Tradeoffs in Regulating Highly Automated Robot Ecologies

WEN SHEN, University of California, Irvine
ALANOUD AL KHEMIRI, Masdar Institute of Science and Technology
WAEL AL-ENEZI, Masdar Institute of Science and Technology
IYAD RAHWAN, Massachusetts Institute of Technology
JACOB W. CRANDALL, Masdar Institute of Science and Technology

Highly automated robot ecologies (HARE), or societies of independent autonomous robots, are rapidly becoming an important part of much of the world's critical infrastructure. These robot societies are strongly influenced by two major forces: individual robot control algorithms and regulation. On one hand, increasingly sophisticated control algorithms govern the behavior of individual robots in the society. On the other hand, a regulatory authority (typically a person or organization) is tasked with setting rules and incentives that promote system-wide stability and efficiency. In this paper, we work toward developing a theory for the regulation of HARE by studying how regulatory power and algorithmic sophistication jointly impact regulability. Via user studies and theoretical analysis, we identify a non-linear interaction between these factors. Our analysis indicates that HARE with limited regulatory power and simple (unsophisticated) robot control algorithms tend to best meet societal objectives. These outcomes have important implications on the design and regulation of HARE.

CCS Concepts: •**Computing methodologies** → **Multi-agent systems; Intelligent agents;** *Computational control theory;* •**Computer systems organization** → **Robotic autonomy;** •**Human-centered computing** → *Empirical studies in HCI;*

Additional Key Words and Phrases: Human-robot ecologies, regulation, robot swarm

1. INTRODUCTION

As robotics advances, much of the world's critical infrastructure is becoming dependent on highly automated robot ecologies (HARE). HARE consist of many independent and autonomous robots, each of which is given goals and control algorithms by its stakeholder. Examples include (1) transportation systems comprised of driverless cars, (2) networks of robotic buildings (designed to preserve water and electricity resources), and (3) some forms of robot swarms [Kolling et al. 2016; Brown et al. 2016] used for law enforcement, waste disposal, national defense, etc.

Robot behavior in HARE is strongly influenced by at least two major forces: robot control algorithms and regulation. Each autonomous robot in the society is equipped with a control algorithm that dictates its behavior. Financial incentives and other performance objectives often drive stakeholders to equip their robots with increasingly sophisticated and adaptive control algorithms [Amin 2000; Wang 2008; Mitchell 2004]. These algorithms are designed to maximize the benefits of individual stakeholders rather than societal objectives. As a result, HARE often fail to achieve socially desirable outcomes. The extent to which they fall short of desirable societal outcomes is captured by the notion of the *price of anarchy* [Koutsoupias and Papadimitriou 1999; May and Arinaminpathy 2010; Heldane and May 2011].

Regulatory authorities are charged with setting rules and incentives that promote system-wide stability and efficiency. For example, a transportation authority assigned to regulate groups of driverless cars could use road structure, signals, and penalties and incentives (e.g., tolls or ticketing) to promote efficient and safe traffic flow. Regulators of new-age power systems could use contracts [Meade and O'Connor 2009], information-based interventions

Author's addresses: W. Shen, Department of Informatics, University of California, Irvine; email: wen.shen@uci.edu; A. A. Khemiri, W. Al-Enezi, and J. W. Crandall, Department of Electrical Engineering and Computer Science, Masdar Institute of Science and Technology; email: jwcrandall@gmail.com; I. Rahwan, Media Lab, Massachusetts Institute of Technology; email: irahwan@mit.edu.

Table I. Example HARE

System	Regulator	Robots	Stake-holders	Algorithms
Transportation systems comprised of driverless cars	Transportation authority	Driverless cars	Passengers	GPS navigation systems, which use multiple data (e.g., maps, sensor data, incentives and penalties, historical data, etc.) as input to a routing algorithm. The routing algorithm computes a path to the passenger's desired destination.
Networked robotic buildings	Utility company	Robotic (smart) buildings	Building inhabitants	Autonomous control algorithms that schedule the activities, many of which require water and electricity, of building occupants. The scheduling algorithm used by a robotic building is designed to maximize its occupants' utilities, including minimizing costs paid to the utility company.
Robotic swarms	Robot operator	Mobile robots	Variable	Typically, these robots use simple stimulus-response algorithms, though more sophisticated algorithms could be used. The robots may respond differently to the same stimuli, as they have different response thresholds and possibly different goals.

[Schultz et al. 2007], and real-time pricing [Borenstein et al. 2002] to influence robotic buildings to reduce peak consumption and match electricity demand to supply. In each case, the extent of jurisdiction and resources given to the regulatory authority (i.e., *regulatory power*) impacts its ability to influence the HARE to meet societal objectives.

The trend toward HARE marks a shift in how humans manage autonomous systems. Whereas traditional robotics systems (for space exploration, national defense, etc.) have had master-slave relationships in which the robots are bound to follow human directives, regulators of HARE have no such assurances. Since the robots are governed by individual stakeholders (and not by the regulator), a regulator can only loosely influence their behavior through the regulations they can initiate and implement. This distinction between HARE and traditional supervisory control systems appears to bring the problem of regulating HARE in close proximity with the challenge of governing human society, though robot societies likely respond very differently to regulations than do human societies.

HARE can potentially be improved to better serve society via better regulation or better robot control algorithms. In this paper, we study how the amount of regulatory power given to the regulator and the degree of algorithmic sophistication given to the robots jointly impact the regulability of HARE. To do this, we discuss two user studies in which participants, acting as the regulator, designed interventions for two different HARE given various levels of regulatory power and algorithmic sophistication. We combine observations from these studies with theoretical analysis to hypothesize general principles regarding the regulability of HARE.

Our findings help inform the design of HARE in at least two ways. First, they shed light on how much regulatory power should be given to regulatory authorities. Second, they highlight how incentive structures can negatively impact our abilities to regulate HARE in the future. Incentives that encourage stakeholders to equip robots with sophisticated control algorithms are likely to make HARE difficult to regulate.

2. HIGHLY AUTOMATED ROBOT ECOLOGIES (HARE)

We define HARE as systems having two components:

(1) *A collection of independent, autonomous robots:* The (possibly networked) robots either share limited resources or participate in the same group activity. Each robot is

Table II. Systems that are similar to HARE, but differ in at least one important way

System	Regulator	Autonomous Entities	Distinctions from HARE
Supervisory control of multiple robots (e.g., [Chen et al. 2011; Zheng et al. 2014])	Operator	Robots or unmanned vehicles	In traditional supervisory-control systems, the unmanned vehicles operate at a lower level of automation [Sheridan and Verplank 1978] than fully autonomous. The regulator can override the process of the unmanned vehicles and/or directly set or alter their goals. Operators have no such luxury in HARE.
Financial markets	Financial governing body (e.g., SEC)	Algorithmic trading software	The autonomous entities in the system are primarily software systems rather than robots. They do not have a physical presence.
Human society	Governments	People	The autonomous entities in the system are people rather than robots. Since people appear to employ different control algorithms than robots, these systems likely differ from HARE with regard to their behavioral dynamics.

supplied and controlled by a different stakeholder, who often has different goals than the regulator.

(2) *A regulatory authority:* The regulator, comprised of an individual or organization, is tasked with regulating robot behavior to ensure that societal objectives are met. In HARE, the regulatory authority can be multiple entities who share the same goals and influence the robots' behavior through distributed cooperative interventions. Such case is beyond the scope of this paper where we assume that the regulatory authority is a single party.

A defining feature of HARE is that the regulator does not own or control the robots. As such, the robots' intents and processes are unknown to the regulator *a priori*. In essence, from the perspective of the regulator, each robot operates at the highest *level of automation* [Sheridan and Verplank 1978] (fully autonomous) in all cases. The regulator cannot intervene in the robots' processes or change the robots' goals. It can only engineer the environment in which the robots operate. Example HARE are listed in Table I.

HARE are similar in many respects to several known and existing kinds of systems, though they differ from these systems in important ways. Three such systems are listed in Table II. Some lessons learned in the study of these systems may also apply to the regulation of HARE. For example, situation awareness [Endsley 1988] and operator workload may have similar impact on supervisory control systems as they do on the regulation of HARE. Likewise, lessons learned in the study of HARE could potentially apply to these systems.

Theoretically, HARE fall into the broad category of multi-agent systems [Shoham and Leyton-Brown 2008], where both the regulatory authority and the robots are autonomous entities with different goals and diverging decision-making processes. Each robot acts as driven by a control algorithm representing the interests of its stakeholder, while the regulator is mandated to achieve societal objectives.

3. REGULATING HARE

When each robot seeks to satisfy its own (individual) goals, collective behavior is typically thought to converge to an equilibrium solution (e.g., a Nash equilibrium [Nash 1950]). However, this solution may not be efficient with respect to societal objectives [Koutsoupias and Papadimitriou 1999; May and Arinaminpathy 2010; Heldane and May 2011]. The regulatory authority is tasked with engineering the environment so as to encourage the robots to act cooperatively. This can be done by either influencing the robots to converge to an alternative (and more efficient) equilibrium solution or to alter the scenario so that it has a unique, more efficient equilibrium. This later problem is that of mechanism design [Hurwicz and Reiter 2006].

The centrality of mechanism design is to implement strategy-proof mechanisms (or payment schemes) that incentivize agents to truthfully reveal their private information [Hurwicz and Reiter 2006; Nisan et al. 2007]. Mechanism design has been applied to many domains such as power grids [Vytelingum et al. 2010], financial markets [MacKie-Mason and Wellman 2006] and transportation systems [Zhang and Pavone 2016; Shen et al. 2016]. Unfortunately, such mechanisms do not always exist, especially in online environments and dynamic settings [Nisan et al. 2007; Pavan et al. 2009; Parkes and Singh 2004]. Due to constraints such as computational complexity and privacy concerns, incentive-compatible mechanisms may not be implementable even if they do exist in theory [McSherry and Talwar 2007; Nisan and Ronen 1999; Feigenbaum and Shenker 2002]. Besides, traditional mechanism design approaches require prior knowledge such as the agents' state and action spaces [Hurwicz and Reiter 2006; Nisan et al. 2007]. However, in reality, regulators of HARE do not have sufficient information *a priori* to design efficient mechanisms (i.e., *interventions*). Moreover, it might be expensive or even unfeasible to obtain necessary information through auctions or similar revealed-preference mechanisms due to data unavailability and time constraints [Myerson 1981; Trigo and Coelho 2011]. Therefore, the regulatory authority must experiment with interventions in real time to identify which interventions will produce desirable outcomes for society. Such tasks are analogous to a class of restless multi-armed bandit problems with unknown dynamics, which are NP-hard [Gittins et al. 2011; Bubeck and Cesa-Bianchi 2012].

The degree to which the regulator develops interventions through this process that meet societal objectives constitutes the *regulability* of the system. Formally, let Φ be the set of possible collective robot behaviors and let $\phi' \in \Phi$ denote the collective robot behavior present in society. Then,

$$regulability = \frac{f(\phi')}{\max_{\phi \in \Phi} f(\phi)}, \tag{1}$$

where $f(\phi) > 0$ is the society's social welfare given collective robot behavior ϕ. Higher values of regulability indicate societies in which societal goals are being met at greater levels.

Regulating complex networks has recently been at the heart of an ongoing discussion [Liu et al. 2011; Ruths and Ruths 2014; Beale et al. 2011; Arinamingpathy et al. 2012], much of which has focused on *controllability*. A system is said to be controllable if there exist time-varying control strategies that move it from any initial state to any other state [Ogata 1997]. Despite its importance, controllability is an insufficient condition for *regulability*, which refers to the ability of regulators to actually select effective control strategies (i.e., *interventions*). Since regulators of HARE do not typically have full knowledge of the goals and algorithms used by the robots, they may fail to find effective interventions even when they exist. Thus, in this paper, we focus on the regulability, rather than the controllability, of HARE.

Regulability depends on several factors such as the frequency of the decision-making process [Vespignani et al. 2009; Johnson et al. 2013], and the switching processes of system states [Preis et al. 2011]. In this paper, we study the impact of two factors on regulability: regulatory power and algorithmic sophistication. We discuss each in turn.

3.1. Regulatory Power

The jurisdiction and resources given to the regulatory authority to carry out its intended functions define *regulatory power*. Regulatory power determines the kinds of interventions the regulator can create and implement. For example, local laws determine whether a transportation authority is allowed to charge tolls, how or in what manner it can change these

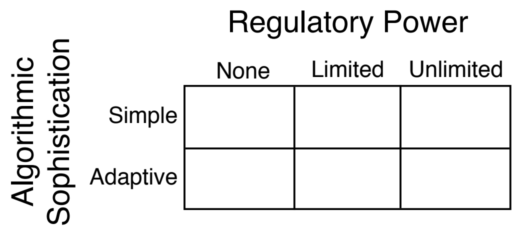


Fig. 1. We conducted two user studies, each using a 2x3 between-subjects design, to investigate how regulatory power and algorithmic sophistication jointly impact the regulability of HARE.

tolls, and how it can enforce payment of tolls. Furthermore, monetary resources impact the kind of toll systems the transportation authority is able to implement and maintain. Similarly, a utility company seeking to modulate the behavior of robotic buildings is limited by laws and resources. These laws and resources govern, among other things, the kinds of information the utility can collect and the pricing incentives it can successfully implement.

In this paper, we consider regulatory authorities who use monetary incentives to influence robot behavior. One important aspect of regulatory power in such cases is the regulator's ability (defined via laws and resources) to change prices over time. As a starting point, we assume that the regulatory authority consists of a single person. Future work should explore whether these results hold for regulatory authorities consisting of groups of people, as well as regulators aided by computational tools.

3.2. Algorithmic Sophistication

In general, it is difficult to quantify the sophistication of an algorithm. Algorithms differ along many dimensions, and may appear complex or simple based on perspective. Important dimensions include the data sources utilized by the algorithm, the depth of reasoning employed by the algorithm, and the adaptivity of the algorithm. In this paper, we study how regulability is impacted by the ability of the robots to learn from past experiences. We refer to algorithms that do not adapt as *simple automation*, and to those that do adapt based on past experience as *adaptive automation*. Thus, in this paper, we use the term *algorithmic sophistication* to refer to the robots' abilities to adapt to past experiences.

4. CASE STUDIES

To begin to understand how regulatory power and algorithmic sophistication jointly impact regulability, we conducted two user studies in which non-expert participants regulated simulated HARE. In the first study, participants used tolls to manage a simple transportation system composed of autonomous driverless cars. In the second study, participants regulated the consumption of a limited water supply. Both studies consisted of 2x3 between-subjects designs in which we varied algorithmic sophistication and regulatory power (as shown in Fig. 1) to determine how these factors jointly impact regulability.

The simulated HARE studied in these studies are rather simple – they do not necessarily capture the full dynamics of real-world HARE. However, these HARE do emulate the basic components of real-world HARE, thus providing a starting point for us to investigate how regulatory power and algorithmic sophistication jointly impact regulability.

4.1. User Study 1 – Regulating Driverless Cars

4.1.1. Scenario. Simulated driverless cars (i.e., the robots) used routing algorithms to navigate through the simple transportation network shown in Fig. 2. The regulatory authority was tasked with regulating the driverless cars in a way that maximized traffic flow through the network, which was measured as the throughput. Here, throughput refers to the average

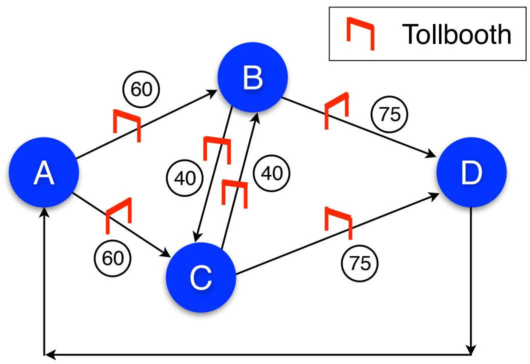


Fig. 2. A simple transportation network utilized by 300 driverless cars. Capacities (C_{ij}) for each road are specified by the circled numbers. $C_{DA} = 300$.

number of cars that have passed through Node D per unit time since the system starts. To do this, the regulator needed to keep the network congestion-free.

Congestion on a road occurred when the number of cars on the road exceeded the road's capacity. The speed of the cars on road ij was proportional to:

$$V_{ij} \propto \frac{1}{1 + e^{0.25(N_{ij} - C_{ij})}} + 0.1 \tag{2}$$

where C_{ij} and N_{ij} were the capacity and the current number of cars on road ij, respectively. Thus, as traffic volume reached the road's capacity, traffic flow slowed substantially.

To influence the cars' decisions, the regulatory authority set tolls on each road via the GUI shown in Fig. 3. The regulator might need to observe the traffic status and the aggregate behavior of simulated cars in the transportation network. Based on observation and interaction with the cars, the regulatory authority was expected to establish models of the HARE and determine effective intervention mechanisms. The regulator might choose to charge relatively high tolls to cars who entered the roads with heavy traffic and collect less to those who select the roads with less congested traffic. Take the network shown in Fig. 2 for example, if road $\vec{BC}$ is overcrowded, a regulator might have the following options to reduce the traffic congestion: increasing the tolls on road $\vec{BC}$, decreasing the tolls on road $\vec{BD}$, increasing the tolls on road $\vec{AB}$, decreasing the tolls on road $\vec{AC}$ or combinations of these methods. By properly balancing the tolls on each road, the regulator was expected to induce the traffic flow to quickly pass through node D so that high throughput could be achieved.

The tolls were announced instantaneously to all of the cars. Initially, tolls on all roads were set to \$0.50. Participants were allowed to increase or decrease each of the tolls as desired (between the values of \$0.00 and \$0.99) by clicking on the corresponding buttons. Participants could click the buttons in succession to quickly make large toll adjustments.

The GUI showed a bird's-eye view of the transportation network, with the current location of each of the 300 cars clearly marked. The GUI also displayed indicators showing the number of cars currently on each road, as well as the capacity of the roads.

Each simulated car received payoffs for arriving at its chosen destination and incurred costs for traversing roads. Formally, the utility for going to node g from node i was given by:

$$u(i, g) = v(g) - c(i, g)\,, \tag{3}$$

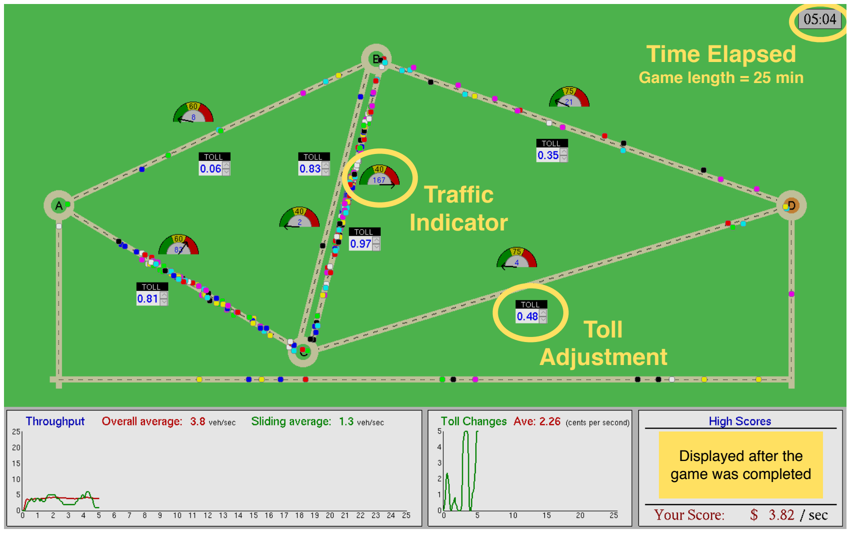


Fig. 3. Screen capture of the user interface used in the transportation scenario. Annotations (in yellow) are overlaid for descriptive purposes.

where $v(g)$ was the payoff received for arriving at node g and $c(i, g)$ was the cost the car incurred for moving to node g from node i. The control algorithm selected destinations (nodes) and routes in attempt to maximize a car's utility. Once a car reached its destination, it immediately selected a new destination. Specifically, the new destination g^* was targeted using the following equation:

$$g^* = \arg\max_{g \in N} u(i, g)\,, \tag{4}$$

where N was the set of nodes in the transportation network.

Note that each time the car reached its currently selected goal, the payoff $v(g)$ for arriving at each node $g \in N$ was re-established by drawing a sample from a normal distribution. The distributions were selected uniquely for each node and each simulated car at the beginning of the game. The cost for traversing each road was also re-estimated. This was done differently according to the levels of algorithmic sophistication used by the societies of the simulated cars. The details will be described in the next subsection.

4.1.2. Experimental Setup. Initially, a total of 300 simulated cars were randomly allocated to the four nodes in the transportation network illustrated in Fig. 2. Each car used a navigation algorithms to determine how to navigate through the network.Two different control algorithms, which differ in their level of algorithmic sophistication, were adopted in this study. The details of these two navigation algorithms are given in Table III. Both navigation algorithm estimated the costs of traversing a road as the operating cost plus the current toll. The algorithms then used Dijkstra's algorithm to determine (in combination with the passenger's payoffs, which were generated randomly in advance) a destination and the least-cost route for getting there.

The two navigation algorithms differed only in the way that they estimated operating costs. Cars given simple automation estimated the time required to traverse a road (an important aspect of the operating cost) under the assumption that no congestion was present in the network. That is, they did not learn from past experiences to update estimated time costs. On the other hand, cars with adaptive algorithms used reinforcement learning, based on their past experiences, to estimate the time required to traverse a road. Different cars were

Table III. Cost estimations for traversing road ij

Level	Cost Estimation
Simple automation	$c_{ij}^t = y \cdot (D_{ij}/L_{ij}) + \tau_{ij}^t$ - D_{ij} was the length of road ij - L_{ij} was the speed limit on road ij - y was the operating cost per unit time - τ_{ij}^t was the toll on road ij at time t
Adaptive automation	$c_{ij}^t = y \cdot x_{ij} + \tau_{ij}^t$, where Initialize: $x_{ij} = D_{ij}/V_{ij}$ Whenever the robot traverses road ij, update: $x_{ij} = \alpha x_{ij} + (1-\alpha)z$, where - $\alpha \in [0,1]$ was chosen randomly for each car - z is the observed time to traverse road ij

Table IV. Factor levels for regulatory power

Level	Description
None	No regulatory authority. No participants needed
Limited	Participants were given a budget limiting the amount of toll changes they could make. The absolute value of each toll change was subtracted from the budget. Initially, participants were given a toll-change fund of \$0.30. This fund increased by \$0.007 in each second. Thus, the total toll-change fund was \$10.80 in a 25-minute game.
Unlimited	Participants were free to change tolls as often and as much as they desired

equipped with different learning rates specified by the parameter α, which was generated randomly for each car.

We consider three factor levels for regulatory power: none, limited and unlimited (see Table **??**). When the regulatory authority was equipped with limited regulatory power, she had a total toll-change fund of \$10.80 in a 25-minute game, compared with an unlimited toll-change fund when she was provided with unlimited regulatory power.

4.1.3. Protocol. Forty-eight graduate students and researcher staff at Masdar Institute of Science and Technology in Abu Dhabi, UAE participated in the study. Note that we recruited non-expert participants (with no or little domain knowledge on traffic management) only in order to eliminate the effect of expertise on the experiments. Each participant experienced the following:

— The participant was randomly assigned to one of the four conditions: Simple-Limited, Adaptive-Limited, Simple-Unlimited, or Adaptive-Unlimited. Twelve participants were assigned to each condition.
— The participant was trained on how to play the game using the assigned regulatory power (limited or unlimited). As part of this training, the participant experimented with the interface while the cars chose routes randomly.
— The participant played a 25-minute game. Initially, cars were randomly placed on the nodes, which immediately caused congestion to develop on several roads. Thus, participants needed to move the system to a congestion-free state as quickly as possible. Cars were biased so that more of the cars preferred node C as a destination. To encourage participants to perform well, a high-score list was maintained and displayed once the game was completed.
— The participant completed a post-experiment questionnaire, which asked which node more cars preferred and whether the cars employed learning algorithms or not.

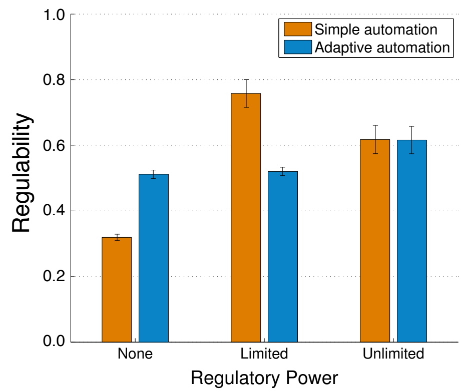


Fig. 4. Average regulability observed in user study 1 (regulation of driverless cars). Error bars show the standard error on the mean.

As part of this study, an additional twelve trials for both the Simple-None and Adaptive-None conditions were carried out. These trials did not require any human subjects. During each game, the data was recorded every 0.5 second for data analysis.

4.1.4. Results. The average regulability (Eq. 1), measured as a proportion of optimal throughput, achieved by participants is shown in Fig. 4. In the absence of regulations, societies of robots equipped with adaptive automation performed much better than those composed of robots using simple automation. However, limited regulatory power reversed this trend. Limited regulatory power led to vastly better outcomes for societies composed of simple robots, but had no impact on societies comprised of adaptive, more sophisticated, robots. While additional (unlimited) regulatory power improved the efficiency of adaptive societies by a small amount, additional (unlimited) regulatory power actually decreased the efficiency of societies comprised of simple robots.

An analysis of variance, where regulability is the dependent variable and algorithmic sophistication and regulatory power are the independent variables, confirms many of these trends. The analysis shows a main affect for regulatory power, $F(1, 66) = 30.47$, $p < 0.001$, but not algorithmic sophistication, $F(2, 66) = 0.32$, $p = 0.572$. There was also a statistically significant interaction affect between algorithmic sophistication and regulatory power, $F(2, 66) = 23.15$, $p < 0.001$. Tukey post hoc analysis shows that simple automation with no regulation was worse than all other conditions ($p < 0.001$), while simple automation with limited regulatory power was better than all other conditions ($p <= 0.03$ for each pairing). Regulatory power had no statistically significant impact on societies of robots that all used adaptive automation.

When the transportation system was congested, Pearson's r correlation (Pearson product-moment correlation coefficient) tests[1] indicated that there was a very strong negative relationship between the regulatory power used and the regulability in the simple automation with unlimited regulatory power scenario ($r(10) = -0.82, p = 0.001$). Nevertheless, it did not necessarily mean that increasing regulatory resources would cause a decline in the regulability of such systems. Instead, we conjectured that excessive resources might divert a regulator's attention away from modeling the system and devising intervention mechanisms. Regulators were prone to put more effort on the implementation of regulations than modeling the systems and making delicate plans for the intervention. Consequently, the regulators

[1]We used the same interpretation of the size of a correlation as Ahlgren et al. [Ahlgren et al. 2003] : None (-0.09 to 0.0), Weak (-0.3 to -0.1), Moderate (-0.5 to -0.3), Strong (-0.7 to -0.5), Very Strong (-1.0 to -0.7)

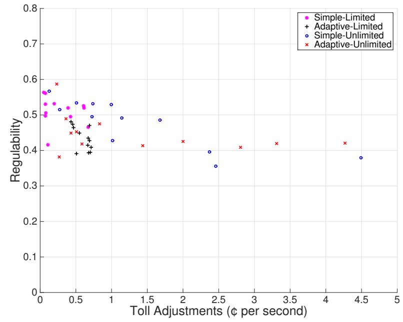


Fig. 5. The correlation between the regulatory power used (denoted as toll adjustments) and the regulability for the time periods when there was congestion.

with unlimited regulatory power were less likely to bring about high system performance than those with limited resources (see Fig. 5). Our results indicated that participants were most probable to succeed when they regulated societies of cars equipped with simple algorithms while provided with rather limited regulatory power.

In summary, societies consisting of robots with simple automation were more efficient when participants were given limited regulatory power. Additional regulatory power reduced societal efficiency. Regulation had little impact when robots used adaptive automation.

4.2. User Study 2 – Regulating Robotic Buildings

4.2.1. Scenario. Eight (simulated) tenants of an apartment building shared a limited water resource. Each tenant's apartment was equipped with sensing and robotic devices that scheduled and executed water-related activities (laundry, dish-washing, plant-watering, etc.) on behalf of the tenant. A tenant programmed its own robotic scheduling devices to execute activities automatically using a control algorithm. Water supplied to the building was collected and then purified via a renewable energy resource, a slow process that limited water availability such that water needs exceeded water supply. A simulated day was divided into six time periods.

The water needs of each tenant were defined by a set of activities. Activity i was defined by the 4-tuple $(t_s(i), t_f(i), s(i), v(i))$, where the time interval $[t_s(i), t_f(i))$ defined the time window during which activity i could be executed, $s(i)$ was the amount of water consumed by activity i, and $v(i)$ was how much the tenant valued the completion of activity i. The utility received for carrying out activity i was given by the following:

$$u(i) = v(i) - c(i)\,, \tag{5}$$

where $v(i)$ was the predefined payoff for performing activity i, and $c(i)$ was the cost given by $c(i) = s(i)p(t)$. Here, $p(t)$ was the per-unit cost of water set by the regulator in period t.

The regulator's job was to set the per-unit cost of water for each time period each day in such a way that the aggregate utility across all tenants, days, and periods was maximized. Participants set prices using the GUI pictured in Fig. 6, which, in addition to allowing participants to change prices, displayed the current water level, the amount of water consumed per period, the number of tasks shed by the robotic devices (color-coded to indicate the value of tasks), and the aggregate and individual happiness of the tenants.

4.2.2. Experimental Setup. As before, we considered two societies: societies in which robot devices used simple algorithms and societies in which devices used adaptive algorithms to schedule activities. As shown in Table V, simple (non-adaptive) algorithms simply executed activity i when it was active, water was available, and $u(i) > 0$. On the other hand, adaptive

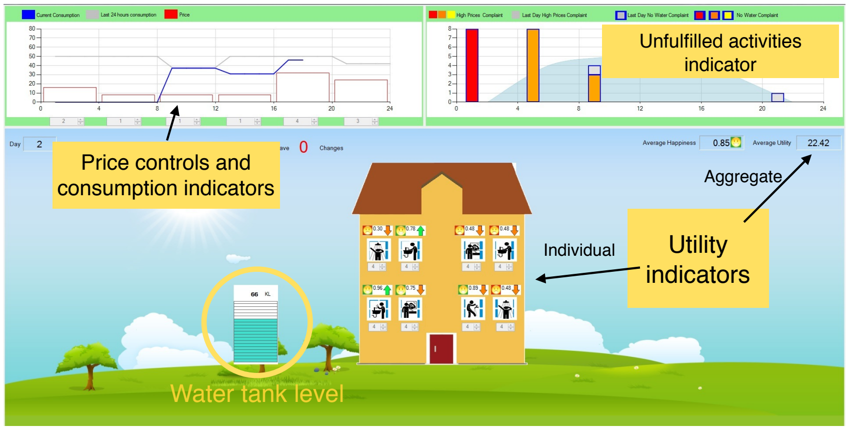


Fig. 6. Annotated screen-shot of the GUI used in user study 2.

Table V. Decision making process on water consumption

Level	Decision Making Process
Simple automation	If $u_i > 0$ and $L > 0$, the tenant consumed water for scheduled activity i; otherwise, the tenant did not consume water. No activity shifting in this case - u_i was the utility received for performing activity i - L was amount of water available to the tenant
Adaptive automation	Initialize: use the same method as simple automation From day 2, the tenant switched to activity i that maximized the expected utility $\hat{u_i}$: $i = \arg\max_{i \in I} \hat{u_i}$ That is, $i = \arg\max_{i \in I}(v(i) - s(i)\hat{p_d(t)})$ Update $\hat{p_d(t)} = \frac{1}{d-1}\sum_1^{d-1} p_{d'}(t)$ where: - $d \in [2, 30]$ was the observed day - $\hat{p_d(t)}$ was the estimated unit cost in t of day d - $p_{d'}(t)$ was the observed unit cost in t of day d' - I was the set of available activities where $s(i) \leq L$ - L was the amount of water available to the tenant

algorithms shifted the tenants activity schedules based on the estimated water supply and price at each time period, which they learned using observations from previous days. That is, adaptive devices shifted the tenant's activity schedule to maximize individual expected utility based on estimated prices and estimated water availability.

As in the previous study, we evaluated the impact of both limited and unlimited regulatory power. Given unlimited regulatory power, participants were allowed to change prices whenever and however they desired. However, given limited regulatory power, participants could only change three prices per day (by a single increment) across all time periods (see Table VI for comparison).

4.2.3. Protocol. Forty students and research staff, with a mean age of 26 and little or no knowledge of water management, from Masdar Institute volunteered for the study. The following protocol was followed for each participant:

Table VI. Factor levels for regulatory power

Level	Description
None	No regulatory authority. No participants needed
Limited	Participants were allowed to change prices three times per day (by a single increment) at maximum across all time periods
Unlimited	Participants were free to change prices as often and as much as they desired

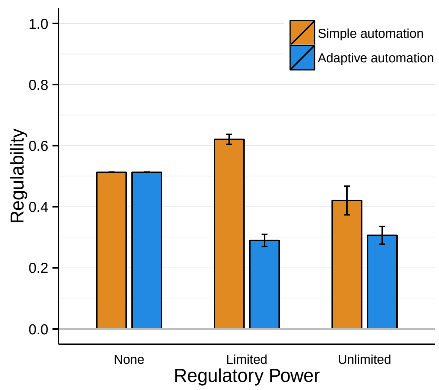


Fig. 7. Regulability during days 26-30 in user study 2 (water management). Error bars show the standard error on the mean.

— The participant was randomly assigned to one of four conditions (Simple-Limited, Simple-Unlimited, Adaptive-Limited, Adaptive-Unlimited). Ten subjects were assigned to each condition.
— The participant was taught, via a slide presentation, how to play the game in the assigned condition. The participant then played the game in a practice scenario in which robot devices made choices randomly.
— The participant played a simulated 30-day game.

As part of this study, an additional ten trials for both the Simple-None and Adaptive-None conditions were carried out. These trials did not require any human subjects.

4.2.4. Results. In this scenario, regulability (Eq. 1) is defined with respect to the aggregate utility achieved by the tenants in the last five simulated days. The average regulability achieved in the study in each condition is shown in Fig. 7. Interestingly, in the absence of regulations, societies of adaptive robots did not perform any better than societies of simple robots. However, as in the first study, limited regulatory power produced higher social welfare in the case of simple automation. Additional (unlimited) regulatory power likewise produced lower aggregate utility than limited regulatory power in the case of simple automation. Both limited and unlimited regulatory power led to substantially lower regulability when robots used adaptive algorithms.

Statistical analysis confirms these trends. A two-way ANOVA, with regulability as the dependent variable and algorithmic sophistication and regulatory power as the independent variables, shows a main affect for both regulatory power, $F(1, 54) = 18.39$, $p < 0.001$, and algorithmic sophistication, $F(1, 54) = 53.53$, $p < 0.001$. There was also a statistically significant interaction affect between algorithmic sophistication and regulatory power, $F(2, 66) = 22.91$, $p < 0.001$. Tukey post hoc analysis shows that, when robots used simple automation, limited regulatory power led to a statistically significant increase in regulability over no regulatory power ($p = 0.037$) and unlimited regulatory power ($p < 0.001$). Simple-Limited was also statistically better than Adaptive-Limited and Adaptive-Unlimited ($p < 0.001$), Simple-Unlimited was better than Adaptive-Unlimited ($p = 0.023$). Finally, limited and unlimited regulatory power led to decreased performance for societies of adaptive robots ($p < 0.001$).

5. PRINCIPLES FOR THE REGULATION OF HARE

While the outcomes of the two studies were not identical, HARE with simple robot control algorithms and limited regulatory power were the most effective systems (of those considered) in both studies. To better understand this phenomena and to determine whether we would expect this result to repeat in other HARE, we begin to formulate a theory to describe how regulatory power and algorithmic sophistication jointly impact regulability. The theory takes the form of several principles, which can inform the design and regulation of HARE.

Our analysis begins with a study of the role of the regulator.

5.1. The Role of the Regulatory Authority

The regulatory authority must perform three tasks:

(1) *Model robot behavior.* The regulator must model the robots' collective behavior in various situations. Formally, a situation consists of the current state of the system at time[2] t (denoted s_t) along with the history of interventions (denoted $h_t = (i_0, \cdots, i_{t-1})$) the regulator has implemented up to time t. Here, i_k is the intervention carried out at time k. Let $\mathcal{M}_t(s, h, i)$ describe how the regulator thinks the robots will react when the regulator issues intervention i given system state s and history of interventions h.
(2) *Plan interventions.* Given $\mathcal{M}_t$, s_t, and h_t, the regulator must determine the intervention i_t, which is drawn from the set of possible interventions, denoted $\Psi(s_t)$.
(3) *Implement interventions.* After selecting intervention i_t, the regulator must implement it.

The three tasks work together synergistically. An effective model of the robot society tends to lead to more effective interventions, while effective planning and implementation of interventions impact the quality of the regulator's model.

The regulator divides its time and resources among the three tasks. Inadequate or excessive attention to any of the tasks is likely to lead to ineffective management of the HARE (Fig. 8). For example, if the regulator spends too much time implementing regulations, less time will be available to model robot behavior and plan interventions. As a result, the regulator may act without proper understanding of the robot society, which could lead the regulator to create ineffective interventions.

In the remainder of this section, we study how regulatory power and algorithmic sophistication jointly impact (1) the *attentional requirements* of each of the three tasks, and (2) the *behavioral tendencies* of people acting as regulators.

5.2. Attention Requirements

Algorithmic sophistication and regulatory power impact the attentional requirements placed on the regulator. In this section, we discuss three principles relating algorithmic sophistication and regulatory power to these attentional requirements.

5.2.1. HARE with higher algorithmic sophistication require more modeling time. Since many variables about the HARE (e.g., the robots' utilities and algorithms) are unknown *a priori* to the

[2]For simplicity, we assume that time is divided into discrete time periods, the length of which can be as small as necessary.

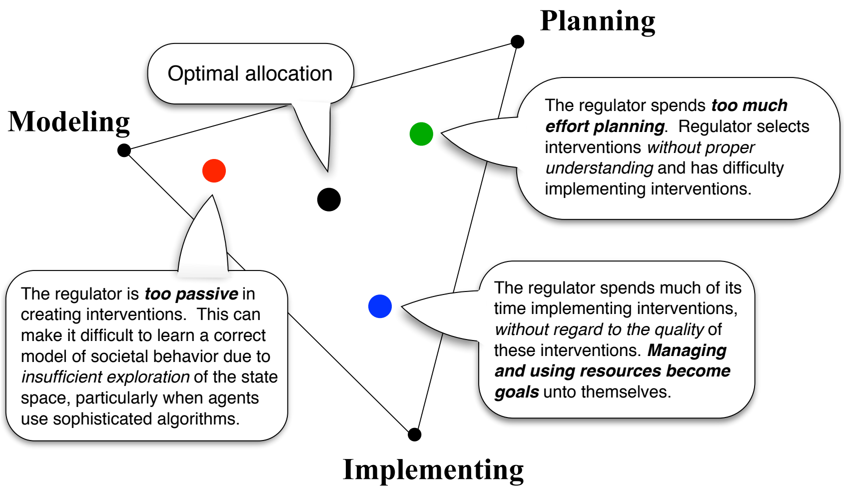


Fig. 8. The regulatory authority divides its attention among its three tasks. Inadequate or excessive attention to any task often leads to ineffective interventions. Points depicted in the probability simplex are conceptual.

regulator, the regulatory authority must formulate a model of robot behavior ($\mathcal{M}_t(s, h_t, i)$) via observations of robot behavior after interventions are issued. Each observation consumes some of the regulatory authority's time and resources.

Algorithmic sophistication tends to alter the amount of attention that must be given to modeling in two ways. First, in line with the idea of neglect benevolence [Walker et al. 2012], algorithmic sophistication impacts how long the regulator must observe the robots' behavior after issuing or altering an intervention (Fig. 9). Simpler algorithms tend to react only to the interventions produced by the regulator, meaning that collective robot behavior will change relatively quickly after a new intervention is issued. On the other hand, more sophisticated (adaptive) algorithms first adapt to the new intervention, and then react to the reactions of other robots to the intervention, and so on. As such, the regulator must observe the robots' response to an intervention (before issuing a new intervention) for a longer time when robots' follow adaptive algorithms. This increases the amount of attention the regulator must give to modeling robot behavior.

Second, algorithmic sophistication impacts the number of observations that the regulator must make to form a good model of the robots. More sophisticated algorithms are typically more sensitive to changes in interventions and world state. As such, more points must be sampled to approximate the function $\mathcal{M}_t$. Furthermore, for any world state s, intervention history h_t, and intervention i, $\mathcal{M}_t(s, h_t, i)$ is typically created by a series of observations. When robots follow simple algorithms, less samples are needed to create a good estimate of $\mathcal{M}_t(s, h_t, i)$ since the behaviors produced by such algorithms are not highly stochastic. However, when robot behaviors are highly variable, more samples are needed. In general, we anticipate that adaptive algorithms are likely to have higher variability in behavior, and hence more samples are required to adequately measure $\mathcal{M}_t(s, h_t, i)$.

The underlying reasons for the two impacts of algorithmic sophistication are still unclear to us. However, one of them might be that societies with more sophisticated automation typically have a higher complexity (measured as entropy shown in Fig. 10) than those equipped with simple automation, while increased complexity requires additional modeling time [Conant and Ashby 1970].

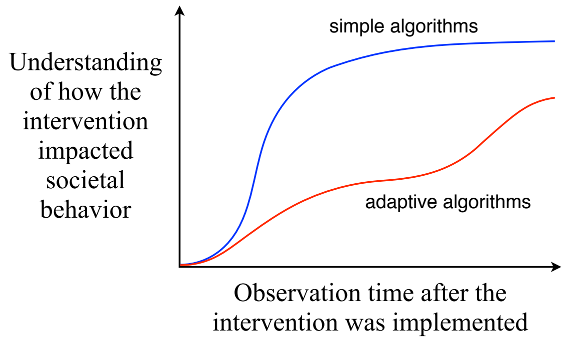


Fig. 9. To fully understand how an intervention impacts collective robot behavior, the regulator must refrain from issuing a subsequent intervention for time dependent on algorithmic sophistication. Plots are conceptual.

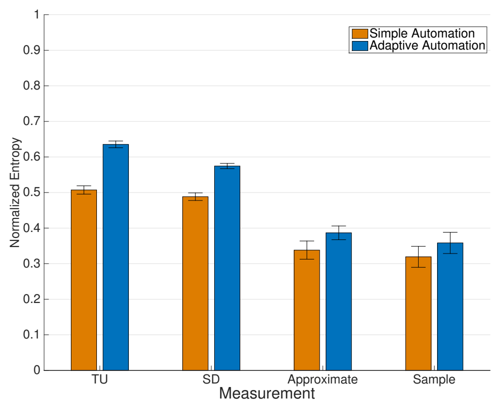
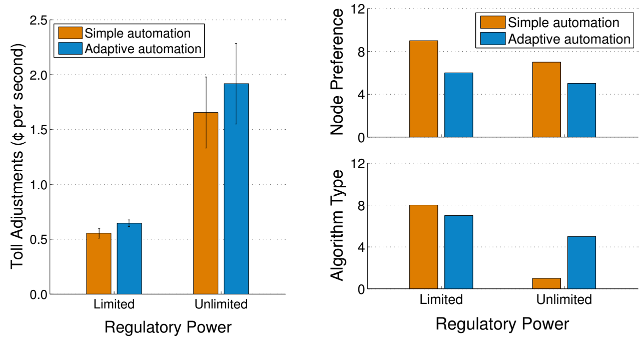


Fig. 10. Data from user study 1. Normalized entropy for societies equipped with simple automation and societies with adaptive automation: temporally uncorrelated (TU) entropy [Krumme et al. 2013], sequence-dependent (SD) entropy [Krumme et al. 2013], approximate entropy [Pincus 1991] and sample entropy [Lake et al. 2002]. Normalized entropy is computed by dividing the respective entropy by the logarithm of the number of different states occurred in a system. Higher entropy indicates higher complexity. Error bars show a 95% confidence interval of the mean. All the results suggested that systems with adaptive automation were more complex than systems with simple automation.

In summary, more sophisticated automation increases both (1) the number of required observations necessary to model robot behavior and (2) the amount of time required to take a single observation. Thus, more sophisticated robot control algorithms means a successful operator will need to spend more time in the modeling task.

5.2.2. HARE with higher algorithmic sophistication require more regulatory power. Increased modeling requirements introduced by higher algorithmic sophistication produce a need for more regulatory power. Since more sophisticated algorithms require more observations, more regulatory resources and time are required to obtain these observations. If the number of required observations grows too quickly with increased algorithmic sophistication, the amount of required regulatory power becomes prohibitive. This offers an explanation for



(a) (b)

Fig. 11. Data from user study 1. (a) The number of toll adjustments made per second. (b) The number of participants that correctly deduced the node most preferred by the cars and the algorithm type (learning or not learning).

why participants were unable to substantially improve societies of robots using adaptive automation in the user studies presented in the previous section (see Fig. 4 and Fig. 7).

5.2.3. Reduced regulatory power reduces planning requirements. Reduced regulatory power means that fewer interventions are possible (i.e., the size of the set $\Psi(s_t)$ is reduced). While this is limiting (since ideal interventions may not be possible), this smaller set of possible interventions has the advantage that the regulator does not need to consider as many possibilities. Thus, the amount of time the regulator must dedicate to planning is reduced, thus freeing up more time for modeling and implementing. This is particularly advantages in time-sensitive situations, as is often the case in HARE.

In summary, our study of the attentional requirements of the regulatory authority suggests that increased algorithmic sophistication in HARE generally makes the regulator's job harder, while reduced regulatory power appears to make it easier (at least with respect to time requirements).

5.3. Attentional Tendencies

In the previous subsection, we studied how algorithmic sophistication and regulatory power impact the attentional *needs* of the regulator. In this subsection, we analyze how regulatory power and algorithmic sophistication impact what people, acting as regulators, actually do with regards to attention allocation among the three tasks. To do this, we consider data from the first user study discussed in the previous section.

Fig. 11a shows the amount of toll adjustments made by participants per second in the first user study. The figure shows that substantially more toll adjustments were made given unlimited regulatory power. While additional toll adjustments appear to be justified in the case of adaptive automation, additional interventions were unnecessary when robots used simple automation. In fact, the results shown in Fig. 4 appear to indicate that such behavior was even harmful to social welfare.

During the user study, we observed that many participants in the Simple-Unlimited condition continually adjusted tolls. Rather than waiting to observe how the robots reacted to toll changes (see Fig. 9), they proceeding to make other toll adjustments when congestion did not immediately clear. As such, they were unable to effectively model robot behavior as manifested by the data shown in Fig. 11b. The figure shows that increased regulatory power led to poorer understanding of the destination most robots preferred (top graph) and whether or not the robots were learning (bottom graph).

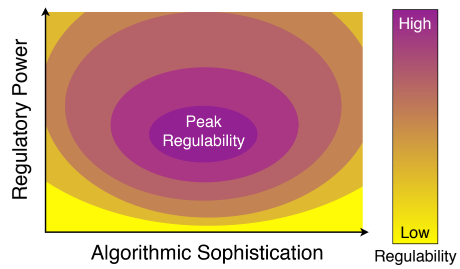


Fig. 12. Our working theory for how regulatory power and algorithmic sophistication tend to jointly impact regulability. Axes scales are not specified.

In summary, when participants had high regulatory power, they were drawn toward using it – they spent additional time implementing interventions in place of modeling and planning. Thus, participants failed to adequately model robot behavior, and therefore could not produce effective interventions.

6. CONCLUSION

Via user studies and an analysis of the tasks required of regulators, we have shown that both high regulatory power and adaptive (more sophisticated) automation can be harmful to the regulability of HARE. On the surface, these results seem counter-intuitive – better robot control algorithms and a greater ability to regulate both seem appealing. However, recent developments in financial markets, wherein sophisticated trading algorithms appear to be making these system unstable and uncontrollable [Beale et al. 2011; Arinamingpathy et al. 2012], support our observations.

Fig. 12 illustrates our working theory for how algorithmic sophistication and regulatory power tend to jointly impact regulability. The figure conveys the general idea that HARE are more efficient when (a) robots employ simple, yet sufficiently capable, algorithms and (b) the regulatory authority has limited regulatory power.

This research highlights a need for future work in several areas, of which we mention three. First, in this paper we considered just a single dimension of algorithmic sophistication: adaptability. Additional studies of how other dimensions of robot control algorithms (such as data availability and depth of reasoning) impact regulability are needed. Second, we assumed throughout this paper that the regulator consisted of a single person. In many HARE, the regulatory authority is much more complex, typically consisting of an organization composed of many people. These people often have access to complex modeling tools to help them predict robot behaviors, plan interventions, etc. Future work should consider how regulatory power impacts regulations created by such regulatory authorities. Third, we investigated how regulatory power and algorithmic sophistication jointly influence humans' ability to regulate HARE in the two case studies. In some scenarios, the implementation of interventions might be automated (which is also more desirable than manual implementation to some extent). However, it is unclear to us that how the limits of automated (or robotic) regulators affect the regulability of HARE.

With the advancement of robotic technologies, HARE are becoming a reality. As human society plans for these systems, it is important that we understand how these systems tend to behave so that we can ensure that they meet societal objectives. In this paper, we have begun to study how regulatory power and algorithmic sophistication jointly impact the regulability of HARE. These findings form a basis for a theory regarding the regulation of highly automated robot ecologies.

REFERENCES

Per Ahlgren, Bo Jarneving, and Ronald Rousseau. 2003. Requirements for a cocitation similarity measure, with special reference to Pearson's correlation coefficient. *Journal of the American Society for Information Science and Technology* 54, 6 (2003), 550–560.

S.M̃. Amin. 2000. Toward self-healing infrastructure systems. *IEEE Computer* 33(8) (2000), 44–53.

N. Arinamingpathy, S. Kapadia, and R.M̃. May. 2012. Size and complexity in model financial systems. *Proceedings of the National Academy of Science* 109(45) (2012), 18,338–18,343.

N. Beale, D.G̃. Rand, H. Battey, K. Croxson, R.M̃. May, and M.Ã. Nowak. 2011. Individual versus systemic risk and the Regulator's Dilemma. *Proceedings of the National Academy of Science* 108(31) (2011), 12,647–12,652.

S. Borenstein, M. Jaske, and A. Rosenfeld. 2002. *Dynamic Pricing, Advanced Metering and Demand Response in Electricity Markets.* Technical Report CSEM WP 105. UC Berkely: Center for the Study of Energy Markets.

D. S. Brown, M. A. Goodrich, S. Y. Jung, and S. Kerman. 2016. Two Invariants of Human-Swarm Interaction. *Journal of Human-Robot Interaction* 5(1) (2016), 1–31.

Sébastien Bubeck and Nicolo Cesa-Bianchi. 2012. Regret Analysis of Stochastic and Non-stochastic Multi-armed Bandit Problems. *Machine Learning* 5, 1 (2012), 1–122.

J. Y. C. Chen, M. J. Barnes, and M. Harper-Sciarini. 2011. Supervisory Control of Multiple Social Robots: Human-Performance Issues and User-Interface Design. *IEEE Transactions on Systems, Man, and Cybernetics, Part C* 41, 4 (2011), 435–454.

R.C̃. Conant and W. R. Ashby. 1970. Every good regulator of a system must be a model of that system. *International Journal of Systems Science* 1(2) (1970), 89–97.

M. R. Endsley. 1988. Design and evaluation for situation awareness enhancement. In *Proceedings of the Human Factors Society's 32nd Annual Meeting.* 97–101.

Joan Feigenbaum and Scott Shenker. 2002. *Distributed algorithmic mechanism design: Recent results and future directions.* September.

John Gittins, Kevin Glazebrook, and Richard Weber. 2011. *Multi-armed bandit allocation indices.* John Wiley & Sons.

A.G̃. Heldane and R.M̃. May. 2011. Systemic risk in banking ecosystems. *Nature* 469(7330) (2011), 351–355.

L. Hurwicz and S. Reiter. 2006. *Designing Economic Mechanisms.* Cambridge University Press.

Neil Johnson, Guannan Zhao, Eric Hunsader, Hong Qi, Nicholas Johnson, Jing Meng, and Brian Tivnan. 2013. Abrupt rise of new machine ecology beyond human response time. *Scientific reports* 3 (2013).

A. Kolling, P. Walker, N. Chakraborty, K. Sycara, and M. Lewis. 2016. Human Interaction with Robot Swarms: A survey. *IEEE Transactions on Human-Machine Systems* 46(1) (2016), 9–26.

E. Koutsoupias and C.H̃. Papadimitriou. 1999. Worst-case equilibria. In *Proceedings of the Symposium on Theoretical Aspects of Computer Science.* 404–413.

Coco Krumme, Alejandro Llorente, Manuel Cebrian, Esteban Moro, and others. 2013. The predictability of consumer visitation patterns. *Scientific reports* 3 (2013).

Douglas E Lake, Joshua S Richman, M Pamela Griffin, and J Randall Moorman. 2002. Sample entropy analysis of neonatal heart rate variability. *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology* 283, 3 (2002), R789–R797.

Y.Ỹ. Liu, J.J̃. Slotine, and A.L̃. Barabási. 2011. Controllability of complex networks. *Nature* 473 (2011), 167–173.

Jeffrey K MacKie-Mason and Michael P Wellman. 2006. Automated markets and trading agents. *Handbook of Computational Economics* 2 (2006), 1381–1431.

R.M̃. May and N. Arinaminpathy. 2010. Systemic risk: the dynamics of model banking systems. *Journal of the Royal Society Interface* 7(46) (2010), 823–838.
Frank McSherry and Kunal Talwar. 2007. Mechanism design via differential privacy. In *Foundations of Computer Science, 2007. FOCS'07. 48th Annual IEEE Symposium on.* IEEE, 94–103.
R. Meade and S. O'Connor. 2009. *Comparison of Long-Term Contracts and Vertical Integration in Decentralised Electricity Markets.* Technical Report EUI RSCAS; 2009/16. Robert Schuman Centre For Advanced Studies, Loyola de Palacio Programme on Energy Policy.
W.J̃. Mitchell. 2004. Beyond the ivory tower: Constructing complexity in the digital age. *Science* 303 (2004), 1472–1473.
Roger B Myerson. 1981. Optimal auction design. *Mathematics of operations research* 6, 1 (1981), 58–73.
J. Nash. 1950. *Non-Cooperative Games.* Ph.D. Dissertation. Princeton University.
Noam Nisan and Amir Ronen. 1999. Algorithmic mechanism design. In *Proceedings of the thirty-first annual ACM symposium on Theory of computing.* ACM, 129–140.
Noam Nisan, Tim Roughgarden, Eva Tardos, and Vijay V Vazirani. 2007. *Algorithmic game theory.* Vol. 1. Cambridge University Press Cambridge.
K. Ogata. 1997. *Modern Control Engineering* (3rd ed.). Upper Saddle River, NJ: Prentice-Hall.
David C Parkes and Satinder P Singh. 2004. An MDP-Based Approach to Online Mechanism Design. In *Advances in Neural Information Processing Systems.* 791–798.
Alessandro Pavan, Ilya R Segal, and Juuso Toikka. 2009. Dynamic mechanism design: Incentive compatibility, profit maximization and information disclosure. *Profit Maximization and Information Disclosure (May 1, 2009)* (2009).
Steven M Pincus. 1991. Approximate entropy as a measure of system complexity. *Proceedings of the National Academy of Sciences* 88, 6 (1991), 2297–2301.
Tobias Preis, Johannes J Schneider, and H Eugene Stanley. 2011. Switching processes in financial markets. *Proceedings of the National Academy of Sciences* 108, 19 (2011), 7674–7678.
J. Ruths and D. Ruths. 2014. Control Profiles of Complex Networks. *Science* 343 (2014), 1373–1376.
W. P. Schultz, J. N. Nolan, R. B. Cialdini, N. J. Goldstein, and V. Griskevicius. 2007. The constructive, destructive, and reconstructive power of social norms. *Psychological Science* 18 (2007), 429–434.
Wen Shen, Cristina V Lopes, and Jacob W Crandall. 2016. An Online Mechanism for Ridesharing in Autonomous Mobility-on-Demand Systems. In *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence.*
T. B. Sheridan and W. L. Verplank. 1978. *Human and Computer Control of Undersea Teleoperators.* Technical Report. MIT Man-Machine Systems Laboratory.
Yoav Shoham and Kevin Leyton-Brown. 2008. *Multiagent systems: Algorithmic, game-theoretic, and logical foundations.* Cambridge University Press.
Paulo Trigo and Helder Coelho. 2011. Collective-intelligence and decision-making. In *Computational Intelligence for Engineering Systems.* Springer, 61–76.
Alessandro Vespignani and others. 2009. Predicting the behavior of techno-social systems. *Science* 325, 5939 (2009), 425.
Perukrishnen Vytelingum, Sarvapali D Ramchurn, Thomas D Voice, Alex Rogers, and Nicholas R Jennings. 2010. Trading agents for the smart electricity grid. In *Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems.* 897–904.
P. Walker, S. Nunnally, M. Lewis, A. Kolling, N. Chakraborty, and K. Sycara. 2012. Ne-

glect Benevolence in Human Control of Swarms in the Presence of Latency. In *IEEE International Conference on Systems, Man, and Cybernetics*. 3009–3014.

F.Ỹ. Wang. 2008. Toward a revolution in transportation operations: AI for complex systems. *IEEE Intelligent Systems* 23(6) (2008), 8–13.

Rick Zhang and Marco Pavone. 2016. Control of robotic mobility-on-demand systems: a queueing-theoretical perspective. *The International Journal of Robotics Research* 35, 1-3 (2016), 186–203.

K. Zheng, D. F. Glas, T. Kanda, H. Ishiguro, and N. Hagita. 2014. Supervisory Control of Multiple Social Robots for Conversation and Navigation. *Transaction on Control and Mechanical Systems* 3, 2 (2014).