid must still fill the entire ambient space to serve as the "conduit" for information flow. For a six-dimensional state space—a humble requirement for a modern robotic system—a modest grid of 100 points per dimension would require 10^{12} nodes, rendering classical storage and computation intractable.

While representation formulas like Hopf-Lax or Cole-Hopf transformation exist for cases of HJ equations [6], and Riccati theory handles linear-quadratic cases, general nonlinear systems—especially those in robotics or games—require robust numerical approximations.

Residual Minimization and Neural Networks

To address these challenges, we turn to the representational power of artificial neural networks. The universality of deep neural networks ensures the efficient approximation of viscosity solutions to HJ equations, which—while lacking classical derivatives on the entire domain—are typically Lipschitz continuous. By parameterizing the solution with a neural network, we avoid grid dependencies and treat the solver as an optimization task, leveraging the computational infrastructure of gradient-based learning and graphics processing units.

It is tempting to formulate this optimization by minimizing the PDE residual, a strategy that has gained immense popularity through the development of physics-informed neural networks (PINNs) [8]. In this framework, one would typically define a loss functional such as

$$\mathcal{L}(u) = \int_\Omega H(x,\nabla u)^2\,dx + \lambda\int_\Gamma (u(z) - g(z))^2\,dz.$$

However, for HJ equations, this direct residual minimization approach is fundamentally ill-posed; as the 1D Eikonal equation in Figure 1 demonstrates, there are infinitely many Lipschitz-continuous functions that satisfy the equation almost everywhere. Thus, the loss function cannot distinguish the unique viscosity solution from these spurious candidates.

Without a mechanism to enforce the entropy-like selection criteria of Crandall and Lions, a neural network that minimizes $\mathcal{L}(u)$ may easily converge to a "physically" incorrect, weak solution. To reliably recover the value function, one must find a way to embed the viscosity solution's selection principles directly into the loss functional.

A Grid-based Method Without Grids

We advocate for an alternative path: rather than minimizing a continuous residual, we minimize a loss derived from a convergent finite difference approximation [7]. The numerical diffusion in a suitable finite-difference approximation regularizes the solution and enforces the selection of the viscosity solution. In a consistent and monotone finite difference method, the viscosity selection criteria are naturally satisfied by the discretization itself. In this framework, the neural network is trained to minimize a loss functional based on a numerical Hamiltonian $\hat{H}$:

$$\mathcal{L}_h(u) = \int_\Omega |\hat{H}(x,\nabla_h u(x))|^2\,dx + \lambda\int_\Gamma |u(z) - g(z)|^2\,dz,$$

where ∇_h denotes a discrete gradient operator that is evaluated using a stencil of size h. A particularly convenient

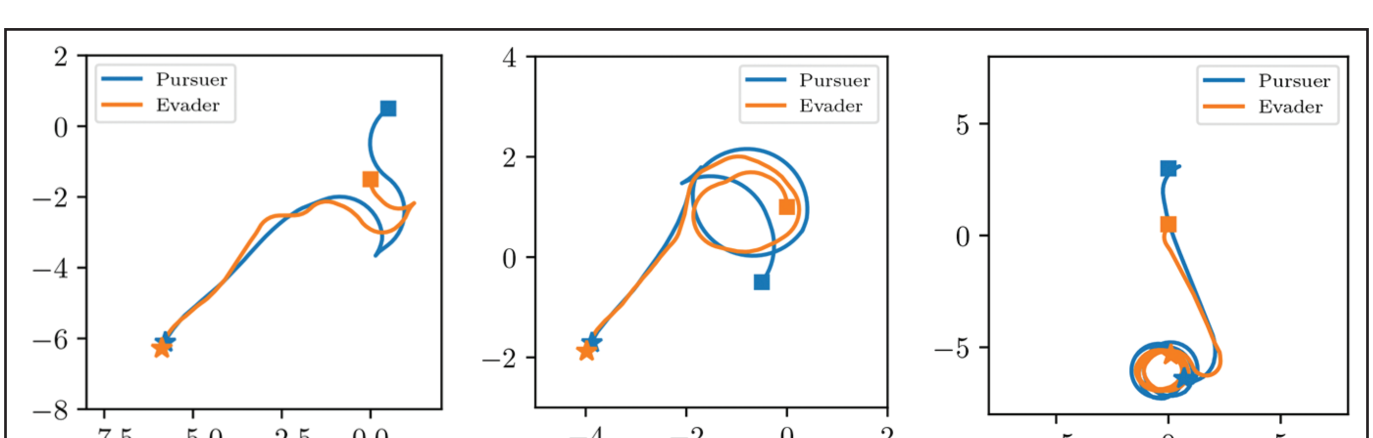

Figure 2. *Three optimal trajectories of the pursuit-evasion game associated with two-car models. In the game, each agent steers a reversible vehicle under a minimal turning radius constraint. The boxes represent the initial position of the game, while the stars represent the end-game position. In the third case, the game enters in an infinite equilibrium loop. Figure courtesy of the authors.*

See **Neural Networks** *on page 8*

The *inControl* Podcast: Building a Global Audience for Control Theory

By Dante Kalise

Alberto Padoan is an assistant professor in the Department of Electrical and Computer Engineering at the University of British Columbia and the creator of *inControl*,[1] the first podcast dedicated to control theory. Since its launch in 2022, the show has grown into a global platform reaching over 150,000 listeners across more than 150 countries.

Dante Kalise recently spoke with Alberto Padoan to discuss how he built his platform and what four seasons of storytelling have taught him about research, creativity, and the future of science communication in control theory. Here they share their conversation with *SIAM News*.

Dante Kalise: *inControl* describes itself as "the first podcast on control theory." What prompted you to start it in 2022?

Alberto Padoan: The origin story is disarmingly simple. The podcast idea started with the simple observation that every technical field I admired had found its way into podcasting—physics, neuroscience, machine learning—except ours. During my postdoctoral appointment at the University of Cambridge in 2018, I first floated the idea while walking to lunch with colleagues. One of them replied: "Who do you think would ever listen to you?" A fair challenge, honestly. But the question wouldn't go away. For quite some time, I kept waiting for someone better positioned, more media-savvy, and simply less shy, to launch it. Time went by, but the podcast did not materialize. Eventually, I realized that waiting was its own kind of answer — if the podcast was going to exist, it would have to start with someone willing to just begin. The pandemic created a strange window for slow-burning ideas, and with the encouragement of my supervisors at ETH Zürich and the backing of the National Centres of Competence in Research (NCCR) Automation,[2] *inControl* went from a passing remark on Trumpington Street to a real project.

One thing that genuinely motivated me from the start was the promise of a legitimate reason to sit with people I deeply admired and ask the kinds of questions that never quite fit into a conference panel Q&A.

DK: Your episodes range from historical portraits to interviews with leading researchers. How do you decide what an episode should be, and who are you aiming to reach?

AP: Our field has no shortage of remarkable stories; I could record for years and barely scratch the surface. My guiding principle is to follow my own curiosity. I tend to pursue questions that genuinely fascinate me, and more often than not, that personal investment seems to resonate with others.

As for the audience, that is the easy one: *inControl* is meant to serve as a global channel for anyone drawn to systems and control, from researchers and students to control aficionados and the genuinely curious from adjacent fields.

DK: Control theory sits somewhat in the background compared to, say, machine learning in public scientific discourse. Do you see *inControl* as a corrective to that?

AP: I wouldn't call it corrective, more of a complement. Machine learning deserves enormous credit for the way it communicates its impact; those advances are real and tangible. But I do think control has historically underplayed its hand. We are behind some of the most extraordinary engineering achievements of our time, from reusable rockets to robots performing acrobatic feats, and, somewhat ironically, the semiconductor fabrication processes that make modern artificial intelligence (AI) physically possible. Control is also behind the quieter but equally profound advances in quantum technologies and systems biology. There is absolutely no reason for an inferiority complex. What I hope *inControl* demonstrates is that when you give these stories the space and narrative they deserve, people pay attention. The appetite is there, we just need to meet it with the same confidence and craft that other fields have brought to their public presence.

DK: After 42 episodes and four seasons, has any episode surprised you in terms of the response it got or something that you learned while making it?

AP: Constantly. The biggest surprise was the appetite for depth. The most listened-to episode isn't a conversation with a prominent guest, it's usually a deep dive into a given topic, say the prehistory of control. That tells me something important: people aren't just looking for names or news; they want narrative, context, and the longer arc of how ideas came to be.

Alberto Padoan (left) and Alessandro Chiuso (right), professor of automatic control at the University of Padova, during the recording of an inControl podcast episode. Photo courtesy of Alberto Padoan.

On a more personal level, hosting the show has sharpened my thinking about what shapes a successful research career. I've become increasingly convinced that luck plays a larger role than we typically admit; perhaps half the story is being in the right place when the right question appears, but the other half seems to be preparation and a broad, genuine curiosity that lets you recognize and respond to those moments when they arrive. Creativity seems to live at that intersection, where deep expertise in some areas meets wide-ranging intellectual restlessness.

DK: Who listens? Have you had feedback from students, practitioners, people outside the field entirely?

AP: The reach has genuinely astonished me. *inControl* is accessed by over 150,000 listeners across more than 150 countries and territories, numbers I never imagined when I recorded that first episode. The core audience is in Europe and North America, but there's meaningful and growing engagement from Asia, Africa, Oceania, and South America. What moves me most is the breadth: I hear from Ph.D. students looking for perspective, senior researchers reconnecting with the broader motivations behind their work, and people from entirely different fields who simply stumbled in and stayed. The project started as an attempt to build the kind of conversation I wished had existed when I was a student. Discovering that so many others felt the same need has been one of the most rewarding surprises of my career.

DK: What's next for *inControl*?

AP: If bandwidth were unlimited, the list would be long: short-form research explainers, collaborative annotation platforms in the spirit of Fermat's Library,[3] and deeper integration with the emerging AI tools that are reshaping how we communicate research. The landscape for science outreach is evolving rapidly, and I find that genuinely exciting.

In practice, with two young children at home and a new position that comes with its own set of responsibilities, I have to be a bit more deliberate about where the energy goes. But the core motivation hasn't changed since that walk to lunch in Cambridge: control deserves a voice that matches the scale of its impact. The audience is there, the task now is simply to keep building.

Dante Kalise is an associate professor in computational optimization and control at Imperial College London. His research focuses on computational methods for optimal control.

[1] https://www.incontrolpodcast.com/
[2] https://nccr-automation.ch/
[3] https://fermatslibrary.com/

Neural Networks

Continued from page 7

choice is the Lax–Friedrichs discretization, where $\hat{H}$ incorporates a controlled amount of numerical diffusion to stabilize the system. With the right amount of diffusion, one can ensure that gradient descent iterations applied to $\mathcal{L}_h(u)$ converge to the unique global minimizer [7].

We can show that, for more general classes of monotone discretizations, gradient descent converges faster for larger values of h [2]. Additionally, training with larger values of h also tends to be more data efficient. So it is impractical to begin minimizing $\mathcal{L}_h(u)$ with a very small h.

At the same time, we are interested in a sufficiently accurate finite-difference approximation of the viscosity solution. Crucially, one can employ a multilevel "warm-start" strategy. While the loss is defined using finite-difference stencils, the method remains grid-free. We do not solve a system on a fixed mesh; instead, we minimize the loss using stochastic gradient descent, in which we sample collocation points x across the domain and evaluate the finite difference $\nabla_h u(x)$ on the fly. By first training the neural network with a larger h, we achieve faster initial convergence. Then, we progressively refine the discretization by decreasing h and continue the training to find a more accurate approximation of the viscosity solution. Training using this hierarchical approach typically requires only a few minutes on a standard laptop to compute high-fidelity value functions for some nontrivial model systems, such as the four-dimensional pursuit-evasion game for two Reeds-Shepp's car models (see Figure 2, on page 7).

Theory-informed Learning

Reflecting on these developments, we see that the success of neural network-based solvers for HJ equations relies on more than approximation power; it requires a deliberate connection to the underlying theory of viscosity solutions. While the standard residual-minimization approach is a powerful general framework, the specific non-uniqueness of HJ weak solutions necessitates a selection principle to recover the value function. By incorporating monotone discretizations directly into the loss functional, we bridge the convergence theory of classical numerical analysis with the scalability of modern deep learning.

This framework suggests a promising path forward for high-dimensional problems. Based on the mathematical foundations of Crandall-Lions and Barles-Souganidis, similar strategies should be applicable to viscous HJ equations in stochastic optimal control and other challenging fully nonlinear or degenerate elliptic operators. Ultimately, by using structural insights from numerical analysis to guide the optimization of neural networks, we can make complex, high-dimensional control tasks accessible on standard hardware — without the memory bottlenecks of the past.

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Carlos Esteve-Yagüe is a faculty member in the Department of Mathematics at the University of Alicante. Richard Tsai is a professor in the Department of Mathematics and the Oden Institute for Computational Engineering and Sciences at the University of Texas at Austin. Alex Massucco is a mathematics Ph.D. student at the University of Cambridge.

Reflections on the Graduate Research Assistantships in Developing Countries Program: A Journey of Two Doctoral Awardees

By Belgis Ainatul Iza and Annisa Rahmita Soemarsono

The continued advancement of mathematics plays a fundamental role in supporting technological innovation, intelligent systems, and sustainable development across the globe. Recognizing the importance of such advancement, the International Mathematical Union[1] (IMU) strengthens mathematical capacity worldwide by providing targeted funding programs that support graduate students, early-career researchers, and institutions to ultimately foster strong, sustainable mathematical communities.

The Commission for Countries[2] (CDC) at the IMU specifically aims to provide financial support for research in developing and middle-income countries. One of the CDC's flagship initiatives is the Graduate Research Assistantships in Developing Countries (GRAID) Program.[3] Established in 2017, the GRAID Program offers modest but strategic financial support to emerging research groups in countries that are classified under Priority 1 or 2 according to the IMU's "Definition of Developing Countries."[4] The initiative allows talented master's and Ph.D. students to pursue their studies on a full-time basis as graduate research assistants in mathematics while simultaneously participating in an active research environment with a local principal investigator (PI) and an international partner (IP).

In 2025, a total of five doctoral students in three research groups[5] received the prestigious GRAID scholarship. We, Belgis Ainatul Iza and Annisa Rahmita Soemarsono, are honored to be the first students from Sepuluh Nopember Institute of Technology (ITS) in Indonesia to receive financial support from SIAM through the GRAID Program. Through this opportunity we were able to work under the direction of PI Mardlijah Mardlijah of ITS and IP Zhai Guisheng of Shibaura Institute of Technology in Japan. Not only are we honored to receive financial support, we feel that programs such as these represent the collective strengthening of applied mathematics research capacity in Indonesia through international collaboration.

Belgis Ainatul Iza

My research lies at the intersection of applied mathematics and control systems, investigating the development of intelligent control algorithms based on fuzzy logic and extended Kalman filters (EKFs) for unmanned aerial vehicle delivery systems. My doctoral dissertation, titled "Designing Fuzzy-PID Control With Robust EKF and Measurement Compensation for Delivery Quadcopters," is highly relevant to Indonesia's national research agenda, particularly in the fields of intelligent transportation systems, autonomous vehicles, and smart logistics.

Annisa Rahmita Soemarsono

In contrast to Iza's research, I study the application of fuzzy optimal control methods for robotic manipulator systems with two degrees of freedom; my dissertation is titled "Fuzzy Optimal Control Problem in Fuzzification and Defuzzification Processes (Case Study: Manipulator System on a Sea Ship)." This work has strong potential applications in marine mechatronics and ship-based robotic systems for surveillance and maritime defense, which is an area of strategic importance for an archipelagic country like Indonesia.

Financial Challenges of Doctoral Research

Despite having strong academic backgrounds, we both faced significant financial constraints prior to receiving the GRAID funding that affected our ability to focus fully on doctoral research. Although we both received some scholarships from outside agencies—Iza from a Fresh Graduate Scholarship at ITS and Soemarsono from the National Research and Innovation Agency[6]—these funds only covered tuition fees and did not include support for living expenses or research activities. This meant taking on teaching and tutoring responsibilities to support our studies, which significantly reduced the time and energy that we could devote to research.

At the time of our GRAID application, neither of us received financial support from private foundations, industrial institutions, or other international programs. The GRAID scholarship thus played a vital role in easing financial pressure and enabling us to pursue research in a full-time capacity.

A Strong Foundation in Mentoring, Leadership, and International Collaboration

We first learned about GRAID through the coordinator of the doctoral study program at ITS, who recognized the alignment between GRAID's objectives and

See **Two Doctoral Awardees** *on page 10*

From left to right: Annisa Rahmita Soemarsono, Belgis Ainatul Iza, Zhai Guisheng (on screen), and Mardlijah Mardlijah meet to prepare an article submission. Photo courtesy of Annisa Rahmita Soemarsono.

[1] https://www.mathunion.org

[2] https://www.mathunion.org/activities/commission-developing-countries-cdc

[3] https://www.mathunion.org/cdc/grants/GRAID

[4] https://www.mathunion.org/cdc/about-cdc/definition-developing-countries

[5] https://www.mathunion.org/cdc/grants/GRAID/awardees-2025

[6] https://www.brin.go.id/en

Take Advantage of SIAM's Visiting Lecturer Program

Hearing directly from working professionals about research, career opportunities, and general professional development can help students gain a better understanding of the workforce. SIAM facilitates such interactions through its Visiting Lecturer Program (VLP), which provides the SIAM community with a roster of experienced applied mathematicians and computational scientists in academia, industry, and government. Mathematical sciences students and faculty—including SIAM student chapters—can invite VLP speakers to their institutions to present about topics that are of interest to developing professional mathematicians. Talks can be given in person or virtually.

The SIAM Education Committee[1] sponsors the VLP and recognizes the need for all members of our increasingly technological society to familiarize themselves with the applications and achievements of mathematics and computational science.

Points to consider in advance when deciding to host a visiting lecturer include the choice of dates; potential speakers and topics; and any additional or related activities, such as follow-up discussions. Organizers can reach out directly to speakers and must address these points when communicating with them. It is important to familiarize lecturers with their audience—including special interests or expectations—so that they can refine the scope of their talks, but just as crucial to accommodate speakers' suggestions so the audience can capitalize on their experience and expertise. Read more about the program and view the current list of participants on the VLP webpage.[2]

[1] https://www.siam.org/get-involved/connect-with-a-community/committees/education-committee

[2] https://www.siam.org/programs-initiatives/programs/visiting-lecturer-program

A Contract of Trust: Artificial Intelligence Usage for SIAM Journal Submissions

By Tamara G. Kolda

The scholarly ecosystem is based on a contract of trust between authors, editors, referees, and readers of scientific publications. Although it may appear as though the diligent SIAM editors and referees are checking every detail of every submission, they are not and have never been expected to do so. Here, for instance, is some guidance that the *SIAM Journal on Mathematics of Data Science*[1] gives to its referees:

> A referee is expected to read the paper with sufficient care to be confident that it is mathematically sound. Nevertheless, it is not necessary to check every detail. The author has final responsibility for the content.

It is impossible for a referee to check every line of every proof, every algorithm, every experiment, and every reference. They spend just a few hours evaluating work that is not their own and potentially outside their exact specialty; in contrast, authors are experts in their own work and have spent months or years developing it. Consequently, significant trust is placed in SIAM authors for the content of their submissions. There is an expectation that they will meet or exceed the usual standards of responsible scholarship, and, in general, they do!

However, there are rising concerns as researchers more frequently incorporate artificial intelligence (AI) tools into their work. Although there is no doubt that AI can be beneficial to scientific research endeavors, AI misuse can result in poor scholarship which inevitably hurts other researchers and negatively impacts the profession as a whole. Not only does it demand more time from referees and editors, but any mistakes that make it past review (as they invariably do) proliferate confusion. It is hard enough to read a mathematical paper, but it is even harder when there are mistakes. This leads to wasted time and effort for readers and can ultimately damage the reputation of the field [6, 9, 12, 13].

[1] https://epubs.siam.org/journal/simods/instructions-for-referees

A particular issue is the rise of fabricated references. These have been documented both in pulished scientific works [6,9], and observed in submissions to SIAM journals. A recent report [2] elucidated the hazards of hallucinated citations:

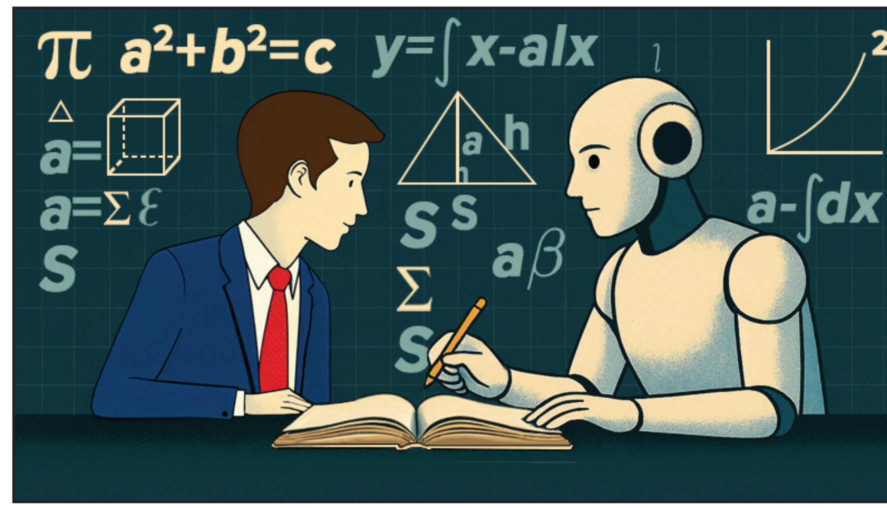
> The appearance of AI-generated hallucinated citations in peer reviewed literature represents a fundamental challenge to the integrity of scientific discourse. Citations serve as the evidentiary foundation of scholarly work, establishing what prior research has demonstrated, enabling reproducibility, and situating new contributions within existing knowledge. When citations are fabricated, these epistemic functions collapse. Readers cannot verify claims attributed to nonexistent sources. Future researchers waste time searching for papers that were never published. The citation graph that structures scientific knowledge becomes contaminated with false linkages.

Fabricated references are just one way that AI is eroding the trust in scientific literature, and it is incumbent upon all of us to take responsibility for maintaining the integrity of our work and our field.

Author Usage of AI Tools

SIAM authors (all of whom must be human) may use AI tools, provided that they properly disclose their usage per the SIAM Publications AI Policy.[2] AI tools can be extremely useful for a variety of tasks; SIAM authors have successfully used AI tools for finding related literature, developing proofs and algorithms, coding, running experiments, and getting feedback on drafts. AI tools can be a powerful aid to research and scholarship, hence we do not discourage their use per se, but we insist upon *responsible use* and *appropriate disclosures*.

[2] https://epubs.siam.org/artificial-intelligence



Irresponsible usage of artificial intelligence for scientific literature is growing, often leading to fabricated references and erroneous results. Image courtesy of SIAM.

AI and Poor Scholarship

There are several common failure modes that researchers should be aware of when utilizing AI. AI tools can generate impressive text, code, and even mathematical proofs, but because their outputs generally appear highly plausible—thanks to their training on vast amounts of data—underlying and significant errors may be difficult to detect. Therefore, we encourage both users of AI tools and those who review their work, such as research supervisors, to be aware of these failure modes and to check for them carefully. Here, we mention a few of the most common failure modes, but this list is not exhaustive.

- **Fabricated references:** This may mean references that do not exist, have incorrect titles or author lists, and so on. It can also mean citing a result that is not actually in the cited paper [2, 3].
- **Unattributed appropriation of scientific ideas:** AI tools contain vast troves of unattributed information, and they can easily produce ideas, including key mathematical and algorithmic innovations, that are not properly credited to original sources [1, 8].
- **Mathematical and coding errors:** AI tools can produce mathematical content and code that appears correct but contains subtle errors that can fool all but the most knowledgeable experts. This is difficult to precisely study, but see [7] for discussion.
- **Inaccurate figures:** AI tools may generate artificial data or improperly graph real data, leading to figures that are inaccurate or misleading [4, 10, 11].

Referee Usage of AI Tools

Referees play a crucial role in our scholarly community; their critical feedback enables editors to identify the most significant scientific contributions to our journals. Additionally, referee feedback can be invaluable to authors by offering them significant ways to improve their work. Referee use of AI tools is another area of growing concern [5].

See **Contract of Trust** *on page 12*

Two Doctoral Awardees

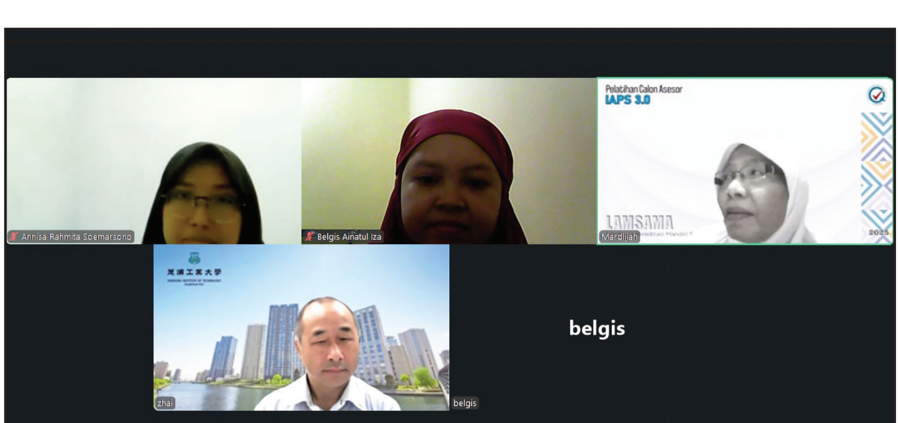
Continued from page 9

the needs of doctoral researchers such as ourselves. We submitted our application as a collaborative proposal with a strong supervisory structure and an established international partnership.

The involvement of Mardlijah as PI and Guisheng as IP reflect the GRAID philosophy of strengthening local research ecosystems through sustained international engagement. Mardlijah is a senior lecturer at ITS who leads the Laboratory of Mathematical Modeling and System Simulation. She has more than 30 years of experience supervising students across the undergraduate, master, and doctoral levels, many of whom have become lecturers and researchers at leading universities across Indonesia or applied their expertise in industry.

Mardlijah's mentoring philosophy emphasizes not only academic excellence but also research productivity and long-term scholarly development. Students under her supervision are actively involved in scientific writing, conference presentations, international networking, and collaborative research in areas like autonomous system control, intelligence control, fuzzy logic modeling, estimation theory, and renewable energy — fields that are increasingly relevant to modern engineering and technological challenges.

Beyond allowing us to work with such a supportive PI, a key strength of the GRAID Program lies in its inclusion of a qualified IP to fortify each project's global reach. Guisheng, who previously served as an adjunct professor at ITS, is a leading expert in control theory whose expertise is especially relevant to our specific dissertation topics. Iza's work on EKF-based fuzzy-proportional-integral-derivative control for quadcopters closely aligns with Guisheng's research in decentralized control, H-infinity control, and the stabilization of dynamic systems. Similarly, Soemarsono's exploration of fuzzy optimal control for manipulator systems overlaps with Guisheng's contributions to adaptive control algorithms and optimization-based control systems in robotics and mechatronics.



Clockwise from top left: Annisa Rahmita Soemarsono, Belgis Ainatul Iza, Mardlijah Mardlijah, and Zhai Guisheng meet for preliminary discussions for publishing a research article. Image courtesy of Annisa Rahmita Soemarsono.

Guisheng has expressed his intention to continue to mentor us both through our doctoral journeys. Support from the GRAID Program will augment this collaboration, providing access to an international research ecosystem; significantly enhancing the quality and impact of our research outputs; and improving research capacity, knowledge exchange, and international visibility in Indonesia and beyond.

Global Networking and Capacity Building

In addition to providing financial support, GRAID fosters global networking opportunities among awardees and researchers. The annual CDC Webinar 2025,[7] is one such example. The event focused on the Volunteer Lecturer Program[8] and allowed host institutions and international lecturers to share their experiences. It also introduced CDC activities that correspond with the upcoming 2026 International Congress of Mathematicians,[9] which will take place in Philadelphia, Pa., in late July and offer further opportunities for global engagement.

Participation in the webinar and other like-minded activities allows us and other GRAID awardees to connect with mathematicians around the world, exchange ideas, and establish collaborations beyond their immediate research groups.

[7] https://www.mathunion.org/cdc/news-and-events/2025-11-03/cdc-webinar-2025-held-november-3-2025
[8] https://www.mathunion.org/cdc/grants/grants-institutions/VLP
[9] https://www.mathunion.org/icm/icm-2026

Looking Ahead

Taking part in the GRAID Program marked a turning point in our doctoral journeys. The support enabled us to completely devote our time to research, contribute to the advancement of applied mathematics with both national and global relevance, and pursue international collaborations that would otherwise be inaccessible.

More broadly, GRAID signifies the importance of sustained international support when building research capacity in developing countries. Through funding initiatives like GRAID, the IMU and SIAM continue to play a strategic role in nurturing future leaders in mathematics and ensuring that mathematical research contributes meaningfully to global scientific progress.

Belgis Ainatul Iza is a mathematics Ph.D. candidate at Sepuluh Nopember Institute of Technology (ITS). She specializes in mathematical modeling, control systems, and state estimation for high-dimensional dynamic systems. Her research advances autonomous aerial system control through the development of robust and intelligent estimation-control frameworks, integrating adaptive filtering and data-driven approaches, while her teaching in data science bridges rigorous mathematical theory with real-world applications. Annisa Rahmita Soemarsono is a mathematics Ph.D. candidate at ITS specializing in systems and control, particularly optimal control theory and fuzzy concepts, and her research contributes to the theoretical development of fuzzy optimal control problems and their implementation in real-world plants. Her teaching in applied mathematics focuses on fundamental mathematical concepts, such as calculus and differential equations, and their applications across various practical contexts.

Congratulations 2026 SIAM Fellows!

SIAM is pleased to announce the newly selected Class of SIAM Fellows—a group of distinguished members of SIAM who were nominated by their peers for exceptional contributions to the fields of applied mathematics, computational science, and data science. Please join us in congratulating these 25 members of our community.

Kenneth Clarkson
IBM Corporation

Patrick Farrell
University of Oxford

Anne Gelb
Dartmouth College

Stefan Güttel
The University of Manchester

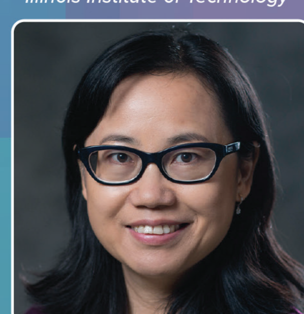
Heather A. Harrington
University of Oxford

Fred J. Hickernell
Illinois Institute of Technology

Sebastian Jaimungal
University of Toronto

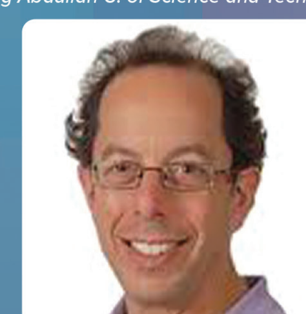
Omar Knio
King Abdullah U. of Science and Technology

Doron Levy
University of Maryland

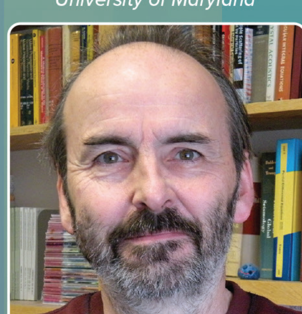


Fengyan Li
Rensselaer Polytechnic Institute

Lin Lin
University of California, Berkeley

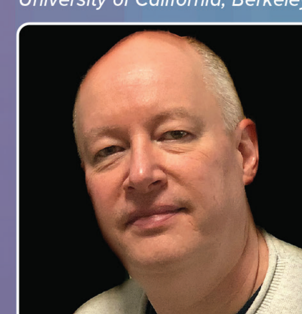


John Lowengrub
University of California, Irvine



Paul A. Martin
Colorado School of Mines

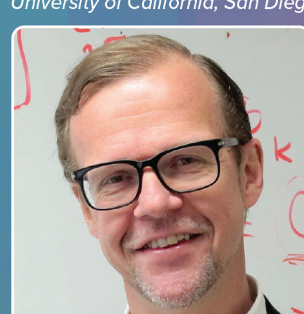
Sonia Martinez
University of California, San Diego



Peter David Miller
University of Michigan, Ann Arbor

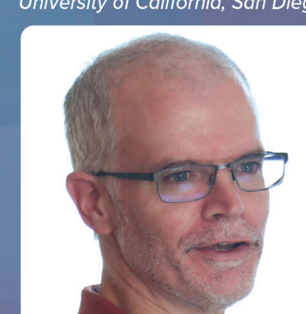
Jiawang Nie
University of California, San Diego

Kui Ren
Columbia University

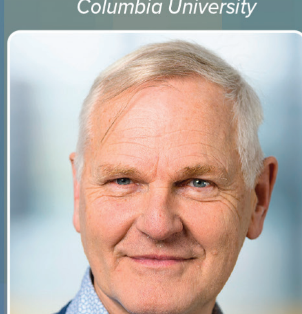


Erkki Somersalo
Case Western Reserve University

Xue-Cheng Tai
Norce Norwegian Research Centre



Jean-Luc Thiffeault
University of Wisconsin, Madison



Cornelis Vuik
Delft University of Technology

Xiao-ping Wang
Chinese University of Hong Kong

Guowei Wei
Michigan State University

Wotao Yin
Alibaba Group US, DAMO Academy

Tao Zhou
Chinese Academy of Sciences

siam. Fellow

Learn more about these esteemed individuals and nominate a colleague by October 15, 2026 for the 2027 Class of SIAM Fellows:

siam.org/prizes-recognition/fellows-program

Southwest Section of SIAM Launches With Vision for Regional Collaboration

By Malena Español, Danny Dunlavy, Frederic Marazzato, and Tonatiuh Sánchez-Vizuet

In January 2026, SIAM approved the formation of the Southwest Section of SIAM[1] (SIAM-SW) to support the applied mathematics community in Arizona, Nevada, and New Mexico. This section's creation reflects a shared goal of strengthening connections among universities, national laboratories, industry professionals, and students across the Southwest region of the U.S.

From the beginning, SIAM-SW's goal has been clear: build an inclusive, sustainable regional network that promotes applied mathematics and fosters valuable professional relationships. The Southwest is home to many prominent research universities, national laboratories, and federal research sites, as well as a rapidly growing student population; however, geographic distances between institutions limit regular interaction. This new section seeks to bridge these gaps.

To celebrate its launch, SIAM-SW is organizing a minisymposium titled "Research Highlights from the Southwest Section of SIAM" at the SIAM Annual Meeting[2] (AN26) in Cleveland, Ohio, this summer. This minisymposium will consist of three parts, each focusing respectively on (1) inverse problems, (2) mathematical biology, and (3) numerical analysis and partial differential equations — fields that showcase the region's intellectual diversity and applied strength. The minisymposium has two main goals. First, it provides an early opportunity for members of the newly formed section to meet, share ideas, and begin shaping future activities. Second, it highlights to the broader SIAM community the depth and vibrancy of applied mathematics research in the Southwestern U.S.

Beyond the inaugural event at AN26, SIAM-SW is already planning its first section conference for the spring of 2027. Although the host institution has yet to be decided, the goal is to hold an annual meeting that rotates through Arizona, Nevada, and New Mexico, strengthening ties among institutions and increasing participation from students and early-career researchers. A key focus will be accessibility, making sure that those unable to attend national conferences still have opportunities to present their work, build networks, and connect with industry and laboratory scientists.

Looking ahead, SIAM-SW aims to strengthen connections among sections nationwide. Informal gatherings of different section officers at AN26, regular cross-section discussions, and shared programming ideas can foster collaboration and increase the impact of regional efforts. The Southwest Section enthusiastically welcomes opportunities to co-organize activities, exchange speakers, and develop inter-sectional initiatives that benefit the broader applied mathematics community.

At its core, SIAM-SW is about connecting institutions, disciplines, and career stages. By establishing a strong regional foundation, we aim to support SIAM's broader mission to advance the use of mathematics in industry and science, encourage fundamental research, and foster the exchange of ideas.

The Southwest has long been a hub of scientific innovation and collaboration. With the establishment of SIAM-SW, the region now has a formal structure through which its applied mathematics community can connect, grow, and contribute more visibly to SIAM. We encourage members and colleagues to visit the SIAM-SW website[3] for news, announcements, and opportunities to get involved. SIAM members with primary addresses in Arizona, Nevada, or New Mexico are warmly encouraged to join the Southwest Section through the SIAM website and become a part of this expanding regional community.

Founding officers of the Southwest Section of SIAM meet to discuss the section's launch. Clockwise from top left: Frederic Marazzato, Malena Español, Tonatiuh Sánchez-Vizuet, and Danny Dunlavy. Image courtesy of Malena Español.

Acknowledgments: From its earliest discussions, the formation of SIAM-SW benefited from the involvement of colleagues across SIAM. The founding officers of SIAM-SW especially thank Noemi Petra for her generous guidance and consistent encouragement throughout the process. We also greatly appreciate the early leadership and insightful input of Cynthia Phillips—SIAM's current president-elect—whose enthusiasm for strengthening regional communities helped shape the section's initial vision. Additionally, we thank Ratna Khatri, Annalisa Quaini, John Zweck, and Roy Goodman for sharing their experiences from established SIAM sections, as well as Jimmie Adriazola, Donatella Danielli, and Rosemary Renaut for their valuable early conversations that helped lay the groundwork for the SIAM-SW.

Malena Español is an associate professor of computational mathematics in the School of Mathematical and Statistical Sciences at Arizona State University. Español serves as chair of Southwest Section of SIAM (SIAM-SW). Danny Dunlavy is a Distinguished Member of Technical Staff in the Center for Computing Research at Sandia National Laboratories and serves as vice chair of SIAM-SW. Frederic Marazzato is an assistant professor in the Department of Mathematical Sciences at the University of Nevada, Las Vegas, and serves as SIAM-SW's treasurer. Tonatiuh Sánchez-Vizuet will soon become an associate professor in the Department of Mathematics of the University of Arizona. Sánchez-Vizuet serves as secretary for SIAM-SW.

[1] https://www.siam.org/get-involved/connect-with-a-community/sections/southwest-section-of-siam/
[2] https://www.siam.org/conferences-events/siam-conferences/an26/
[3] https://sites.google.com/view/southwest-section-of-siam

Contract of Trust

Continued from page 10

Because of the confidential nature of referee work, SIAM currently prohibits its referees from using AI tools. SIAM is exploring how AI tools might support referees in the future. We would stress, however, that these tools may only be used to *assist* them in their work. It might be used for tasks such as replicating computational experiments, filling in steps in a proof, or finding related works. A key ingredient in the scholarly contract is that referee reports are based on the expertise and judgement of the referees *themselves*.

Penalties for Irresponsible AI Usage

Because we operate on a contract of trust, poor scholarship in any part of a manuscript makes everything suspect. How can we trust the mathematical content if some of the references are fabricated? How do we make sense of the results if the figures are nonsensical? Even if the primary content *appears* to be correct, poor scholarship in other parts of the manuscript can undermine confidence in the work as a whole.

For this reason, SIAM editors and referees may reject an article for poor scholarship, even if there is no specific technical error. SIAM may impose additional penalties, such as a ban on future submissions to SIAM publications. We highlight two areas that have already resulted in author integrity investigations at SIAM:

1. Increasing numbers of fabricated references are appearing in SIAM submissions. We expect that we've only found the tip of the iceberg, as articles with fraudulent references have thus far only come to light by happenstance, such as a referee finding their own name attached to a reference they didn't write. Fabricated references are a serious violation of academic integrity. If we discover that submitted content (including work that has already been published) contains fabricated references, the consequences will include **banning the authors from submitting to SIAM publications for a minimum of one year.**

2. Substandard submissions are increasing, apparently due to the ease of creating mathematical papers with the help of AI. Substandard submissions consist of papers that fail to clarify their mathematical contributions, are very far outside the journal scope, have limited mathematical substance, have pages of equations without context, contain incoherent or incorrect arguments, or have insufficient or inappropriate references. We certainly understand that even excellent authors have occasional weak papers, and we do not intend to penalize authors for a single substandard submission. However, authors that repeatedly submit low-quality work at a high rate will be subject to **a ban from submitting to SIAM publications for a minimum of one year.**

Key Takeaways

Responsible use of AI is essential to maintaining the integrity of our journals and our scientific work. We ask that SIAM authors continue to maintain their usual highest standards in their research, extending this to the new domain of research assisted by AI. Further, we encourage conversations on this topic with coauthors and colleagues, sharing best practices and maintaining alertness to potential problematic usage of AI.

For those that want to explore the broader impact that irresponsible use of AI tools has on scientific literature, we recommend reading through the references provided.

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Tamara G. Kolda is a mathematical consultant under the auspices of her California-based company, MathSci.ai. She is a SIAM Fellow, co-founded and served as editor-in-chief of the SIAM Journal on Mathematics of Data Science, and currently serves as SIAM's Vice President for Publications.

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Upcoming Deadlines

siam 2026

SIAM Conference on Discrete Mathematics (DM26)

June 22–25, 2026 | San Diego, California, U.S.
siam.org/dm26 | #SIAMDM26

ORGANIZING COMMITTEE CO-CHAIRS
Vida Dujmovic, *University of Ottawa, Canada*
Jacques Verstraete, *University of California, San Diego, U.S.*

EARLY REGISTRATION RATE DEADLINE
May 26, 2026

HOTEL AND TRANSPORTATION INFORMATION
Visit conference website for additional information.

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SIAM Conference on the Life Sciences (LS26)

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Nessy Tania, *Pfizer Research & Development, U.S.*

SIAM Conference on Mathematics of Planet Earth (MPE26)

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Kara Peterson, *Sandia National Laboratories, U.S.*

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EARLY REGISTRATION RATE and HOTEL RESERVATION DEADLINE FOR AN26, LS26, MPE26, and ED26:
June 8, 2026

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SIAM Conference on Mathematics of Data Science (MDS26)
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SIAM Conference on Imaging Science (IS26)
siam.org/is26 | #SIAMIS26 | November 16–19, 2026
https://www.siam.org/conferences-events/siam-conferences/is26/submissions/

SIAM International Conference on Data Mining (SDM26)
siam.org/sdm26 | #SIAMSDM26 | November 19–20, 2026
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Visit the conference webpages for additional information.

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SIAM Conference on Nonlinear Waves and Coherent Structures
May 26–29, 2026
Montréal, Québec, Canada
Sponsored by the SIAM Activity Group on Nonlinear Waves and Coherent Structures

SIAM Conference on Optimization
June 2–5, 2026
Edinburgh, United Kingdom
Sponsored by the SIAM Activity Group on Optimization

SIAM Conference on Discrete Mathematics
June 22–25, 2026
San Diego, California, U.S.
Sponsored by the SIAM Activity Group on Discrete Mathematics

SIAM Conference on Mathematics of Planet Earth
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SIAM Conference on the Life Sciences
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SIAM Symposium on Algorithm Engineering and Experiments
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SIAM Section Activities and Updates

Read below for highlights from Section events that took place throughout 2025.

The 10th Annual Meeting of the **Central States Section of SIAM** was held on October 11–12, 2025, at the University of Arkansas, Fayetteville. The meeting drew 223 registered participants from across the Central States region and beyond. The scientific program included three plenary lectures, 151 mini-symposium presentations, 11 contributed talks, and 22 poster presentations. The section also held their first SIAM-CSS Student Conference, a one-day event that brought together approximately 25 participants from Oklahoma and Arkansas. The conference featured four plenary talks delivered by faculty members, and eight research talks presented by graduate students.

Central States Section of SIAM 2025 Annual Meeting held October 11–12, 2025, at the University of Arkansas, Fayetteville, AK

The **D.C.-Maryland-Virginia Section of SIAM** organized the 5th East Coast Optimization Meeting (ECOM), a two-day annual section meeting on April 17 - 18, 2025, at the Center for Mathematics and Artificial Intelligence (CMAI) at George Mason University. The theme of the meeting was "Optimization and Digital Twins." The meeting comprised of mini courses by two distinguished SIAM member speakers, Matthias Heinkenschloss (Rice University), and Rainald Lohner (George Mason University) and targeted students and early career researchers. The meeting also included five keynote talks and 26 contributed talks targeting mostly students, postdocs, and early career faculty. The meeting had 146 registered participants. Sponsored by SIAM, NSF Division of Mathematical Sciences, Sandia National Laboratories, and CMAI, the meeting was highly successful with engaging sessions and plentiful networking opportunities for the local SIAM community.

D.C.-Maryland-Virginia Section of SIAM joint 5th East Coast Optimization Meeting (ECOM) with NSF, DMS, SNL, and CMAI, on April 17–18, 2025 at George Mason University, Fairfax, VA.

The 18th **East Asia Section of SIAM Conference** took place at De La Salle University in Manila, Philippines from June 30 through July 4, 2025. The conference encompassed all facets of applied mathematics as it pertained to science, industry, engineering, and technology in East and Southeast Asia. Additionally, the Section awarded EASIAM Student Paper Prizes to the following SIAM members recognizing their outstanding work in applied mathematics or scientific computing.

First prize winner: Dr. Chushan Wang, *National University of Singapore, Singapore*
Second prize winners: Dr. Chenguang Duan, *Wuhan University, P. R. China*, and Dr. Kengo Suzuki, *Kyoto University, Japan*.

East Asia Section of SIAM Conference on June 30–July 4, 2025, held at De La Salle University, Manila, Philippines.

The **Mexico Section of SIAM** successfully held its 2025 Annual Meeting from August 13-15, hosted by the Faculty of Physical and Mathematical Sciences (FCFM) at the Universidad Autónoma de Chiapas (UNACH), in Tuxtla Gutiérrez, Chiapas, Mexico. The academic program featured a broad range of activities, including: five plenary lectures delivered by nationally and internationally recognized experts; two specialized short courses, aimed at advanced training in applied mathematics; and 105 contributed talks, organized into 13 thematic mini-symposia covering areas such as mathematical modeling, data science, stochastic processes, complex networks, optimization, industrial applications, bioengineering, and public health. A total of approximately 125 participants attended the meeting, including a significant number of undergraduate and graduate students, reflecting the Section's strong commitment to supporting early-career researchers and fostering the next generation of applied mathematicians in Mexico.

Mexico Section of SIAM Annual Meeting on August 13–15, 2025, at the Universidad Autónoma de Chiapas (UNACH), Tuxtla Gutiérrez, Chiapas, Mexico.

The **Northern and Central California Section of SIAM** held their second SIAM Northern and Central California Sectional Conference on October 27-28, 2025, at the Lawrence Berkeley National Laboratory. 211 participants engaged in a packed program of technical talks, interactive panels, and hands-on workshops. The programming reflected the community's wide-ranging expertise, spanning machine learning, high-performance computing, life sciences, control theory, uncertainty quantification, and numerical methods. Speakers included: SIAM member Rob Falgout (LLNL), on Multigrid methods in space and time for extreme-scale scientific computing, and SIAM member Suzanne Sindi (UC Merced), on Mathematical Models as Discovery Tools: Bridging Scale and Uncertainty in Complex Biological Systems.

The **Northern and Central California Section of SIAM** Conference was held October 27–28, 2025, at the Lawrence Berkeley National Laboratory, Berkeley, CA.

The **Southern California Section of SIAM** organizing committee planned the Southern California Applied Mathematics Symposium (SOCAMS) on April 26, 2025, at the University of California, Riverside (UCR) with support from SIAM, National Science Foundation (NSF), UCR's College of Natural & Agricultural Sciences (CNAS), Riverside Artificial Intelligence Research and Education Institute (RAISE), Research and Economic Development (RED), and the UCR math department. The 300-person conference connected researchers from universities throughout Southern California who work in all areas of applied and computational mathematics to exchange ideas. This one-day event provided a platform for young faculty, post-docs, and graduate students to showcase their research work in an informal and collaborative atmosphere. The goal is for societal benefits, dissemination of results, graduate training, public outreach, increase of public literacy and public engagement in mathematics, improvement of STEM education, and educator development. The meeting included five plenary speakers, 77 contributed talks in seven parallel sessions, and 40 poster presenters.

The **Southern California Section of SIAM** Southern California Applied Mathematics Symposium (SOCAMS) held April 26, 2025, at the University of California, Riverside, CA.

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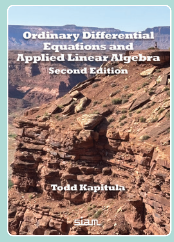

Ordinary Differential Equations and Applied Linear Algebra, Second Edition

Todd Kapitula

This book helps students master linear algebra and ODEs in a one-semester course. The second edition of Ordinary Differential Equations and Applied Linear Algebra expands the learning experience by introducing case studies at the end of every chapter that examine SIR models, a model for lead poisoning, and the dynamics of strongly damped forced oscillators, among others. It adds end-of-chapter projects that allow students to explore the interplay between the creation of a mathematical model, the solution of the model, and the physical implications of the mathematical solution. Also new to the second edition is access to over 300 online homework problems embedded within the CMS *myOpenMath*.

2026 / xvi + 314 pages / Softcover / 978-1-61197-877-3
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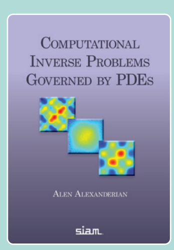

Computational Inverse Problems Governed by PDEs

Alen Alexanderian

This textbook focuses on computational methods for inverse problems that are governed by partial differential equations (PDEs). The author considers deterministic and Bayesian formulations and highlights how traditional tools from deterministic inversion can be integrated into solution methods for Bayesian inverse problems. Advanced topics such as post-optimality sensitivity analysis, optimal design of experiments, and Bayesian inversion under model uncertainty are also included.

2026 / xvi + 320 pages / Softcover / 978-1-61197-881-0
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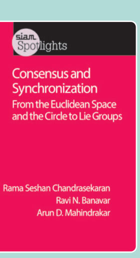

Consensus and Synchronization: From the Euclidean Space and the Circle to Lie Groups

Ravi N. Banavar, and Arun D. Mahindrakar

Coordination, consensus, and synchronization are found in diverse natural phenomena and engineering applications. Examples are flocking birds, illuminating fireflies, schooling fish, and distributed control and sensing. The simplest of such problems are set in the Euclidean spaces and the circle. This book moves beyond this domain to the more sophisticated setting of Lie groups with bi-invariant metrics and extends the mathematical theories of consensus and synchronization for generic scenarios. This is relevant to applications such as robotics, autonomous vehicles, and spacecraft.

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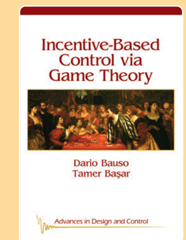

Incentive-Based Control via Game Theory

Dario Bauso and Tamer Başar

Engineering systems in today's economy are increasingly shaped by sharing—through shared logistics, joint investments, virtual power plants, and other cooperative structures—requiring models that account for decentralized decision-making and collective action. A central challenge is aligning self-interested behavior with system-wide objectives. Incentive-Based Control via Game Theory addresses this need with a design-oriented framework that uses game theory to engineer mechanisms and control strategies that drive agents toward stable, socially desirable outcomes under uncertainty. The book introduces engineering-focused topics rarely treated elsewhere, including dynamic coalitional games, reverse Stackelberg games, and rigorously analyzed best-response dynamics, while maintaining an application-driven perspective that connects mathematical theory to real-world implementation.

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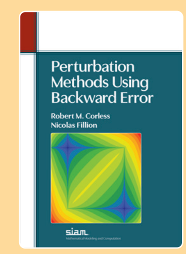

Perturbation Methods Using Backward Error

Robert M. Corless and Nicolas Fillion

Perturbation methods are old but powerful, and they remain in widespread use. Rather than producing numbers or pictures, they yield formulas whose value depends on the skill of the person (or machine!) interpreting them. This unique book presents several classical methods for solving perturbation problems. To ensure a uniform presentation and more reliable, interpretable results, it consistently uses backward error analysis. This provides a systematic way to assess the validity of approximate solutions while encouraging the modeler to examine how small changes in the data or model affect the result. To support this, the book uses the concept of a condition number, familiar from numerical analysis.

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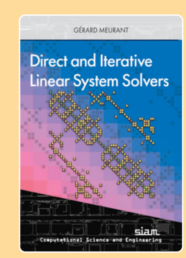

Direct and Iterative Linear System Solvers

Gérard Meurant

Solving linear systems of equations is ubiquitous in scientific computing; therefore, numerical algorithms for solving them are paramount. This book describes the state of the art in direct and iterative methods for solving nonsingular linear systems of equations. Finite precision arithmetic and numerical experiments are emphasized. The author considers several variants of elimination methods, classical iterative methods, variants of the conjugate gradient method, and Krylov methods for nonsymmetric systems and describes many preconditioners. He describes and analyzes many numerical experiments with these methods, provides templates of codes for implementing these methods, and introduces more recent techniques like mixed precision and randomization.

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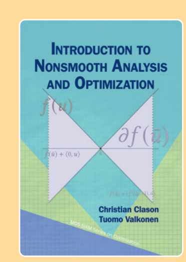

Introduction to Nonsmooth Analysis and Optimization

Christian Clason and Tuomo Valkonen

This book offers a unified and rigorous introduction to the infinite-dimensional analysis and algorithmic solution of nonsmooth optimization problems arising in imaging, inverse problems, machine learning, and optimal control. It develops the necessary tools of nonsmooth, set-valued, and variational analysis, and presents state-of-the-art first- and second-order algorithms with careful convergence and stability analysis. The treatment is self-contained and accessible, including novel calculus results tailored to relevant infinite-dimensional settings. Throughout, theory is closely integrated with computation, and the book is accompanied by Julia code that enables readers to reproduce numerical experiments and explore practical implementations.

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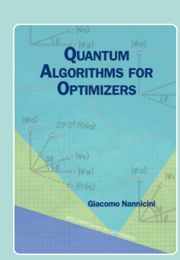

Quantum Algorithms for Optimizers

Giacomo Nannicini

This book presents a self-contained introduction to quantum algorithms, with a focus on quantum optimization—quantum approaches to solving optimization problems. It equips readers with the essential tools to assess the strengths and limitations of these algorithms, emphasizing provable guarantees and computational complexity. The first comprehensive treatment of quantum optimization, it provides a rigorous introduction to the computational model of quantum computers and to the theory of quantum algorithms, contains detailed discussions of some of the most important developments in quantum optimization algorithms, and summarizes the most significant advances in the open literature.

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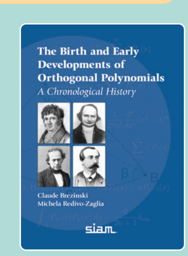

The Birth and Early Developments of Orthogonal Polynomials: A Chronological History

Claude Brezinski and Michela Redivo-Zaglia

The shape of the Earth was a significant scientific question in the eighteenth century. It leads to the discovery of orthogonal polynomials. Over time, as interest in the gravitational problem of spheroids waned, the intrinsic mathematical interest in orthogonal polynomials took precedence. This is the first book to describe the history of orthogonal polynomials, covering their birth and early developments from the end of the 18th century to the middle of the 20th century. It includes biographies of principal and lesser-known figures, anecdotes, and accounts of the countries and institutions involved. The book will appeal to researchers, students, and those interested in the history of mathematics.

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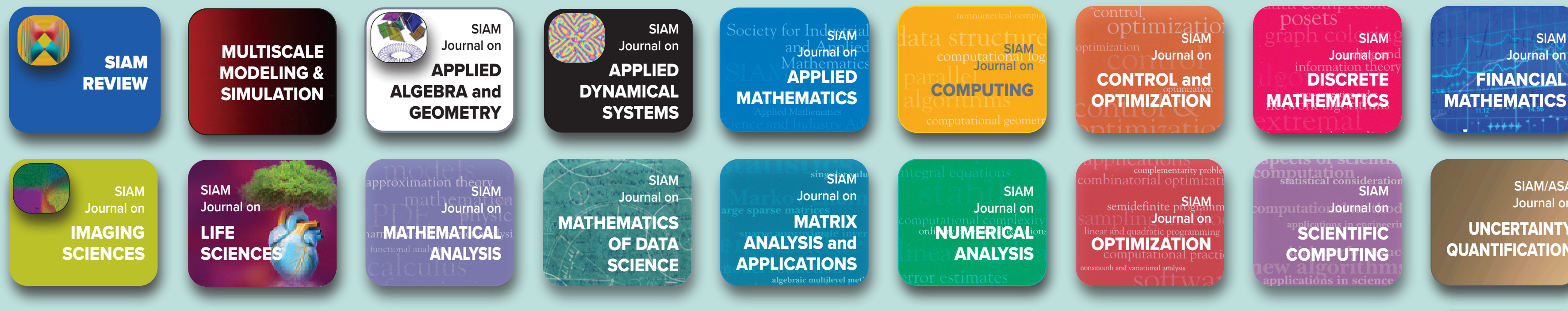

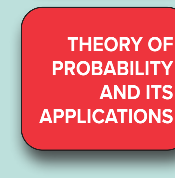

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