

**Stevens Institute Series on
Complex Systems and Enterprises**

William B. Rouse, Series Editor

SOCIAL-BEHAVIORAL MODELING FOR COMPLEX SYSTEMS

Edited By:

Paul K. Davis

Angela O'Mahony

Jonathan Pfautz



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Social-Behavioral Modeling for Complex Systems

Stevens Institute Series on Complex Systems and Enterprises

Series Editor: William B. Rouse

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Foreword

Trying to understand human behavior has probably been a human passion since the first cavewoman tried to figure out why her mate could never remember to wipe his feet before coming inside. We're still at it, working with ever more sophisticated approaches and for increasingly important outcomes.

My own experience in this area started out when I was working at NASA to help design an autopilot for the Space Shuttle vehicle. It worked great when there was no *astronaut in the loop*, but when they started wrangling the controls themselves, the astronauts were not exactly enamored with my design and the way it behaved. Dismay would be a word that might apply here, but I went back to school to figure out why and soon became enmeshed in trying to understand human self-motion perception and control, by bringing together established theory, controlled experimentation, and computational modeling. It was an eye-opener on how complicated even the simplest of human behaviors could be, as well as the beginning of a long foray into developing and using computational models in this arena.

Of course, as I later discovered, there's a long history of this, perhaps going as far back as the 1880s with Ernst Mach and his pioneering work in visual and vestibular psychophysics and certainly at least the 1940s to Norbert Wiener with his introduction of cybernetics and the mathematical modeling of both humans and machines. Since then, many other disciplines have contributed and elaborated on this idea, from the basic sciences of neurophysiology and cognitive science to the more applied efforts in human systems engineering and robotics. Moving into the domain of computational representation has forced many of us to sharpen our approach to describing behaviors, formalizing our theories, and validating them against *real* data. As one of my mentors once told me (and I paraphrase a bit here): "The rubber hits the road when you start hacking code."

This movement by the research community has been documented in a number of efforts. In 1998, the National Research Council (NRC) published a review of potential models that might be usefully embedded in existing military simulations to provide greater realism by including the *human*

element (National Research Council 1998). The report concluded that there was no single framework or architecture that could *meet all the simulation needs of the services*, but it did provide an extensive review of computational behavioral models, in-depth discussions of different functional areas (e.g. attention, memory, learning, etc.), and considerations for small unit representation (i.e. groups of individuals). A follow-on NRC study in 2008 provided a somewhat broader review, covering models of not only individuals but also organizations and societies (National Research Council 2008). This study also discussed different categories of models – both formal and informal – and common challenges across the community (e.g. interoperability, inconsistent frameworks, verification, etc.). And, like almost all NRC reports of this ilk, there were a number of recommendations proposed, in this case, covering areas from basic theory development to data collection methods and tools for model building.

Although many insights from these and other studies remain relevant, much has happened in the last decade, in terms of new basic research results, new applications afforded by the acceleration of technology (particularly in sensing, networking, computation, and memory), and, not least, a resurgence of a general interest in natural and artificial cognition, with the recent reemergence of artificial intelligence and machine learning. For example, on the basic research side, a revolution in neuroimaging methods is linking the underpinning of human thinking – across individual and societal levels. On the applied side, masses of data on human behavior are now being collected to describe and predict activity in a huge variety of applications spanning everyday consumer devices, socio-commercial networks, and population monitoring systems installed by local and national governments, to name a few. Online populations can now support *crowd-sourced* and *A/B* experiments that drive how corporations interact with their customers and governments with their citizens.

A reexamination of the issues addressed by the earlier studies is clearly called for, in light of what's happened over the last decade. This volume does just that and is a particularly welcome addition to the research community. It is structured to address issues of science, modeling, and relationships among theory, modeling, empirical research, and computational social science. It candidly emphasizes past shortcomings in these relationships and current progress that's been made in improving those relationships. One can sense a good deal of excitement among the contributors – both established researchers in their chosen fields and fresh PhDs – because so much is happening on so many fronts, including theory development, data collection, and computational methods of inquiry. It's also a delight to see chapters bringing to bear new insights from the study of nonhuman social systems, neuropsychology, psychology, and anthropology, among other disciplines. And, having spent much of my career concerned about real-world problems needing insights