BASCPS: How does behavioral decision making impact the security of cyber-physical systems?

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Abstract. We study the security of large-scale cyber-physical systems (CPS) consisting of multiple interdependent subsystems, each managed by a different defender. Defenders invest their security budgets with the goal of thwarting the spread of cyber attacks to their critical assets. We model the security investment decisions made by the defenders as a security game. While prior work has used security games to analyze such scenarios, we propose behavioral security games, in which defenders exhibit characteristics of human decision making that have been identified in behavioral economics as representing typical human cognitive biases. This is important as many of the critical security decisions in our target class of systems are made by humans. We provide empirical evidence for our behavioral model through a controlled subject experiment. We then show that behavioral decision making leads to a suboptimal pattern of resource allocation compared to non-behavioral decision making. We illustrate the effects of behavioral decision making using two representative real-world interdependent CPS. In particular, we identify the effects of the defenders’ security budget availability and distribution, the degree of interdependency among defenders, and collaborative defense strategies, on the degree of suboptimality of security outcomes due to behavioral decision making. In this context, the adverse effects of behavioral decision making are most severe with moderate defense budgets. Moreover, the impact of behavioral suboptimal decision making is magnified as the degree of the interdependency between subnetworks belonging to different defenders increases. We also observe that selfish defense decisions together with behavioral decisions significantly increase security risk.

Keywords: Security games · Cyber-physical systems · Human behavioral decision making · NESCOR · SCADA.

1 Introduction

Cyber-Physical System (CPS) structures can help in tackling modern and future technical and operational challenges in different domains such as transportation,
healthcare, digital manufacturing, and renewable energy systems. However, the tight integration of the human, physical, and cyber components also increases the attack surface of these systems. Facing increasingly sophisticated attacks from external adversaries, CPS owners have to judiciously allocate their (often limited) security budgets so as to reduce security risks. Since a CPS typically has many legacy components, improving the security of all of them at the same time is infeasible. This resource allocation problem is further complicated by the fact that a large-scale CPS consists of multiple interdependent subsystems managed by different operators, with each operator in charge of securing her own subsystem. Examples include the power grid (energy generators, utilities, domestic and industrial consumers, etc.) and a transportation network (federal and state transportation agencies, private toll road operators, vehicle owners, navigation software vendors, etc.). As a result, the security losses incurred by each operator will ultimately depend not only on her own security investments, but also on the decisions of other stakeholders in the CPS.

Game theory has played a key role in reasoning about such security decision making problems, due to its ability to systematically capture incentives and optimal actions of defenders and attackers. Specifically, existing work has modeled these scenarios as an interdependent security game [12,18,30,36,39,56]. These are a well-known class of strategic games where the security risk faced by a defender depends on her individual security investments, the security investments by other defenders she interacts with, and the attackers’ optimal strategy in response to these investments. However, existing work has relied on classical models of decision making, where all defenders and attackers are assumed to make fully rational risk evaluations and security decisions [5,27,37].

Contrary to this focus on perfectly rational decision making for security games, behavioral economics and psychology have shown that humans consistently deviate from these classical models of decision-making. Most notably, research in behavioral economics, an important and emerging field for which Kahneman (in 2002) and Thaler (in 2017) won the Nobel Memorial prize in Economic Sciences, has shown that humans perceive gains, losses and probabilities in a skewed, nonlinear manner [29,38]. In particular, humans typically overweight low probabilities and underweight high probabilities, where this weighting function has an inverse S-shape, as shown in Figure 1. Many empirical studies (e.g., [20,29]) have provided evidence for this class of behavioral models, which form part of the foundation for prospect theory.

While a rich literature on prospect theory exists in economics and psychology, most of the existing work studying the security of interdependent systems does not take into account the aforementioned human behavioral decision making effects. These effects are relevant for evaluating CPS security since decisions on implementing security controls are not made purely by automated algorithms, but rather through human decision making by plant managers, system operators, or CISOs [15,41]. Three notable exceptions where behavioral decision making for security have been studied are [1,26,46]. In [1], the authors studied the impact of probability weighting on the security investments of a single defender
Fig. 1: Prelec Probability weighting function which transforms true probabilities $p$ into perceived probabilities $w(p)$. The parameter $\alpha$ controls the extent of overweighting and underweighting, with $\alpha = 1$ indicating non-behavioral or rational decision making. The smaller the value of $\alpha$, the greater is the degree of misperception.

Fig. 2: Overview of the interdependent security game framework. This CPS consists of three interdependent defenders. An attacker tries to compromise critical assets using stepping stone attacks starting from node A. Interdependencies between assets are represented by edges. The red attack path shows example of how such interdependency affects the defenders.

protecting isolated assets. In [26], the authors studied the impacts of probability weighting on certain specific classes of interdependent security games. Similarly, [46] incorporated prospect theoretic models in the theoretical analysis of the security of drone-based delivery systems. However, there are limitations to all of these in the context of multi-defender interdependent CPS. First, in both of [1,46], the authors modeled a single defender CPS system while [26] assumed that each node is managed by a different defender, neither of which is true in general for interdependent CPS. Moreover, prior work does not leverage human subject experiments to demonstrate the degree of bias of decision-makers in the behavioral models.

Our contributions:
In this paper, we study the effects of human behavioral decision making on the security of large-scale CPS with multiple defenders. We design a reasoning and security investment decision making technique that we call BASCPS (Behavioral Security in Cyber Physical Systems), pronounced as BASS-CPS. In such large-scale interdependent systems, stepping-stone attacks are often used by external attackers to exploit vulnerabilities within the network in order to reach and compromise critical targets [22,27,50]. In stepping stone attacks, intruders compromise computing assets within a defended network by first gaining elevated privileges on an asset that is at the periphery of the network. From that, the attacker gains access to a connected asset and so on in a “stepping stone” manner till some valued target deep inside the defended network is compromised. These stepping-stone attacks can be captured via attack graphs, representing the possible paths an attacker may take to reach targets within the CPS [37]. Through
estimating which path(s) in the attack graph the current attack is taking, the
defender can allocate the security resources appropriately. We propose a behavior-
ial security game model, consisting of multiple defenders and an attacker, in
which the interdependencies between the defenders' assets are captured via an
attack graph. Specifically, we consider two classes of defenders.

**Behavioral defenders**: These defenders make security investment decisions un-
der two types of cognitive biases. First, following prospect-theoretic, non-linear
probability weighting models, they misperceive the probabilities of a successful
attack on each edge of the attack graph. Second, they have a bias toward spread-
ing their budget so that a minimum, non-zero investment is allocated to each
dge of the attack graph. This second kind of bias is motivated by behavior that
we observe in our human subject experiments.

**Non-behavioral or rational defenders**: These defenders make security in-
vestment decisions based on the classical models of fully rational decision mak-
ing. Specifically, they correctly perceive the risk on each edge within the attack
graph of the CPS network.

We first analyze the security investments of the decision makers in the CPS,
and compare the strategies of behavioral and non-behavioral defenders. We ob-
serve that behavioral defenders typically spread their budget throughout their
subnetwork, while non-behavioral defenders concentrate their resources on pro-
tecting the more critical edges of their subnetwork. This distinction, which is a
direct consequence of skewed risk perceptions, will result in higher overall system
loss under behavioral probability weighting, due to underinvestment in the crit-
ical parts of the system. In conducting our analysis and obtaining these insights
based on a behavioral model, we address several domain-specific challenges in
the context of security of CPS. These include augmenting the attack graph with
certain parameters such as sensitivity of edges to security investments (Equation
(1)) and the estimation of baseline attack probabilities (Table 1).

One may wonder why we need to consider human cognitive biases in se-
curity decision making. Why can we not trust ruthlessly rational optimization
algorithms which have been studied in the security context [37, 55] with such
decisions? The kinds of decision making in our target application domain of in-
terdependent CPS involves significant investments in security controls, security
policies, or changes in the system architecture. Hence, the decision making is
often done by system operators, plant managers, or security executives, albeit
with help from threat assessment tools [47,50]. Also, at Security Operations Cen-
ters (SOCs), operators make near real-time decisions about prioritizing various
security alerts. There are many articles discussing the prevalence of human fac-
tors in security decision making, both in popular press [13,53] and in academic
journals [15,16], none of which however shed light on the impact of cognitive
biases on the overall system security.

We perform a human subject study with 145 students to validate our behav-
orial model and to collect model parameters. We evaluate BASCPS using two
realistic interdependent CPS and attack paths through them. The first system
is a distributed energy resource (DER) with attack scenarios developed by the
US National Electric Sector Cybersecurity Organization Resource (NESCOR) working group [31]. The second system is a SCADA industrial control system, modeled using NIST guidelines for ICS [49]. We do a benchmark comparison with a prior solution for optimal security controls with attack graphs [47], and quantify the level of underestimation of loss compared to the BAS CPS evaluation when defenders are behavioral.

In summary, this paper makes the following contributions:

1. We propose a behavioral security game model for the study of security of multi-defender CPS where defenders' assets have mutual interdependencies. To the best of our knowledge, we are the first to bring in behavioral aspects of human decision-making to CPS security and we quantify the suboptimality of the security budget allocations due to behavioral decision making.

2. We illustrate the effects of a prospect theoretic model of decision making (specifically, nonlinear probability weighting) through two interdependent real-world CPS. We also model the security-relevant aspects.

3. We analyze the different parameters that affect the security of interdependent CPS under our behavioral model, such as the available security budget, budget distribution between defenders, types of defense mechanisms, degree of interdependency between defenders, and sensitivity of edges. Our insights in some cases are novel, while in other cases they run counter to prior work with purely rational defenders.

The rest of the paper is organized as follows. Section 2 presents the behavioral security game model and analyzes the differences in investment decisions between behavioral and non-behavioral defenders. In Section 3, we present human experiments validation of our model. We evaluate the DER.1 and SCADA-based attack scenarios in Sections 4 and 5, respectively. Section 6 presents discussion of our approach and some limitations. We discuss related literature in Section 7. Section 8 concludes the paper.

2 Behavioral Security Games

In this section, we present our proposed model of behavioral security games, establishing a theoretical basis that can be used to model any multi-defender interdependent CPS. A simple example of our setup is shown in Figure 2, which represents a system consisting of 3 interdependent defenders. An external attacker, starting from node A, uses a stepping stone attack (e.g., the path of bold edges in the attack graph) to reach the critical assets of the defenders. The critical assets are those that are associated with a financial loss when compromised (e.g., $v_m$ for defender 1 in the figure). Each defender aims to allocate her security budget on the network edges in a way that safeguards the attack paths reaching her critical assets. We formalize this scenario in this section.

\footnote{We assume that defenders perceive the attacker as non-behavioral; in reality the attacker can be behavioral as well. Our assumption of a non-behavioral attacker gives the worst case loss as a behavioral attacker may not choose the path of true highest vulnerability due to probability misperceptions.}
2.1 Model and preliminaries

We study security games consisting of one attacker and multiple defenders interacting through an attack graph $G = (V, E)$. The nodes $V$ of the attack graph represent the assets in the CPS, while the edges $E$ capture the attack progression between the assets. In particular, an edge from $v_i$ to $v_j$, $(v_i, v_j) \in E$, indicates that if asset $v_i$ is compromised by the attacker, it can be used as a stepping stone to launch an attack on asset $v_j$. The default probability that the attacker can successfully compromise $v_j$, having compromised $v_i$, is denoted by the edge weight $p_{i,j}^0 \in [0,1]$. By “default probability” we mean the probability of successful compromise without any security investment in protecting the assets. Each defender $D_k \in D$ is in control of a subset of assets $V_k \subseteq V$, and can make security investments on a subset of edges $E_k \subseteq E$. This is motivated by the fact that a large CPS comprises a number of smaller subnetworks, each owned by an independent stakeholder. Among all the assets in the network, a subset $V_m \subseteq V$ are critical assets, the compromise of which entails a financial loss for the corresponding defender. Specifically, if asset $v_m \in V_m$ is compromised by the attacker, any defender $D_k$ for whom $v_m \in V_k$ suffers a financial loss $L_m \in \mathbb{R}^+$. To protect the critical assets from being reached through stepping stone attacks, the defenders can choose to invest their resources in strengthening the security of the edges in the network. Specifically, let $x_{i,j}^k$ denote the investment of an eligible defender $D_k$ on edge $(v_i, v_j) \in E_k$, and let $x_{i,j} = \sum_{D_k \in D} x_{i,j}^k$ be the total investment on that edge by all eligible defenders. In addition, let $s_{i,j} \in [1, \infty)$ denote the sensitivity of edge $(v_i, v_j)$ to the total investment $x_{i,j}$. For larger sensitivity values, the probability of successful attack on the edge decreases faster with each additional unit of security investment on that edge. Then, the probability of successfully compromising $v_j$ starting from $v_i$ is given by,

$$p_{i,j}(x_{i,j}) = p_{i,j}^0 \exp\left(-s_{i,j} \sum_{D_k \in D \text{ s.t. } (v_i, v_j) \in E_k} x_{i,j}^k\right).$$  \hspace{1cm} (1)

Under this assumption, the probability of successful attack on an edge $(v_i, v_j)$ decreases exponentially with the sum of the investments on that edge by all defenders. This probability function falls within a class commonly considered in security economics (e.g., [8, 21]), and further enables analytical tractability of the defenders’ decision making problem. In this context, analytical tractability means guarantee of convexity of total loss functions (with the ability to solve and analyze the solutions), and existence of Pure Strategy Nash Equilibrium. Note that any log-convex function for the probability of successful attack enables such analytical tractability in these decision making problems [8]. Our proof in Appendix A applies generally to any such log-convex function.

The attacker initiates attacks on the network from a source node $v_s$ (or multiple possible source nodes), and attempts to reach a target node $v_m \in V_k$, i.e., a critical node for defender $D_k$. Let $P_m$ be the set of all attack paths from $v_s$ to $v_m$. We assume the worst-case scenario, i.e., the attacker exploits the most
vulnerable path to each target. Mathematically, this can be captured via the following total loss function for $D_k$,

$$
\tilde{C}_k(x_k, x_{-k}) = \sum_{v_m \in V_k} L_m \left( \max_{P \in P_m} \prod_{(v_i, v_j) \in P} p_{i,j}(x_{i,j}) \right). 
$$

(2)

Each (rational) defender $D_k$ minimizes $\tilde{C}_k(x_k, x_{-k})$ in (2), which is the sum of losses of all of $D_k$’s critical assets, subject to her total security investment budget $B_k$, i.e., $\sum_{(v_i, v_j) \in E_k} x_{i,j} \leq B_k$. Note that $x_k$ and $x_{-k}$ are the vector of investments by defender $D_k$ and defenders other than $D_k$, respectively. Our setup corresponds to a single-shot game where the defender moves first and spends all her security budget, after which the attacker moves. This investigation can serve as a foundation for future work on multi-shot games, where significant additional complexities will arise, including the need to create realistic models of human decision making in dynamic security games.

### 2.2 Behavioral probability weighting

Behavioral economics and psychology literature has shown that humans consistently misperceive probabilities by overweighting low probabilities, and underweighting high probabilities [29,43]. More specifically, humans perceive a “true” probability $p$ as probability $w(p)$, where $w(\cdot)$ is known as a **probability weighting function**. A commonly studied functional form for this weighting function was formulated by Prelec in [43], and is given by

$$
w(p) = \exp \left( - (-\log(p))^\alpha \right), \quad p \in [0,1],
$$

(3)

where $\alpha \in (0,1]$ is a parameter that controls the extent of misperception. When $\alpha = 1$, we have $w(p) = p$ for all $p \in [0,1]$, which corresponds to the situation where probabilities are perceived correctly, i.e., a non-behavioral defender. Smaller values of $\alpha$ lead to a greater amount of overweighting and underweighting, as illustrated in Figure 1.

We now incorporate this probability weighting function into the security game of Section 2.1. In a **behavioral security game**, each defender misperceives the attack success probability on each edge according to the probability weighting function in (3). Substituting (3) in the total loss function (2), a behavioral defender $D_k$ chooses her investments $x_k$ to minimize her **perceived** total loss

$$
C_k(x_k, x_{-k}) = \sum_{v_m \in V_k} L_m \left( \max_{P \in P_m} \prod_{(v_i, v_j) \in P} w\left(p_{i,j}(x_{i,j})\right) \right),
$$

subject to her budget constraint $\sum x_{i,j} \leq B_k$. Note that $w(p_{i,j}(x_{i,j}))$ is the perceived attack probability on the edge $(v_i, v_j)$ with total investment $x_{i,j}$. The total loss function $C_k(x_k, x_{-k})$ given by (4) is convex (see proof in Appendix A).

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5Our formulation also captures the case where each defender faces a different attacker who exploits the most vulnerable path from the source to that defender’s assets.
A set of security investments by the defenders is said to be a Pure Strategy Nash Equilibrium (PNE) if no defender can improve her utility by unilaterally changing her investment [34]. The concept of PNE is widely used to determine the course of action among multiple players in a non-cooperative setting. In this paper, we study the security outcomes of the system at the PNE of the above game, and how those outcomes vary with the behavioral probability weighting parameter $\alpha$. Note that Nash equilibrium is also relevant for behavioral setups, since mistaken probability judgments of behavioral players do not necessarily imply limited strategic reasoning.

To find these Nash equilibria, we use the notion of best response dynamics [24], where the investments of each defender $D_k$ are iteratively updated based on the investments of the other defenders. For our behavioral security game, in each iteration, the optimal investments for defender $D_k$ can be calculated by solving the convex optimization problem in (4). For our experiments, we run the best response dynamics until they converge to a Nash equilibrium [27], and then study the security outcomes at that equilibrium.

Our model can also capture the effects of learning by the human subjects as they proceed through multiple rounds of the game (in each round, each defender plays the single-shot game, allocating all her security budget). The model for defender $D_k$ in a multi-round defense game can be captured by our model in (4) with $\alpha_k(i)$ as the behavioral level in round $i$. While it may be expected that learning will move a subject toward a more rational model, i.e., $\alpha_k(j) > \alpha_k(i)$ for $j > i$, we find in practice that this is not the case for all subjects (Section 3.1).

2.3 Motivational example

We provide a simple example to illustrate the investment decisions by behavioral and non-behavioral defenders, and provide some intuition on why the optimal defense strategies under the two decision-making models differ. In this section, we use the notion of a min-cut of the graph. Specifically, given two assets $s$ and $t$ in the graph, an edge-cut is a set of edges $E_c \subset E$ such that removing $E_c$ from the graph also removes all paths from $s$ to $t$. A min-cut is an edge-cut of smallest cardinality over all possible edge-cuts [54]. As the example will show, the optimal investments by a non-behavioral defender (i.e., $\alpha = 1$) will generally concentrate...
the security investments on certain critical (i.e., min-cut) edges in the network. In contrast, behavioral defenders tend to spread their budgets throughout the network.

Consider the attack graph shown in Figure 3a, with a single defender $D$ and a single target asset $v_5$ (with a loss of $L_5 = 1$ if successfully attacked). Let the defender’s budget be $B$, and let the probability of successful attack on each edge $(v_i, v_j)$ be given by $p_{i,j}(x_{i,j}) = e^{-x_{i,j}}$ (assuming $p^0_{i,j} = 1$). This graph has two possible min-cuts, both of size 1: the edge $(v_s, v_1)$, and the edge $(v_4, v_5)$. The total loss function (2) for the defender is given by

$$C(x) = \max \left( e^{-(x_{s,1} + x_{1,2} + x_{2,4} + x_{4,5})}, e^{-(x_{s,1} + x_{1,3} + x_{3,4} + x_{4,5})} \right)$$

which reflects the two paths from the source $v_s$ to the target $v_5$. Note that an optimal solution of a constrained convex optimization problem satisfies the KKT conditions [23]. One can verify (using KKT conditions [23]) that it is optimal for a non-behavioral defender to put all of her budget only on the min-cut edges, i.e., any solution satisfying $x_{s,1} + x_{4,5} = B$ and $x_{1,2} = x_{2,4} = x_{1,3} = x_{3,4} = 0$ is optimal. The intuition of the above result is that for a non-behavioral defender, the probability of successful attack on any given path is a function of the sum of the security investments on the edges in that path. Thus, any set of investments on min-cut edges would be optimal since the sum of investments would be the whole security budget on each path of the graph.

Now consider a behavioral defender, i.e., a defender with $\alpha < 1$. With the above expression for $p_{i,j}(x_{i,j})$ and using Prelec function (3), we have $w(p_{i,j}(x_{i,j})) = e^{-x_{i,j}^{\alpha}}$. Thus, the total loss function (4) for a behavioral defender is

$$C(x) = \max \left( e^{-x_{s,1}^{\alpha} - x_{1,2}^{\alpha} - x_{2,4}^{\alpha} - x_{4,5}^{\alpha}}, e^{-x_{s,1}^{\alpha} - x_{1,3}^{\alpha} - x_{3,4}^{\alpha} - x_{4,5}^{\alpha}} \right),$$

which includes the two paths from the source $v_s$ to the target $v_5$. Again, one can verify (using the KKT conditions [23]) that the optimal investments are

$$x_{1,2} = x_{2,4} = x_{1,3} = x_{3,4} = 2^{\frac{1}{\alpha+1}} x_{s,1},$$
$$x_{s,1} = x_{4,5} = \frac{B - 4x_{1,2}}{2} = \frac{B}{2^{4(2^{\frac{1}{\alpha+1})}}},$$

Comparing these two cases, the optimal investments of the non-behavioral defender yield a total loss of $e^{-B}$, whereas the investments of the behavioral defender yield a total loss of $e^{-2^{\frac{1}{\alpha+1}}} e^{\frac{B}{1+2^{\frac{1}{\alpha+1}}}}$, which is larger than that of the non-behavioral defender.

**Interpretation:** The reason for this discrepancy can be seen by examining the Prelec probability weighting function in Figure 1. Specifically, when considering an undefended edge (i.e., whose probability of successful attack is 1), the marginal reduction of the attack probability on that edge as *perceived* by a behavioral defender is much larger than the marginal reduction of true attack probability on that edge. Thus the behavioral defender is incentivized to invest some non-zero amount on that edge. Therefore, a behavioral defender splits her
investments among the two non-critical sub-paths in the attack path. Note that the same insight holds for different baseline probabilities, but this shifting effect is greater when the slope of the behavioral probability weighting curve is higher (i.e., close to values of 1, 0, or where the cross-over happens between the behavioral curve and the diagonal). A rational defender, on the other hand, correctly perceives the drop in probability, and thus prefers not to invest on the non-critical sub-paths, instead placing her investment only on the critical edges \((v_s, v_1)\) or \((v_4, v_5)\) or both.

2.4 Motivational Example with different sensitivities

In the above example, we assumed all edges have the same sensitivity to investments. In cases where critical edges have equal or higher sensitivity than non-critical edges, the same insight as above holds. Specifically, when edge \((v_i, v_j)\) has sensitivity \(s_{i,j}\), one can verify (using KKT conditions) that the optimal investments by a behavioral defender are given by

\[
x_{1,2} = x_{2,4} = x_{3,4} = 2 \frac{1}{x_{1,3}} \left( \frac{s_{1,j}}{s_{4,5}} \right) \frac{s_{4,5}}{x_{4,5}} x_{s,1},
\]

\[
x_{s,1} = \left( \frac{x_{s,4}}{x_{4,5}} \right) \frac{s_{4,5}}{x_{4,5}} x_{4,5} = B - \sum_{\forall (i,j) \neq (v_4, v_5)} x_{i,j}.
\]

The insight here is that the investment decision has two dimensions: behavioral level and sensitivity ratio of non-critical edges to critical edges. Specifically, as the defender becomes more behavioral, she puts less investments on edges with higher sensitivity.

2.5 Spreading nature of security investments

We augment our model with another aspect of behavioral decision making, which we call spreading. Such a behavioral defender spreads her defensive investments on all edges throughout the attack graph, even when some edges are highly unlikely to be exploited for attacks. Our use of spreading is inspired by Naive Diversification from behavioral economics [10], where humans have a tendency to split investments evenly over the available options. This phenomenon has not been reported earlier for security decision making, to the best of our knowledge, and we infer this behavior from our human subject study. We capture this effect by adding another constraint to our model in (4): for each defender \(D_k\), we set \(x_{i,j}^k \geq \eta_k\), where \(\eta_k\) is the minimum investment the defender makes on any edge. The value \(\eta_k = 0\) gives us the behavioral decision with no spreading, i.e., with only behavioral probability weighting.

3 Human Subject Experiments

To validate our behavioral security model, incentivized experiments were conducted on 145 students in the Vernon Smith Experimental Economics Laboratory at Purdue University. Subject demographics are presented in Appendix B.
Subjects participated in the role of a defender, and allocated 24 discrete defense units over edges in each network. Subjects made their decisions on a computerized interface, and faced 10 rounds for each network, receiving feedback after each round indicating whether the attack was successful or not (i.e., whether the valuable asset was compromised). Subjects received comprehensive written instructions on the decision environment that explained how their investment allocation mapped into the probability of edge defense, and what was considered a successful defense. Subjects received a base payment of $5.00 for their participation. In addition, we randomly selected one round from each network and if the subject successfully defended the critical node in that round she received an additional monetary payment.

3.1 Network (A) with critical edge

This human experiment is on a network similar to Figure 3a, except that there is only one critical edge \((v_4, v_5)\) i.e., \(v_s = v_1\). Figure 4 shows the average investment allocation to the critical edge, based on 1450 investment decisions (i.e., 10 decisions from each of the 145 subjects). It shows the proportion of subjects who are non-behavioral (those at the vertical red line of \(\alpha = 1\), 27%), as well as heterogeneity in \(\alpha\), with observations further to the left being more behavioral.
Subjects to the left of the $\alpha = 0.4$ line (approximately 10 units allocated to the critical edge) are not necessarily exhibiting $\alpha < 0.4$. Those who allocate between 5 and 10 units to the critical edge could have a strong preference for spreading. Those who allocate less than 5 units to the critical edge cannot be explained by a strong preference for spreading, as there are 24 units in total to be spread over 5 edges. These subjects are probably using some other unidentified decision heuristic. Figure 5 shows the mean of subjects’ investments in each round. After round 4, the average investment on the critical edge in each round is higher than the initial amount of investment in round 1. The average increase summed across the 10 rounds is one defense unit. This means that subjects become less behavioral on average through learning. However, looking beyond the average, we note that individuals can be divided into three categories depending on their learning through rounds. The first category makes worse decisions in later rounds (26.90% of the subjects), the second category exhibits no learning (40.69%), and the third category improves their investments (32.41%).

3.2 Network (B) with cross-over edge

This experiment used the attack graph from Figure 3b. This attack graph is suitable to separate the spreading behavioral bias from the behavioral probability weighting, since for any $0 < \alpha \leq 1$, the optimal decision is to put zero defense units on the cross-over edge ($v_2, v_3$). Figure 6 shows the average investment allocation on the cross-over edge based on 1450 investment decisions. We see that the proportion of subjects that are non-behavioral, i.e., invest nothing on the cross-over edge, is 29%. Figure 7 shows the average of subjects’ investments on the cross-over edge in each round, which shows a weak downward trend. Taken together, these human experiments provide support for our behavioral model with the probability weighting and spreading factors.

4 CPS System A: Distributed energy system

In this section, we use our proposed model to evaluate the security outcomes of a practical CPS. Specifically, we examine the effect of different system parameters on the degree of suboptimality of security outcomes due to behavioral decision making.

4.1 DER.1 system description:

The US National Electric Sector Cybersecurity Organization Resource (NESCOR) Technical Working Group has proposed a framework for evaluating the risks of cyber attacks on the electric grid [31]. A distributed energy resource (DER) is described as a cyber-physical system consisting of entities such as generators, storage devices, and electric vehicles, that are part of the energy distribution system [31]. The DER.1 failure scenario has been identified as the riskiest failure
Fig. 8: Attack graph of a DER.1 failure scenario adapted from [27]. It shows stepping-stone attack steps that can lead to the compromise of PV (i.e., \( G_0 \)) or EV (i.e., \( G_1 \)). There are two defenders whose critical assets are \( G_0 \) and \( G_1 \), while \( G \) is a shared critical asset.

scenario affecting distributed energy resources according to the NESCOR ranking. Here, there are two critical equipment assets: a PhotoVoltaic (PV) generator and an electric vehicle (EV) charging station. Each piece of equipment is accompanied by a Human Machine Interface (HMI), the only gateway through which the equipment can be controlled. The DER.1 failure scenario is triggered when the attacker gets access to the HMI. The vulnerability of the system may arise due to various reasons, such as hacking of the HMI, or an insider attack. Once the attacker gets access to the system, she changes the DER settings and gets physical access to the DER equipment so that they continue to provide power even during a power system fault. Through this manipulation, the attacker can cause physical damage to the system, and can even lead to the electrocution of a utility field crew member.

To analyze the above system within our behavioral security game model, we follow the model proposed by [27], which maps the above high level system overview into an attack graph as shown in Figure 8. We generate the attack graph using the CyberSage tool [50], a Cyber Security Argument Graph Evaluation tool for CPS security assessment. In this attack graph, node labels starting with “w” are used to denote the non-critical assets/equipment used as part of the attack steps, and \( G_0 \), \( G_1 \), and \( G \) represent the critical assets which are the attacker’s goals. For the attacker’s goals, \( G_0 \) represents a physical failure of the PV system, \( G_1 \) represents a physical failure of the EV system, and \( G \) means that a failure of either type has occurred. The goal \( G \) may signify non-physical losses (e.g., reputation losses) for the DER operator as a result of a successful compromise. The first defender is responsible for defending the critical asset \( G_0 \), the second defender for defending \( G_1 \). Both defenders share the common asset \( G \).

4.2 Experimental setup:

Each edge in the attack graph in Figure 8 represents a real vulnerability. To create the baseline probability of attack on each edge (i.e., without any security investment), we first create a table of CVE-IDs (based on real vulnerabilities
Table 1: Baseline probability of successful attack for vulnerabilities in DER.1 and SCADA failure scenarios.

| Vulnerability (CVE-ID)                  | Edge(s)                             | Attack Vector | Score |
|-----------------------------------------|-------------------------------------|---------------|-------|
| DER.1 application                       |                                     |               |       |
| Physical access (CVE-2017-10125)        | \((v_9, w_7), (w_18, w_16)\)        | Physical      | 0.71  |
| Network access (CVE-2019-2413)          | \((v_9, w_8), (w_18, w_17)\)        | Network       | 0.61  |
| Software access (CVE-2018-2791)         | \((v_7, w_6), (w_8, w_6)\)          | Network       | 0.82  |
| Sending cmd (CVE-2018-1000095)          | \((v_6, w_5), (w_15, w_14)\)        | Network       | 0.88  |
| SCADA application                       |                                     |               |       |
| Control Unit (CVE-2018-5313)            | \((\text{Vendor}, \text{Control}_1), (\text{Vendor}, \text{Control}_2)\) | Local         | 0.78  |
| Remote authentication (CVE-2010-1132)   | \((s, \text{Vendor})\)              | Network       | 0.9   |
| Remote cmd injection (CVE-2011-1566)    | \((\text{Control}, \text{RTU}_1), (\text{Control}, \text{RTU}_2)\) | Network       | 1.0   |
| Authentication bypassing (CVE-2019-6519)| \((\text{Corp}, \text{DMZ}_1), (\text{Corp}, \text{DMZ}_2)\) | Network       | 0.75  |

We next explore the effects of behavioral decision making on the system’s security. Specifically, we measure the total system loss, given by the sum of the losses experienced by the two defenders in the system. Loss only accrues if \(G_0\), \(G_1\), or \(G\) are compromised. We assume that the total budget available at the defenders’ organization is \(B\), and that an amount \(BT\) of this budget is set aside for security investments. We refer to \(BT < 0.2B\), \(0.2B < BT < 0.6B\), and \(BT > 0.6B\), as low, medium, and high security budgets, respectively. For our numerical simulations in this failure scenario, we set \(B = 20\) for most of our simulations, we vary \(\alpha \in [0, 1]\) which is consistent with the range of behavioral parameters from prior experimental studies (e.g., \([2, 20]\)) as well as from our user study. We observe that the same insights hold for \(\alpha \in (0, 0.4)\) (e.g., in the baseline comparison in Figure 9). This is expected since the form of the probability weighting function does not change as \(\alpha\) decreases.

4.3 Results and insights

**Experiment A.1: Baseline comparison**: We begin by comparing BASCPs with the seminal work of [47] on attack graph generation and investment decision analysis. In [47] the defense mechanism is to select the minimal set \(C\) of edges that, if removed from the attacker’s arsenal, will prevent her from reaching the target asset (there can be multiple sets in case of non-uniqueness). This is equivalent to our min edge-cut. More recent approaches (e.g., \([19, 59]\)) conceptually follow the same strategy for security investment with attack graphs. We compare [47] with loss under both behavioral and non-behavioral defense placements in BASCPs. We compare the two methods in Figure 9 by calculating the ratio of total system loss estimated under the method of [47] over that reported in the CVE database for 2000-2019), with each CVE-ID representing one possible method for exploiting the vulnerability. We then followed previous works in [25,58] to convert the attack’s metrics (i.e., attack vector, attack complexity, and need of authentication [35]) to a baseline probability of successful attack. Table 1 illustrates the process.
estimated by BASCPS. Note that the defense investments given by BASCPS for non-behavioral defenders is identical to that determined by [47]. However, if indeed investment decisions are made by subjects with human decision making biases, prior work will underestimate the loss in the system. The degree of underestimation can be as high as 3.34X in DER.1 and 3.57X in SCADA and that degree is inversely related to the value of $\alpha$. Figure 10 compares the system loss for rational defenders vs that determined by BASCPS under different spreading levels by behavioral defenders. The under-estimation is as high as 8.33X for DER.1 and 826X for SCADA and that degree is directly related to the value of $\eta$.

**Experiment A.2: Choice of defense mechanism.** Next, we compare the security outcomes under two potential defense mechanisms. The first defense mechanism is individual defense, in which each defender can spend her security budget only on the edges connecting assets inside her subnetwork. In the previous experiment, we have only considered these types of individual investments. An alternative to this defense mechanism is joint defense, where each defender can choose to spend her security budget on any edge in the network (i.e., she can choose to help defend the subnetworks of other defenders). Figure 11 illustrates that a joint defense mechanism always outperforms the individual defense mechanism. The advantage of joint defense is higher under asymmetric budget allocation among the defenders. Further, the improvement under joint defense holds with both behavioral and non-behavioral defenders. A good example of this is that if both defenders are non-behavioral, and defender 1 has only 20% of the total security budget, the joint defense mechanism decreases the total loss by 88.5% over the individual defense mechanism. Also, under the same budget allocation, if both defenders are behavioral with $\alpha_1 = \alpha_2 = 0.6$, the joint defense mechanism decreases the total loss by 81.2% over individual defense.
We also note that two behavioral defenders who cooperate can, despite their suboptimal decisions, achieve a lower total loss compared to two non-behavioral defenders making individual defense decisions in the asymmetric budget setup. For instance, from Figure 11, we observe that two defenders with a high degree of behavioral decision making (i.e., $\alpha_1 = \alpha_2 = 0.6$) will attain a lower total loss than two non-behavioral defenders with selfish decisions when the budget asymmetry is 40:60 or greater. This is explained by the fact that enabling cooperative defense allows the defender with higher budget to put part of her excess security budget as security investment on the other defender’s subnetwork. It therefore has considerable potential in mitigating the effects of suboptimal behavioral decision making.

**Experiment A.3: Interdependency among different defenders.** We next study the effects of the degree of interdependence among the defenders on the system’s security. In the DER.1 failure scenario, the degree of interdependency increases if the HMI of the PV and the EV are communicating. Therefore, making any progress in the attack steps towards one device affects the other device as well (e.g., having software access to the PV enables sending commands to either the PV or the EV). This is represented in Figure 8 by introducing additional edges interconnecting the “w” nodes from the two different sides of the network.

Figure 12 illustrates that as the number of interdependent edges between the two defenders increases, the total system loss increases in both non-behavioral and behavioral security games. Further, we observe that the degradation is more pronounced under behavioral decision making. For instance, suppose there are 12 interdependent links among the two defenders (i.e., the PV and EV HMIs are communicating at all levels). If both defenders are behavioral with $\alpha_1 = \alpha_2 = 0.6$, the total system loss increases by 1230% over the case of 2 interdependent links. This increase is smaller (500%) when the defenders are non-behavioral.
The insight behind these differences is that as the number of interdependent links increases, the number of paths between the source and target nodes increases as well. In this case, behavioral defenders will increasingly spend their budget suboptimally on the criss-crossing edges instead of optimally investing on the critical edges, leading to higher losses.

**Experiment A.4: Sensitivity of edges to investments.** We next consider the effects of different sensitivities of edges to security investments. Recall that higher sensitivity edges are those for which the probability of successful attack decreases faster with each unit of security investment. We show the result in Figure 13 by using as the independent variable the ratio of sensitivity of non-critical to critical edges. First, assume critical edges correspond to mature systems that are already highly secure and difficult to secure further. For our model, this translates to high (resp. low) $s_{ij}$ for non-critical (resp. critical) edges. We observe that as the sensitivity ratio increases, all defenders put more investments on the non-critical edges, but the increase is slower in behavioral defenders. However, lower sensitivity ratio will result in investing almost all budget on these critical edges, even for behavioral defenders.

5 CPS System B: SCADA Control System

We next evaluate BASCPS on the SCADA system in Figure 14. We provide a subset of the evaluations here; the remainder, which provide identical insights to DER.1 are in Appendix D.

5.1 SCADA system description:

The SCADA system (in Figure 14) is composed of two control subsystems, where each incorporates a number of cyber components, such as control subnetworks and remote terminal units (RTUs), and physical components, such as, valves controlled by the RTUs. This system is architected following the NIST guidelines for industrial control systems [49]. For example, each subsystem is separated from external networks through a demilitarized zone (DMZ). The system implements firewalls both between the DMZ and the external networks, as well as between the DMZ and its control subnetwork. Therefore, an adversary must bypass two different levels of security to gain access to the control subnetworks.

Mapping this system to our proposed security game model, each control subnetwork is owned by a different defender. These two subsystems are interdependent via the shared corporate network, as well as due to having a common vendor for their control equipment. The resulting interdependencies map to the attack graph shown in Figure 15. The “Corp” and the “Vendor” nodes connect the two subnetworks belonging to the two different defenders and can be used as jump points to spread an attack from one control subsystem to the other. A critical node has the loss amount denoted within the node (“L = X”). We consider external attackers who attempt to gain access to the RTUs through attacks initiated from either the corporate network or the vendor network. The
Fig. 14: A high level network overview of a SCADA-based system, adapted from [27] consisting of two control subnetworks. These two subnetworks are interdependent due to sharing a common vendor for their control network and RTUs, and through their common connection to the corporate network.

Fig. 15: The attack graph for a SCADA-based control network, adapted from [27]. The attacker's starting node is S. Each target node has an associated loss (denoted as L within the node).

corporate network “CORP” is owned by both defenders. The compromise of a control network “CONTROL i” leads to loss of control of all 3 connected RTUs.

Now, we present our simulations of failure scenario of Scada system with studying some important parameters in the behavioral security game.

5.2 Experimental Setup:

Similar to the DER.1 system, the choice of baseline probability of attack is also based on CVE vulnerabilities (Table 1). The choice of the budget levels has a similar intuition as the DER.1 failure scenario, but differs in values due to the increased number of critical assets in this attack graph. Specifically, in this section, $BT = $10 and $20 reflect low and moderate budgets, respectively, and $BT \geq $30 reflects high budgets.

5.3 Results and insights

Experiment B.1: Comparison with the DER.1 attack graph. Figure 16 shows the effect of behavioral probability weighting on the total system loss with
Fig. 16: Total loss of the SCADA system as a function of budget. The effects of human behavior decision making are higher for this attack graph compared to the DER.1 scenario, due to the increase in the degree of interdependency and the number of critical assets.

Fig. 17: Total loss as a function of the number of RTUs per defender. We observe that the effect of increasing the number of critical assets is more pronounced when the degree of behavioral decision making is higher as the suboptimal decisions affects all critical assets.

Fig. 18: Comparison between individual and joint defense investment mechanisms. We observe that joint defense can outperform individual defense (i.e., lower losses), particularly when behavioral probability weighting is higher and under asymmetric budget distribution.

two behavioral defenders. Comparing Figure 16 with Figure 19 shows that the relative difference in total loss between non-behavioral and behavioral defenders is much higher in the SCADA network compared to the DER network. This is due to more interdependencies between the two defenders in the SCADA attack graph – 4 edges per defender in SCADA compared to 1 in DER. Also, there are more critical assets per defender in SCADA, as all assets (firewalls, control units, and RTUs) are critical. In general, tighter interdependencies among defenders imply that behavioral decision making is going to be more damaging.

Experiment B.2: Number of critical assets. Here we consider scaling up the SCADA system, with each defender owning more physical assets and correspondingly having a larger number of RTUs. We make replicas of these RTUs for each defender, and assume that the defender has the same security budget $BT = 25$, done to measure the effect of suboptimal decisions as the CPS size grows. Again, we notice that as the number of RTUs increases, the difference between system loss with behavioral players versus non-behavioral players is magnified as shown in Figure 17. For instance, we observe that when $\alpha = 1$, a change from 3 RTUs per player to 18 RTUs per player yields a relative increase of 344% in system loss, while the same change with $\alpha = 0.4$ results in a higher increase of 882%. As the size of the CPS grows, the budget stays constant and hence the magnitude of the loss increases. As the decision becomes behavioral, at large CPS sizes, the scarce defense budget is improperly allocated and this magnifies the loss. The impact of behavioral decisions is more damaging here than in the DER case because of the highly critical edges between the control network and the RTUs. A non-behavioral defender protects these critical edges,
but a behavioral one mistakenly distributes her budget between these and other edges.

**Experiment B.3: Choice of defense mechanism.** As in the DER system, we observe the merits of cooperation (i.e., joint defense) in decreasing the total loss to the defenders (Figure 18). The effect is more pronounced for a higher degree of behavioral bias of the defenders. For example, at moderate budget \( BT = 20 \), the relative decrease in total system loss due to joint defense at \( \alpha_1 = \alpha_2 = 0.4 \) is 25% while \( \alpha_1 = \alpha_2 = 0.8 \), the decrease is lower (10%). Thus, as the defenders exhibit higher degree of cognitive bias, it is more advantageous to adopt joint defense mechanisms.

**Experiment B.4: Centralized defense merits.** Next, we compare the outcomes of decentralized decision-making by two defenders with a centralized defense method where a central planner owns both subnetworks and aims to minimize the system loss by allocating the budget appropriately. We observe that when the defenders have a symmetric budget, the outcomes of central and distributed planning coincide. As the budget asymmetry increases, the difference between the two defense methods increases as well. Figure 21 (in Appendix D) shows this trend for two budget choices, \( BT = 10 \) and \( BT = 20 \). We observe that with the lower budget, the suboptimality due to selfish decision making is more pronounced. Further, we observe that interventions by a social planner have a higher benefit when the defenders are behavioral. In particular, when \( BT = 10 \), the relative difference between social and selfish for \( \alpha = 1 \) is 5.7%, while it is higher (14%) for \( \alpha = 0.6 \).

### 6 Limitations and Discussion

**Guiding security decision-makers:** Here we have studied the impacts of human behavioral decision making on the security of an interdependent system. We believe this opens up a new dimension of intervention in securing interdependent systems. How does one guide security decision makers to the appropriate levels of behavioral weighting for a given system? How does one incentivize multiple stakeholders to cooperate to achieve greater system-level security? What is the role of a central regulatory agency in incentivizing the security-beneficial investments by individual stakeholders? In this context, the insights gained from our analysis would be useful for configuring real-world systems with optimal parameter choices. For example, following the result of Fig. 11, we can start to quantify the benefit of joint defense relative to individual defense by each defender.

We can also quantitatively show the decision maker the improvement in system security (under various systems conditions) when moving from her current (sub-optimal) investments to that given by a (rational) algorithm (e.g., BASCPS with \( \alpha = 1 \) or \([47]\)). In contrast to the line of work that studied placing response actions solely based on the system admin’s intuition (e.g., \([32, 48]\)), BASCPS solves a rigorous convex optimization problem \((4)\) to determine how to distribute the mitigation actions across the critical edges.
**Human subject experiments:** The use of student subjects as opposed to security professionals is for practical reasons, as it is difficult to collect enough number of security professionals at one time and place for a controlled experiment and importantly, it would be very expensive to incentivize such professionals with monetary payments. For reference, the average payment a subject earned for the two networks described plus the participation fee was $10.93. Although, we think that students (with instructions) are proxying for general “human” performance, it should be noted that they are (most likely) not the best case performers. On the other hand, the empirical evidence of differing behavior of professional (of a relevant field) and student subject pools is mixed. There are cases where behavior differs in an expected way, with professionals being less biased than students. However, more generally the biases found in student subject pools do exist in professional subject pools. In our environment, we anticipate that security professionals exhibit higher levels of rational behavior relative to our subject experiment. However, even small deviations from rationality can result in sub-optimal security investments that are empirically important due to the magnitude of losses associated with compromised ‘real-world’ assets.

**Loss aversion:** In addition to misperceptions of probabilities, empirical evidence shows that humans perceive utilities and losses differently than simple expected values. In particular, humans avoid uncertain outcomes and overweight losses compared to gains (loss aversion). A richer behavioral model, *cumulative prospect theory* [28], incorporates these aspects. However, in our setting, this richer model does not significantly change the total loss function of the defenders. Specifically, the attack on an asset is either successful or it is not. If the reference total loss is zero for each asset (i.e., without a successful attack), then the index of loss aversion only scales the loss $L_m$ by a scalar constant without changing the optimal decision on the investments.

**Uncertainty in estimation of probability of successful attacks:** In our evaluation, we have assumed that each defender has a correct probability assessment (i.e., $p_{ij}^0$ is estimated correctly). However, there are practical scenarios in which this assumption does not hold. In this context, we should note that the behavioral decision making affects the problem of resource allocations even under such uncertainty. We provide a brief discussion and analysis of such scenario in Appendix E.

**Multi-hop dependence:** In several cybersecurity scenarios, the ease of an attacker in achieving an attack goal depends not just on the immediate prior attack step but on steps farther back. In such scenarios, the simpler formulation of using probabilities on each edge and assuming independence of the events of traversing the different edges can lead to inaccurate estimates. However, we follow several prior works (e.g., [37, 55]) that leveraged the property that in most cases, a node has the highest dependence on the previous node, in order to build computationally tractable analysis tools. Moreover, to handle this issue in our model, we introduce the notion of *k-hop dependence* whereby the probability of reaching a

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6See Part IV, in Chapter 17, [17] for a survey and discussion on this topic.
particular node depends not just on the previous hop node, but nodes up to \( k \) hops away. We provide a brief discussion of such setup in Appendix F.

7 Related Work

Security in interdependent systems: The problem of securing systems with interdependent assets has been handled in several prior works \([37,55]\). The common theme is that a successful attack to one asset may be used to compromise a dependent asset. The notion of attack graphs \([25]\) is a popular abstraction for capturing the security interdependencies. The specific works differ in what the assets are (physical or virtual, resource-constrained nodes, networking assets, etc.), the level of observability into the states of the assets, and the probabilistic reasoning engine used. Our work here differs from these works in that the prior work creates algorithms to make the security control decisions, while we are considering humans with cognitive biases making these decisions.

Game-theoretic modeling of security: Game theory has been used to describe the interactions between attackers and defenders and their effects on system security. A commonly used model in this context is that of two-player games, where a single attacker attempts to compromise a system controlled by a single defender (e.g., \([33,40,45,51,57]\)). Game theoretic models have been further used in \([9,56]\) to study the interaction between one defender and (multiple) attackers attempting Distributed Denial of Service (DDoS) attacks. Our work differs from both lines of literature in that we consider the interdependencies between multiple defenders in the network.

Game theoretic models for the study of CPS security have been proposed in \([42,60]\). The authors in \([60]\) proposed a Stackelberg game model, in which a defender attempts to maintain high performance in a SCADA control system against cyber attacks launched by fully rational jammers. The work in \([42]\) proposed a single-defender game-theoretic approach to minimize loss due to attacks in water distribution networks. However, these works have not taken into account the interdependencies between multiple defenders.

Lastly, the major difference of our work with all aforementioned literature is that existing work has focused on classical game-theoretic models of rational decision making, while we analyze behavioral models of decision making. Notable departures from classical economic models within the security and privacy literature are \([3,4]\), which identify the effects of behavioral decision making on individual’s personal privacy choices using human subject experiments without exploring rigorous mathematical models of players behavior. The importance of considering similar models in the study of system security has been recognized in the literature \([14]\). To the best of our knowledge, the only study that provides a theoretical treatment of behavioral decision making in certain specific classes of interdependent security games is \([26]\). That research, however, is theoretical in scope and does not consider the more realistic attack scenarios that we consider here.
Human behavior in security: A large body of literature has considered models from behavioral economics in the context of security applications, such as internet security and information security, via psychological studies; see [6] for survey or through human subject experiments [7, 44]. Our work differs from these in that we explore a rigorous mathematical model of defenders’ behavior, model the interaction between multiple defenders (in contrast to the study of only one defender for all of these studies), and consider interdependent assets (in contrast to these studies which reason about binary decisions on isolated assets).

8 Conclusion

We studied behavioral security games to evaluate the effects of human behavioral decision making on the security of large-scale CPS with multiple defenders. We compared the strategies of behavioral and rational defenders, where behavioral defenders exhibit nonlinear probability weighting and a tendency to spread security investments across assets. We observed that behavioral decision makers tend to allocate their budget across the network, while non-behavioral decision makers concentrate their budget on critical edges. We presented two real case studies of interdependent CPS: a distributed energy resources system and a SCADA-based control network. We studied the effects of several game parameters including the defense budget availability and distribution, and collaborative defense mechanisms, on the security risks of the system in the presence of behavioral decision making.

We find that the suboptimal pattern of resource allocation by humans exhibiting behavioral decision making characteristics can considerably increase the security risks of interdependent CPS, with the suboptimality becoming more pronounced under moderate security budgets. Using better security risk evaluations and expert input (which can alter the patterns of behavioral decision makers toward rational decision making) can ultimately lead to improvements of CPS security. A complementary approach is to enable collaborative defense strategies, or centralized planning, which can lead to a reduction in security risks even with behavioral decision making.

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Appendix

A Convexity of the Total Loss Function

Lemma 1. Let the probability successful function $p_{i,j}(x_{i,j})$ be twice-differentiable and log-convex. Then, the total loss function in (4) is convex.

Proof: We drop the subscript $i,j$ in the first part of this analysis for better readability. Now, beginning with the probability weighting function defined in (3), we have

$$w(p(x)) = \exp \left[ - \left( - \log(p(x)) \right)^\alpha \right] = (g \circ h)(x),$$

where $g(x) = \exp(-x)$ and $h(x) = (- \log(p(x)))^\alpha$. We prove that $h(x)$ is concave:

$$h'(x) = -\alpha(- \log(p(x)))^{\alpha-1} \frac{p'(x)}{p(x)}$$

$$h''(x) = \alpha(\alpha - 1)(- \log(p(x)))^{\alpha-2} \frac{(p'(x))^2}{(p(x))^2}$$

$$+ \alpha(- \log(p(x)))^{\alpha-1} \left[ \frac{(p'(x))^2 - (p(x))(p''(x))}{(p(x))^2} \right].$$

Since $0 \leq p(x) \leq 1$, we have $0 \leq - \log(p(x)) \leq \infty$ for all $x$. Moreover, $0 < \alpha \leq 1$ and thus the first term in the R.H.S. of $h''(x)$ is negative. Also, since $p(x)$ is twice-differentiable and log-convex, $(p'(x))^2 < (p(x))(p''(x))$ [11], which ensures that the second term is also negative. Therefore, $h(x)$ is concave. Since $g(x)$ is convex and non-increasing while $h(x)$ is concave, $w(p(x))$ is convex.

Now, with the total loss function defined in (4), $w(p_{i,j}(x_{i,j}))$ is convex (as shown above). Since $w(p_{i,j}(x_{i,j}))$ is monotone, thus $\prod_{(v_i, v_j) \in P} w(p_{i,j}(x_{i,j}))$ is convex [11]. Moreover, the maximum of a set of convex functions is also convex [11]. Finally, since the total loss function $C_k(x_k, x_{-k})$ is a linear combination of convex functions, the total loss function defined in (4) is convex. That concludes the proof.

B Human Experiments Details

Human Experiments Demographics: The 145 human subjects in our experiment are comprised of 78 males (53.79%) and 67 females (46.21%). They belong to various majors on campus, with the three largest being Management/Business (24.8%), Engineering (24.2%), and Science (23.5%). Regarding year in college, 6.9% are 1st year, 13.1% are 2nd year, 21.38% are 3rd year, 35.86% are 4th year, and 22.76% are graduate students. Regarding the GPA distribution, 44.83% have GPAs between 3.5 and 4, 35.17% between 3 and 3.5, and 17.93% between 2.5 and 3.
Fig. 19: Total loss as a function of the security budget. The adverse effects of behavioral decision making are most severe with intermediate budgets. At either high or low budgets, the amount of the budget, rather than its allocation, determines security.

Fig. 20: Total loss as a function of the number of defenders. We observe that the loss increases superlinearly (i.e., the per-defender loss is increasing as the CPS grows). This is due to the increased risks resulting from interdependencies in the defenders’ critical assets.

C DER.1 Extended Results

Experiment A.5: Amount of security budget. We next consider the system defense, and vary the available total security budget for defending the DER system, under symmetric budget distribution between the two defenders. Figure 19 shows the effect of behavioral decision making on the security level of the DER system as a function of the total budget. We observe that the effect of behavioral decision making with intermediate security budgets (i.e., $BT = 5$ and $BT = 10$) is more severe than both very low budget (i.e., $BT = 1$) and very high budget (i.e., $BT = 20$). For instance, with $BT = 1$, the total loss when both defenders are behavioral with $\alpha_1 = \alpha_2 = 0.6$ has a relative increase of 1.11% over a system in which both defenders are non-behavioral, while at $BT = 5$ and $BT = 10$, a similar change in behavioral levels yields a higher increase of 12.41% and 28.24% in the total loss, respectively.

This effect can be intuitively interpreted by noting that with a low security budget, all defenders suffer mainly due to the scarcity of protection resources, and are less affected by how their budget is distributed. At very high budgets on the other hand, the total loss experienced by both behavioral and non-behavioral decision makers is very close to zero (since the probabilities of successful attack on each edge decrease exponentially with the amount of investment on that edge), and thus suboptimal investment decisions do not have a considerable impact on overall security. In other words, we observe that judicious (non-behavioral) investments are most crucial in determining the security of the system when the allocation, rather than the amount, of the security budget is the deciding factor in determining risks.
**Experiment A.6: Number of defenders.** We create a network with multiple defenders where we make replicas of these two subnetworks, and assume that each new installed equipment corresponds to a new defender’s subnetwork. We consider a symmetric distribution of the security budget over all defenders, with each defender having a security budget of $10. We notice in Figure 20 that as the number of defenders increases, the difference between total losses between non-behavioral and behavioral games increases in a super-linear manner. For instance, we observe that when the number of defenders is 4, a change from non-behavioral to behavioral defenders ($\alpha = 0.6$) increases the loss by 8.65%, while the same change in $\alpha$ in the larger network with 16 defenders results in a higher increase of 26.17%. This phenomenon is due to the interdependencies between the subnetworks. For instance, if there are two defenders, each will incur a loss in two cases: when either her target asset is successfully compromised or the other defender’s target asset is successfully compromised (as it can lead to the compromise of their common goal $G$). On the other hand, if there are 16 defenders, for each defender, there are 16 possible paths through which she suffers a loss. This also explains why the total loss in the system increases with increasing number of defenders—the individual budget of each defender stays the same but the number of ways in which her asset can be compromised increases linearly.

**Experiment A.7: Asymmetry in budget distributions.** We next analyze the effect of asymmetric budget distribution in the two-defender network facing an attacker. The total security budget is $10. Figure 11 illustrates the total loss as a function of the fraction of defender 1’s budget. For the individual-defense loss (solid lines), we observe that the suboptimality of behavioral decision making is more pronounced with higher budget asymmetries. For example, if defender 1 has 20% of the total budget, the relative increase in total loss from $\alpha = 1$ to $\alpha = 0.4$ is 25%. In contrast, the same change of $\alpha$ when the budget is symmetric results in only a 6% relative increase in the total loss. This observation can be explained by two facts. First, with suboptimal behavioral allocation, the poorer defender wastes even her constrained budget on non-critical edges. Second, the richer player also allocates her resources suboptimally. This leads to this magnified relative increase in losses under budget asymmetry.

### D Scada Extended Results

**Experiment B.5: Amount of security budget.** Figure 16 shows the effects of budget availability on system security. We observe that for moderate budgets, behavioral decision making increases the total loss up to 60% over non-behavioral decision making. On the other hand, with high budgets ($BT \geq 30$ in our simulations), behavioral decision making has a negligible effect on the total loss, which is very close to zero. The intuition is similar to that in Section 4: the negative effect of behavioral decision making is more pronounced with moderate budgets as the allocation of the security budget for protecting the different assets is most critical.
Experiment B.6: Interdependency among different defenders. As in the DER system, we again observe effect of interdependency between defenders on the security of the SCADA system. We consider medium budget choice (i.e., $BT = 25$) for this experiment. In the SCADA system, the degree of interdependency increases if assets from one subnetwork can access assets in the other, without going through the Corporate or Vendor nodes. For example, if the attacker gets access to Control unit 1, this enables her to compromise RTU2 as well, in addition to RTU1. Figure 23 illustrates this effect—as the number of interdependent edges between the two defenders increases, the total system loss increases in both non-behavioral and behavioral security games. The highest level of interdependency is when there are two edges between DMZ1 and DMZ2, between Control1 and Control2, and the controller to the 3 RTUs of the other defender. An example of this phenomenon is that if both defenders are non-behavioral and the level of interdependency is the highest, the total system loss is higher by 462% over the case of the lowest level of interdependency (2 interdependent links). We also see that as the interdependency between the different defenders increases, the suboptimal security decisions have greater adverse impact on the total system loss.

Experiment B.7: Sensitivity of Edges to Investments. In this experiment, we repeat the sensitivity sweeping analysis of Experiment A.7 for the SCADA attack graph. The investments under different sensitivity ratios are shown in Figure 22, with insights similar to those explained for the DER.1 attack scenario.
E  Uncertainty in Attack Probability

Recall that in our evaluation, we have assumed that each defender has a correct probability assessment (i.e., $p_{ij}^0$ is estimated correctly). However, there are practical scenarios in which this assumption does not hold (see Section 6). Here, we analyze the effectiveness of behavioral decision making when uncertainty is taken into account. In other words, when probabilities in the attack graph cannot be simply assumed correct. We model such uncertainty by replacing $p_{ij}^0$ in (1) with $q_{ij}^0$ where $q_{ij}^0 \sim N(p_{ij}^0, \sigma)$ where $\sigma$ is the standard deviation (uncertainty) of the probability of attack. The interesting question that we answer here is: How well does behavioral decision making compare to rational decision making when true attack graph edge values are uncertain? In our experiments, we varied $\sigma$ from 0 to 0.3 with the restriction of $0 < q_{ij}^0 \leq 1$ since it is a probability. Figure 24 shows the percentage of relative difference in total system loss due to uncertainty for DER.1 failure scenario for the different uncertainty levels. Note that rational defenders have much lower relative loss since they put most investments on critical edges. On the other hand, the effect is higher for moderate and highly behavioral defenders (i.e., $0.4 \leq \alpha \leq 0.6$) since such uncertainty shifts the probability to different regions in Figure 1. The same insights holds for SCADA system. We remove the details of SCADA uncertainty experiments in the interest of space. This shows that even if the probability of successful attack is not estimated perfectly, the rational behavior (which is the security investments placed by $\alpha = 1$) gives more accurate estimation of the expected system loss compared to the decisions with behavioral biases.
Fig. 25: The attack graph in (a) is converted to the attack graph (b) to consider 2-hop dependency whereby the probability of reaching \( v_5 \) depends on which path is used.

F Multi-hop dependence

To handle the multi-hop dependence (mentioned earlier in Section 6) in our model, we introduce the notion of \( k \)-hop dependence, whereby the probability of reaching a particular node depends not just on the previous hop node, but nodes up to \( k \) hops away. The value of \( k \) is a specification provided by the security admin, either for the entire graph or for individual nodes.

BASCPs handles this type of dependencies by considering all paths of length \( k \) ending at node \( i \). Specifically, let this set of paths be \( P_i \). Then the original attack graph is converted to one where node \( i \) has \( |P_i| \) incident edges with a splitting of the previous node into multiple virtual nodes if needed. The different probabilities on the different edges capture the relative ease of an attacker to reach \( i \) through the different paths. We show an example of this in Figure 25b which is created from attack graph in (a) in which node \( v_5 \) has 2-hop dependence, say because if the attacker has come to \( v_4 \) through \( v_2 \), then her job is easier than if she has come through \( v_3 \). There are 2 paths; correspondingly, the previous node \( v_4 \) is split into two virtual nodes \( v^a_4 \) and \( v^b_4 \). For the example case of the upper path being easier, \( p_{v^a_4,v_5} > p_{v^b_4,v_5} \). This same approach can be used when the dependence is not on contiguous nodes, but on a decision taken early on in the attack path, by splitting into multiple paths. One subtle consideration is that when there is a security investment on an edge of the original attack graph, that should be mirrored on all the edges that have been derived from that edge. One potential problem with our approach is that it blows up the size of the attack graphs. The helpful factor here is that most nodes have only 1-hop dependence in practice and this property has been leveraged in the past to build computationally tractable analysis tools [37, 52, 55].