Estimating a System's Mean Time-to-Compromise

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Abstract:
Mean time-to-compromise is a comparative security metric that applies lessons learned from physical security. To address this need in the SCADA world specifically and the corporate IT security world more generally, we propose a mean time-to-compromise (MTTC) interval as an estimate of the time it will take for an attacker with a specific skill level to successfully impact a target system. We also propose a state-space model (SSM) and algorithms for estimating attack paths and state times to calculate these MTTC intervals for a given target system. Although we use SCADA as an example, we believe our approach should work in any IT environment.

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One of the challenges network security professionals face is providing a simple yet meaningful estimate of a system or network's security preparedness to management, who typically aren't security professionals. Although enumerating system flaws can be relatively easy, seemingly simple questions such as, “How much more secure will our system be if we invest in this technology?” or “How does our security preparedness compare to other companies in our sector?” can prevent a security project from moving forward.

This has been particularly true for our area of research-the security of Supervisory Control and Data Acquisition (SCADA) and industrial automation and control systems (lACS) used in critical infrastructures such as petroleum production and refining, electricity generation and distribution, and water management. Companies operating these systems must invest significant resources toward improving their systems' security, but upper management's understanding of the risks and benefits is often vague. Furthermore, competing interests for the limited security dollars often leave many companies basing decisions on the best sales pitch rather than a well-reasoned security program.

The companies operating in these sectors aren't unsophisticated. Most have many years of experience making intelligent business decisions on a large variety of multifaceted issues on a daily basis. For example, to be profitable, refining and chemical companies must optimize hundreds (or thousands) of process feedback loops, an extremely complex process. Yet, models based on key performance indicators (KPI) have simplified the problem to the point where upper management can make well-reasoned decisions on global operations without getting mired in the details.[1]

In our discussions with management and security administrators at these companies, they repeatedly pointed out those similar types of performance indicators could be useful for making corporate security decisions. What these companies wanted wasn't proof of absolute security, but rather a measure of relative security. To address this need in the SCADA world specifically and the corporate IT security world more generally, we propose a mean time-to-compromise (MTTC) interval as an estimate of the time it will take for an attacker with a specific skill level to successfully impact a target system (see the “A brief history of MTTC” sidebar). We also propose a state-space model (SSM) and algorithms for estimating attack paths and state times to calculate these MTTC intervals for a given target system. Although we use SCADA as an example, we believe our approach should work in any IT environment.

Lessons Learned from Physical Security

Determining a safe's burglary rating is similar to determining a network's security rating. Both involve a malicious agent attempting to compromise the system and take action resulting in loss. Safes in the US are assigned a burglary and fire rating based on well-known Underwriters

Safes in the US are assigned a burglary and fire rating based on well-known Underwriters Laboratory testing methodologies such as UL Standard 687.[2]

The UL rating system is based on the concept of *net working time* (NWT)-that is, the time spent attempting to break into the safe by testers using specified sets of tools, such as diamond-grinding tools and high-speed carbide-tip drills. TL-15 means that the safe has been tested for an NWT of 15 minutes using high-speed drills, saws, and other sophisticated penetrating equipment. TL-30 means that the safe has been tested for an NWT of 30 minutes. The UL testing procedure also categorizes the sets of tools allowed into levels: TRTL-30 indicates that the safe has been tested for an NWT of 30 minutes, but with an extended range of tools such as torches.

UL testing engineers confirmed that they use design-level knowledge about a safe when planning and executing attacks. They also confirmed that although attackers can use perhaps dozens of strategies to access a safe, they actually only try a few. Finally, each of the safe's surfaces represents an attack zone, which might alter the attacker's strategies.

A few observations about this process merit mention:

- It implies that given the proper resources and enough time, any safe can eventually be broken into.
- A safe receives a burglary rating based on its ability to withstand a focused attack by a team of knowledgeable safe crackers following a well-defined set of rules and testing procedures.
- The rules include using well-defined sets of common resources for safe cracking.
- The resources available to the testers are organized into well-defined levels that represent increasing cost and complexity and decreasing availably to the average attacker.
- Although other possibilities for attack might exist, testers will use only a limited set of strategies based on their detailed knowledge of the safe.

Most important, the UL rating doesn't promise that the safe is secure from all possible attack strategies. An attacker could quite possibly uncover a design flaw that would let him or her break into a given safe in a time under the rated period. However, from a statistical viewpoint, we can reasonably assume that as a group, TL-30 safes are more secure than TL-15 safes. This ability to efficiently estimate a comparative security level for a given system is the core objective of our proposed methodology.

Learning from the philosophy of rating safes, we developed a methodology for rating a target network. Our methodology makes the following assumptions.

- Given proper resources and enough time, an agent skilled in electronic warfare can successfully attack any network.
- A target network or device must be capable of surviving an attack for some minimally acceptable benchmark period (the MTTC).
- Most attackers will use a limited set of strategies based on their expertise and knowledge of the target.
- We can statistically group attackers into levels, each with a common set of resources, such as access to popular attack tools or a level of technical knowledge and skill.

These assumptions let us calculate the MTTC using various methods.

Attack Zones

Just like a safe has different sides requiring their own attack strategies, a complex network consists of several generally homogeneous zones. Thus, we begin by dividing a topological map of the target network into attack zones, as Figure 1 shows. Each zone represents a network or network of networks separated from other zones by boundary devices. In our example, the system of interest is layered into three zones: zone 1 is the process-control network (PCN, the target of interest), zone 2 is the enterprise network (EN), and zone 3 is the Internet.

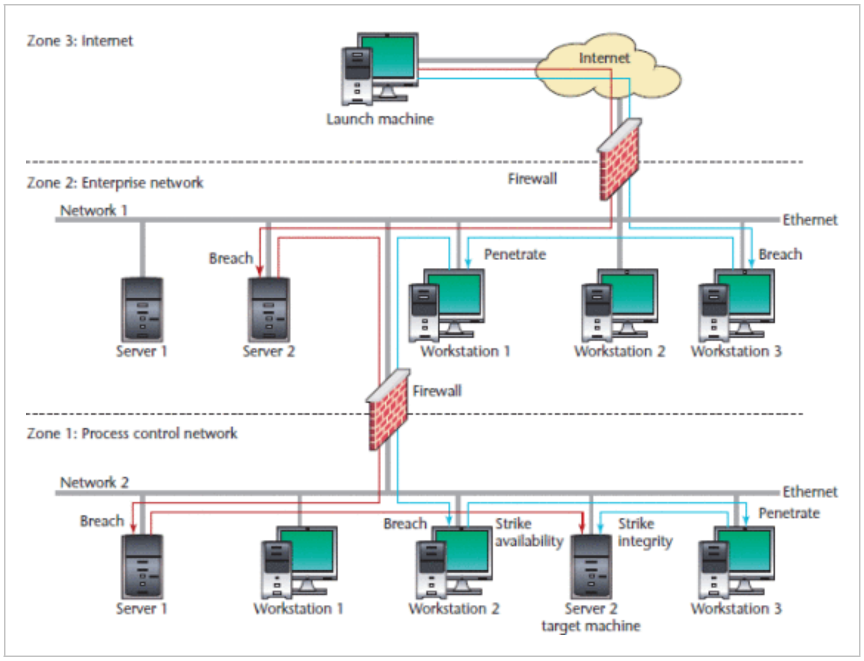

Figure 1.
An example of attack zones and attacker movement through the zones to strike a target device on the target network. The blue and red lines represent two possible attack paths.

We assume that consistent security practices (such as operating system deployment, patching practices, and communications protocol usage) are in effect within a zone. These practices could be good or bad (that is, users perform patching randomly), but are consistent within the zone.

The concept of zones is important for two reasons. First, when staging an attack from within the target network, attackers will likely use a different set of strategies than they would when attacking from the Internet. Dividing the topological map into zones lets us represent each zone with its own SSM. Second, assuming a consistent practice within a zone lets us simplify the model to keep it manageable.

Predator Model

Sean Gorman[3] and Erland jonsson[4] provided the motivation and insight to pursue a predator-prey-based SSM. For this article, our proposed SSM (see Figure 2) is for attacks launched remotely from the Internet. It consists of three general states:

- *Breaching* occurs when the attacker circumvents a boundary device to gain user or root access to a node on the other side of the boundary.

- *Penetration* is when the attacker gains user or root access to a node without crossing a boundary device.

- *Striking* is impacting the target system's or device's confidentiality, integrity (take unauthorized control), or availability (deny authorized access).

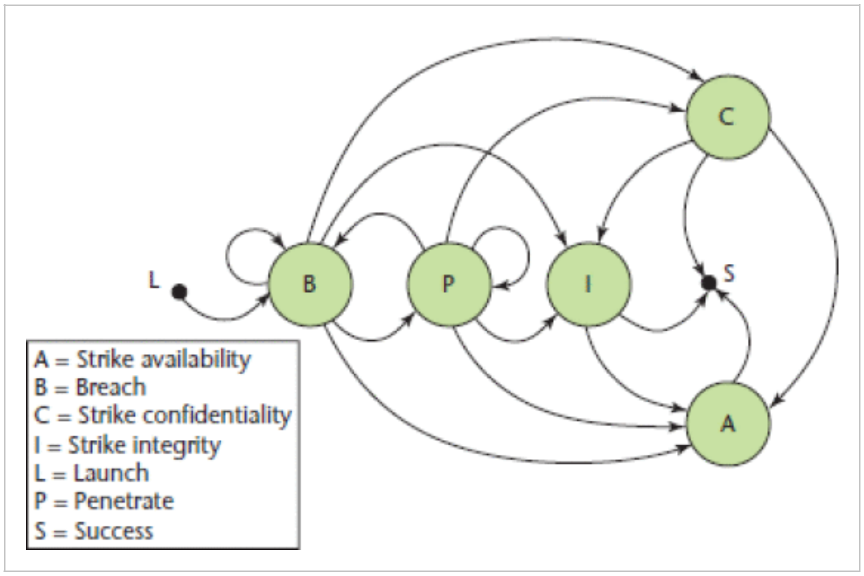

Figure 2.
State-space predator model for attacks launched from the Internet. Our proposed SSM consists of three general states: breach, penetrate, and strike.

Although we could hypothesize many more states, our experimentation indicates that having more than five states adds little to the model's output yet greatly increases the calculations' complexity. For example, Miles McQueen and others suggest reconnaissance states. However, reconnaissance states can add significant complexity to the process because virtually all states will require some reconnaissance to be transited. So, we could consider reconnaissance as a substate and include it in a primary state's calculations.

The attacker compromises one or more nodes while moving toward the target, as Figure 1 shows. With layered network architectures, the resulting sequence of states-a Markov chain-betrays the attacker's path and strategy.

Attack-Path Model

We use the state-space predator model to map the attack-path model-an SSM of all possible attack paths from the launch node to the target device, accounting for network topology and security policies. Consider the network in Figure 1. If we make three simplifying assumptions-that the attacker only moves forward toward the target, that the attacker can't compromise the firewalls (that is, the attacker can penetrate them, but not take them over completely), and that the attacker can't compromise the target device from a device outside of the target zone-we get the attack path model shown in Figure 3.

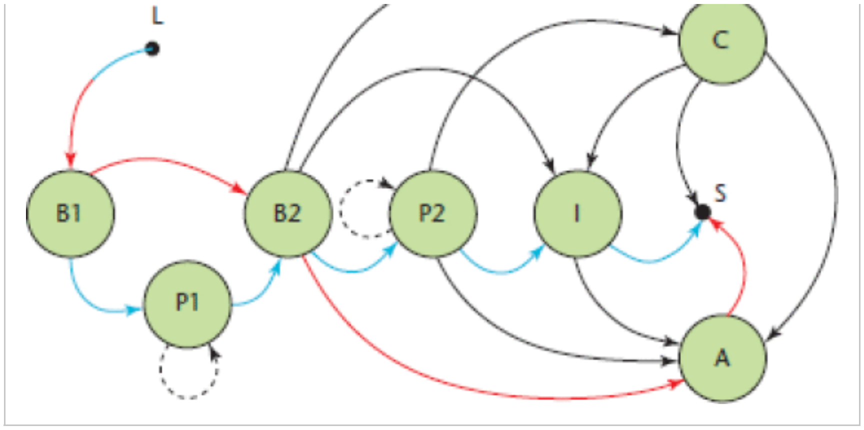

Figure 3.
Attack-path model for the network shown in Figure 1 with simplifying assumptions. The blue and red paths correspond to the same-colored paths in figure 1. We omit the dashed transitions from the simplified attack-path model.

The assumption that the attacker only moves forward toward the target reflects our philosophy that motivated attackers won't deliberately increase their attack time with unnecessary actions and ensures that each analysis produces a consistent attack-path model. The second and third assumptions might not be typical of most networks and could be removed. However, for this article's purpose, they simplify the attack-path model to clearly illustrate its salient features.

Estimating State Times

The next step is to estimate state times. Numerous methodologies exist for this purpose. We use a statistical algorithm based on a modified version of McQueen and colleagues' time-to-compromise model.[5] This algorithm lets us estimate the duration of the breach, penetrate, and strike states. Elsewhere, we present a simple attack-tree-based technique that we can use to obtain a formalized estimate for the state times in systems in which algorithms are unavailable.[6]

To differentiate between McQueen and colleagues' TTCM and our modified version, we call our version the state-time estimation algorithm (STEA).

We divide the attacker's actions into three statistical processes:

- *Process* 1-when the attacker has identified one or more known vulnerabilities and has one or more exploits on hand.
- *Process* 2-when the attacker has identified one or more known vulnerabilities but doesn't have an exploit on hand.
- *Process* 3-when no known vulnerabilities or exploits are available.

Equation 1 shows the time-to-compromise (T) — that is, the total time of all three processes:

$$T = t_1 P_1 + t_2(1 - P_1)(1 - u) + t_3 u(1 - P_1). \tag{1}$$

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Process 1

We hypothesize process 1 to have a mean time of one day ($t_1 = 1$ day). We expect this time to change with experience and defer to McQueen and colleagues[7] for supporting arguments.

Equation 2 shows the probability that the attacker is in process 1:

$$P_1 = 1 - e^{-V \times M/K}, \tag{2}$$

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where V is the average number of vulnerabilities per node within a zone, M is the number of exploits readily available to the attacker, and K is the total number of nonduplicate software vulnerabilities in the National Vulnerability Database.

In the absence of statistical data, we hypothesize that the distribution of attackers versus skill levels is normal and introduce a skills indicator that represents the attacker's percentile rating and can take on any value from 0 (absolute beginner) to 1 (highly skilled attacker). To get M, we multiply the skills indicator and the total number of exploits readily available to all attackers (m). McQueen and colleagues chose m to be 450 based on exploit code publicly available over the Internet through sites such as Metasploit (www.metasploit.com). We use the same value for m.

We hypothesize that we can extend K to represent other classes of vulnerabilities, such as nonduplicate vulnerabilities in the protocol used to strike the target device.

Process2

We hypothesize process 2 to have a mean time of 5.8 days (($t_2 = 5.8$ days $\times ET$, where ET is the expected number of tries). Again, we expect this time to change with experience, and we defer to McQueen and colleagues for supporting arguments? Equation 3 shows how we calculate EY:

$$ET = \frac{AM}{V} * \left(1 + \sum_{tries=2}^{V-AM+1}\left[tries * \prod_{i=2}^{tries}\left(\frac{NM-i+2}{V-i+1}\right)\right]\right), \tag{3}$$

View Source

where AM is the average number of the vulnerabilities for which an exploit can be found or created by the attacker given their skill level, and NM is the number of vulnerabilities that an attacker with this skill level won't be able to use.

Process3

This process hypothesizes that the rate of new vulnerabilities or exploits becomes constant over time.i' To calculate this, we need a probability variable u that indicates that process 2 is unsuccessful:

$$u = (1-s)^V \tag{4}$$
$$t_3 = ((1/s) - 0.5) \times 30.42 + 5.8\text{days} \tag{5}$$

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Equations 4 and 5 differ from McQueen and colleagues' equations in that we use s (the skills indicator) in place of AM/V.

The STEA model's strength is that we can modify it to include other time for substates (such as reconnaissance) and adapt it to incorporate environmental variables that affect the state times (such as patching intervals). To illustrate this flexibility, we included a rather abstract variable in the calculation-namely, the frequency of access-control list rule reviews. To do this, we first assumed that boundary devices such as routers and firewalls offer security by reducing the number of vulnerabilities that are visible to the attacker. That is, only a portion of the network's attack surface is visible to the attacker.[9] We then assume that a boundary device's effectiveness decays if a network administrator doesn't regularly review its rule sets. We incorporated this relationship into Equations 2 and 4 to produce equations 6 and 7:

$$P_1 = 1 - e^{-\alpha \times V \times M / K} \tag{6}$$
$$u = (1 - s)^{\alpha \times V} \tag{7}$$

View Source

where α is visibility ($\alpha = 1$ when estimating penetration state times).

Finally, we worked with a firewall expert at the British Columbia Institute of Technology to determine a possible correlation between visibility and update/review frequency. He estimated that

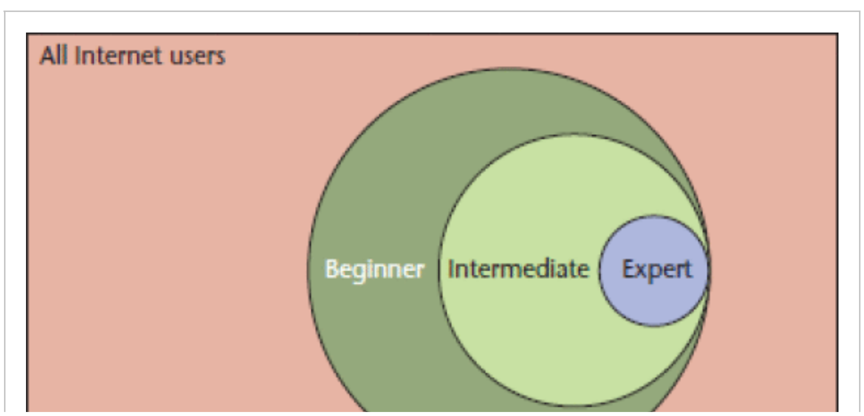
- no reviews, $\alpha = 1.00$;
- semi-annual reviews, $\alpha = 0.30$;
- quarterly reviews, $\alpha = 0.12$; and
- monthly reviews, $\alpha = 0.05$.

We need further research to support these estimations, but they're sufficient as a proof of concept.

This is just one example of the opportunity to add environmental variables that might eventually prove to be important indicators of relative security performance. Other factors we've experimented with include patch intervals, operating system diversity, and password policies. If industrial controlloop-optimization research is any indication, considerable future research will explore which indicators are truly important and how they affect the MTTC.

Attacker Skill Levels

Attacker skill levels are based on capabilities. Attackers are classified as beginners (that is, script kiddies) if they're only capable of using existing code, tools, and attacks to exploit known vulnerabilities. An intermediate attacker can also modify existing code, tools, and attacks to exploit known vulnerabilities. An expert attacker can also create new code, tools, and attacks and identify previously unknown vulnerabilities. The Venn diagram in Figure 4 shows the relationship between attacker skill levels.



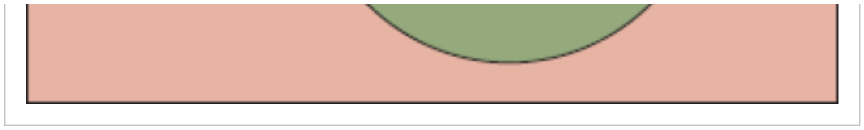


Figure 4.
Venn diagram of capabilities-based attacker skills levels. Beginner attackers are only capable of using existing exploit code, tools, and attacks. Intermediate users are capable of both using and modifying existing exploit code, tools, and attacks. In addition to these capabilities, expert users can identify new vulnerabilities and create novel tools and attacks.

We quantify an attacker's skill level as s for use in the STEA. In the absence of meaningful statistical data, we base s on learning curves, with $s = 1.0$ for an expert, $s = 0.9$ for an intermediate, and $s = 0.5$ for a beginner attacker. In each of these cases, s actually represents the top of the skills group. We need further research to support these estimations, but they suffice as a proof of concept.

Building MTTC Intervals

We use the predator model to create an attack-path model of each system being measured. Using the STEA, we estimate each state time for each attacker skill level and tabulate the results in a first set of tables (one for each system). We calculate the mean time for each attack path and each attacker skill level using the attack-path model and state times and tabulate the results in a second set of tables (three for each system). We then use the attack-path model to estimate each attack path's probability.

Presently, we give each attack path an equal probability. In practice, we expect this won't be true; however, it provides a metric letting us compare two or more systems until reliable statistical data is available. Markov chains of variable length represent the collection of attack paths, and the attack-path model becomes a variable-length Markov chain model. We add the product of each attack path probability and its mean time to the second set of tables and then sum the products to produce a mathematical expectation for the MTTC. The leftmost boundary of each MTTC interval (the shortest attack path), the rightmost boundary (the longest attack path), and the MTTC itself are read directly from the second set of tables.

A Brief History of Mean Time-To-Compromise

The concept of mean time-to-compromise (MTTC) isn't new-for example, Erland Jonsson and Tomas Olovsson use mean-time-to-breach to analyze attacker behaviors' and the Honeynet community uses MTTC to measure a system's ability to survive Internet exposure. These works, however, view MTTC as an observable variable rather than a calculated indicator of relative security. Miles Mcqueen and his colleaques+' move toward the latter. Their methodology uses directed graphs to calculate an expected time-to-compromise for differing attacker skill levels. Other works look at probabilistic models to estimate security. However, as Mcqueen and colleagues point out, many of the techniques proposed for estimating cybersecurity require significant detail about the target system, making them unmanageable as a comparative tool for multiple systems.

To address this issue, our model focuses on being a comparative tool for attacks launched remotely from the Internet. We also propose several averaging techniques to make it a more generally applicable methodology while still allowing meaningful comparisons. We developed our model, along with its supporting methodology, with emerging industrial security standards in mind-specifically those the International Electrotechnical Commission (IEC)4 and the International Society for Measurement and Control (ISA)5,6 are developing.

We ignored some security aspects in the MTTC framework because we developed it to be part of a Hierarchical Holographic Model (HHM), which will include models for attacks exploiting additional failure mechanisms such as social engineering and compromising emanations (Tempest). To quote Yacov Haimes, “the basic philosophy of HHM is to build a family of models that address different aspects of the system.“[7]

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Choosing the appropriate attack paths for the MTTC calculation is pivotal. The full attack-path model, shown in Figure 3, has 140 attack paths. Including all of these paths would result in an artificially high MTTC because most attack paths include one or more penetration states. We can't completely ignore penetration because attackers use it to escalate privileges or strengthen a distributed DoS attack. A motivated attacker won't spend an unnecessary amount of time penetrating a network and tends to choose the shortest attack paths. We therefore only allow a single penetration of each network when calculating the MTTC. The attack-path model is the same as is shown in Figure 3 except we omit the dashed transitions, reducing the total number of attack paths to 28.

Case Study

A utility company wants to compare systems in two facilities to determine how to focus its resources. Both systems have topologies identical to the system in Figure 1 (the framework doesn't require identical topologies; we use them only for illustrative purposes). Both facilities have limited manpower and financial resources for security, but have different priorities. Staff at facility 1 believes it should review its firewall rules only on an annual basis, and focus on patching systems on the primary EN (zone 2). As is common in the SCADA world, facility l's staff largely ignores patching on the PCN (zone 1). Consequently, it averages 2 and 10 vulnerabilities per node on the EN and PCN, respectively.

In contrast, facility 2 reviews its firewall rules on a quarterly basis, but as a result has less time for

In contrast, facility 2 reviews its firewall rules on a quarterly basis, but as a result has less time for patch management. Furthermore, it tries to patch both the EN and PCN with the same team. Thus, it averages 4 and 6 vulnerabilities per node on the EN and PCN, respectively.

Corporate management wishes to know which facility has the best philosophy so they can deploy it across the corporation.

Figure 3 shows the attack-path models for both systems with the dashed transitions omitted. We calculate the breach, penetrate, and strike integrity state times for each attacker skill level using the STEA and tabulate them as shown in Table 1 for system 2. Without encryption, we estimate striking confidentiality to be one day for all attacker skill levels. Striking availability is trivial, so also estimated to be one day for all attacker skill levels.

Table 1. State times for system 2 (days).

SKILL LEVEL	BREACH1	PENETRATE1	BREACH2	PENETRATE2	STRIKE CONFIDENTIALITY	STRIKE INTEGRITY	STRIKE AVAILABILITY
Expert	5.7	5.0	5.6	4.6	1.0	4.6	1.0
Intermediate	11.7	5.5	9.1	5.2	1.0	5.2	1.0
Beginner	38.1	11.3	33.0	9.5	1.0	9.5	1.0

We calculate and tabulate the attack path times, resulting in 28 estimates for each skill level. Next, we multiply the time for each attack path by its probability (1/28) and sum the products to produce the MTTC as Table 2 shows for system 2 and an attacker with intermediate skills. The shortest path, longest path, and MTTC are read directly from these tables. Figure 5 shows the MTTC intervals for both systems.

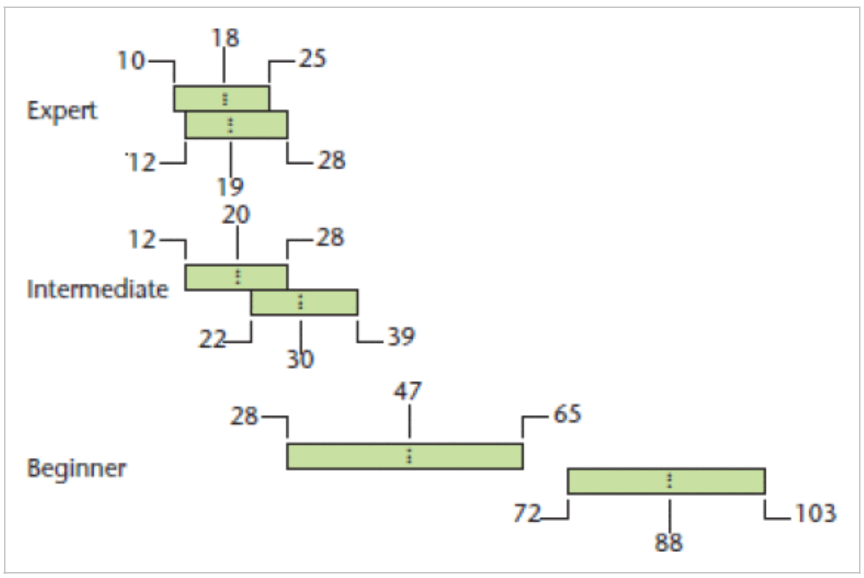

Figure 5.
Example of MTTC intervals (in days) for our case study. MTTC intervals are shown in pairs with the top interval representing system 1 and the bottom interval representing system 2.

Table 2. Attack path times and MTTC calculation for system 2 and for an attacker with intermediate skills.

ATTACK PATH	PROBABILITY	PATH TIME	PRODUCT
L, B1, B2, C, S	1/28	21.8	0.78
L, B1, B2, I, S	1/28	26.0	0.93
L, B1, B2, A, S	1/28	21.8	0.78

L, B1, B2, C, I, S	1/28	27.0	0.96
L, B1, B2, C, A, S	1/28	22.8	0.81
L, B1, B2, I, A, S	1/28	27.0	0.96
L, B1, B2, C, I, A, S	1/28	28.0	1.00
L, B1, P1, B2, C, S	1/28	27.3	0.98
L, B1, P1, B2, I, S	1/28	31.5	1.13
L, B1, P1, B2, A, S	1/28	27.3	0.98
L, B1, P1, B2, C, I, S	1/28	32.5	1.16
L, B1, P1, B2, C, A, S	1/28	28.3	1.01
L, B1, P1, B2, I, A, S	1/28	32.5	1.16
L, B1, P1, B2, C, I, A, S	1/28	33.5	1.20
L, B1, B2, P2, C, S	1/28	27.0	0.96
L, B1, B2, P2, I, S	1/28	31.2	1.11
L, B1, B2, P2, A, S	1/28	27.0	0.96
L, B1, B2, P2, C, I, S	1/28	32.2	1.15
L, B1, B2, P2, C, A, S	1/28	28.0	1.00
L, B1, B2, P2, I, A, S	1/28	32.2	1.15
L, B1, B2, P2, C, I, A, S	1/28	33.2	1.19
L, B1, P1, B2, P2, C, S	1/28	32.5	1.16
L, B1, P1, B2, P2, I, S	1/28	36.7	1.31
L, B1, P1, B2, P2, A, S	1/28	32.5	1.16
L, B1, P1, B2, P2, C, I, S	1/28	37.7	1.35
L, B1, P1, B2, P2, C, A, S	1/28	33.5	1.20
L, B1, P1, B2, P2, I, A, S	1/28	37.7	1.35
L, B1, P1, B2, P2, C, I, A, S	1/28	38.7	1.38
		MTTC (intermediate)	30.3

Note: L = launch, B = breach, P = penetrate, C = strike confidentiality, I = strike integrity, A = strike availability, and S = success.

Our model suggests that the company must focus resources on system 1 to improve its MTTC. We can use the cost of each mitigating action being considered to calculate cost/ i1 MTTC ratios, which we can compare to determine the most cost-effective option.

We encourage you to email us for detailed calculations.

Future Research

We recognize that the model presented in this article only covers a subclass of electronic attacks-that is, those launched remotely from the Internet. We also recognize that our current SSM and STEA focus primarily on software vulnerabilities. Numerous attack classes (and therefore attacks) are outside our model's scope at this time; however, we believe that our framework provides a foundation for future research.

Consider scenarios in which a threat agent breaches a plant's physical security and then logs onto an HMI and strikes the system's confidentiality or integrity. Or consider another attacker who takes a sledge hammer to a remotely situated target device and strikes availability. These scenarios involve four states: breach, strike confidentiality, strike integrity, and strike availability-remarkably similar to the states in the SSM we present here. We therefore expect that security architects can modify our SSM to identify attack paths for other attack classes, such as social engineering or physical attacks. Similarly, we also expect that security architects can modify the STEA to estimate state times for other vulnerability classes, such as protocol and human vulnerabilities (for example, poor password selection). Identifying and describing a set of models that covers the target system's entire attack surface is an area of considerable future research. This is why we're pursuing an HHM that will act as the glue to unify our models.

Although our HHM is outside this article's scope, it deserves some mention to put the framework presented into proper perspective. We're working toward creating a set of models that work together to give a view of a system's security (physical, electronic, and so on) that's appropriate for each level in an organization's hierarchy (executives, IT managers, and so on). Consider the company executives who want an overall view of the entire system. Security architects would integrate the models to create MTTC intervals whereby an interval's leftmost boundary might be due to physical security and the same interval's rightmost boundary might be due to electronic security. They will determine the MTTC using something along the lines of Equation 8. The company's IT managers, however, would be presented with MTTC intervals only for electronic attacks, whereby an interval's leftmost boundary might be due to compromising emanations (Tempest) and the same interval's rightmost boundary might be due to software vulnerabilities.

$$\mathrm{MTTC}_{\mathrm{OVERALL}} = (\mathrm{C}_1 \star \mathrm{MTTC}_1) + (\mathrm{C}_2^\star \mathrm{MTTC}_2) + \ldots + (\mathrm{C}_N \star \mathrm{MTTC}_N), \tag{8}$$

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where C is the weighting or probability coefficient, and MTTC_N is the attack class (electronic, physical, and so on).

We should also be able to extend our model to account for numerous environmental factors, such as patch intervals, operating system diversity, and pass-word policies. Determining which indicators are truly important and how they affect the MTTC is also an area for considerable research. Our next endeavor will be to improve our estimates and will focus on visibility (α) versus firewall update/review frequency. We're researching the use of common vulnerability scanners such as Nessus (www.nessus.org) and Nmap (insecure.org/nmap) to identify how many vulnerabilities are visible behind the firewall to obtain measured values for α.

In the long term, we need to collect relevant statistical data to set the MMTC intervals confidence levels. Promising sources for this statistical data are the Honeynet Project (www.honeynet.org) and the results of penetration team testing in the field. Both will help us to improve our state time estimations and to identify predominant attacker strategies. Our experience with the Industrial Security Incident Database leads us to believe that this might even help identify how an attacker's strategies are modified according to environmental conditions (such as network topology and defenses) and attacker skill levels.

Finally, we hypothesize that the distribution of attackers with skills ranging from beginner to expert will be normal. Our recent research pursues key risk indicators to identify the key skills and resources used for each of the three attacker levels and to relate these to the attacker's skill level through learning curve theory.

The findings of this preliminary research indicate that MTTC could be an efficient and powerful tool for comparative analysis of security environments and solutions. By deliberately restricting the variety of possible states (and nodes on attack trees) and selecting marker strategies rather than exhaustive lists, the model allows reasonable comparisons for decision-making purposes.

The selection of time as the unit of measurement is paramount to the model's strength. Time intervals are useful for intelligently comparing and selecting from a broad range of mitigating actions. We can compare and choose among two or more entirely different mitigating solutions based on which solution has the lowest cost in dollars per day and yet meets or exceeds a benchmark MTTC.

The MTTC framework can also identify how hard or weak a system is as seen by the attacker compared with peer systems in the same industry. MTTC industry averages (and other averages) can be collected over time and used to make peer comparisons. Above average MTTC intervals would likely encourage an opportunistic attacker to move to another target, whereas below-average MTTC intervals would encourage the opposite. □

Keywords

IEEE Keywords
Data security, Companies, Resource management, SCADA systems, System testing, Intelligent systems, Costs, Electrical equipment industry, Industrial control, Petroleum industry

INSPEC: Controlled Indexing
SCADA systems, computer crime, computer networks, DP management

INSPEC: Non-Controlled Indexing
network security, mean time-to-compromise intervals, MTTC security metric, physical security, SCADA security, corporate IT security, state-space model, attack path estimation, state time estimation

Author Keywords
Predator, Security, Network Security, SCADA, SCADA Security, Computer Security, Critical Infrastructure, Critical Infrastructure Protection, Markov, Compromise, Time-to-Compromise, Mean Time-to-Compromise, MTTC, Process Control, State Space Model, Attack Path

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