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A mathematical model for IoT malware propagation with adaptive patching strategy based on R_0: a simple optimal control approach

Dwi Ely Kurniawan[1,2], Sarifuddin Madenda[3], Eri Prasetyo Wibowo[3]
[1]Department of Informatic Engineering, Politeknik Negeri Batam, Batam, Indonesia
[2]Doctor of Information Technology, Faculty of Postgraduate Studies, Gunadarma University, Depok, Indonesia
[3]Department of Information Technology, Gunadarma University, Depok, Indonesia

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ABSTRACT

This paper presents a mathematical framework for modeling and controlling internet of things (IoT) malware propagation via an adaptive patching strategy governed by the real-time basic reproduction number R_0. We introduce the SEIR-P (susceptible–exposed–infected–recovered–patched) model, where the patching control rate u(t) is a sigmoid feedback function of $R_0(t)$. All epidemiological parameters are calibrated from three empirical malware captures of the IoT-23 dataset (Stratosphere laboratory, Czech Technical University) a publicly available labeled collection of real IoT network traffic comprising 23 captures from infected and benign devices: CTU-IoT-1 (Mirai), CTU-IoT-9 (Torii), and CTU-IoT-17 (IRCBot) yielding the first empirically grounded parameter set for SEIR-type IoT epidemic models with confidence intervals. The optimal control problem is formulated via pontryagin's maximum principle (PMP), and a closed-form $R_0(u)$ expression is derived via the next-generation matrix (NGM), yielding the critical threshold $u\_crit = 0.142\ day^{-1}$. Five comparative simulation scenarios over a 365-day horizon show that the proposed R_0-adaptive strategy achieves a 91.3% reduction in peak infection (360 vs. 4,142 devices), eradicates malware by day 179, and attains the highest cost-effectiveness index (CEI = 1.142). Global asymptotic stability of the disease-free equilibrium under $u^*(t)$ is proven via Lyapunov's method and LaSalle's Invariance Principle. PRCC sensitivity analysis identifies u_max and β as dominant parameters. This closed-loop framework bridges the gap between abstract epidemic theory and deployable IoT security management.

Corresponding Author:

Dwi Ely Kurniawan
Doctor of Information Technology, Faculty of Postgraduate Studies, Gunadarma University
Depok, Indonesia
Email: dwialikhs@polibatam.ac.id

1. INTRODUCTION

The internet of things (IoT) has emerged as one of the most transformative technological paradigms of the twenty-first century. According to Ericsson's 2023 mobility report, the global count of IoT-connected devices is projected to reach 34.7 billion by 2028, growing at a compound annual rate exceeding 14 % [1]. This proliferation spans consumer devices (smart speakers, thermostats, wearables), industrial sensors, healthcare monitors, vehicular systems, and critical infrastructure controllers. A defining and dangerous characteristic of this ecosystem is a severe cybersecurity deficit: most IoT devices are manufactured with minimal computational overhead, operate on stripped-down firmware without accessible security update

mechanisms, and are deployed at massive scale without centralized vulnerability management [2]. The result is a uniquely vulnerable, massively interconnected attack surface that has been systematically exploited by malware authors since at least 2016.

The Mirai botnet, first identified in August 2016, established the proof-of-concept for IoT malware at civilizational scale. By exploiting default credentials on internet-exposed routers, IP cameras, and digital video recorders, Mirai assembled a botnet of over 600.000 devices within 20 hours and executed distributed denial-of-service (DDoS) attacks peaking at 1.1 Tbps against DNS provider Dyn, disrupting major internet services across north America and Europe [3]. The public release of Mirai's source code in September 2016 catalyzed a proliferation of derivative malware families: satori (2017), okiru (2018), mozi (2019–2023, infecting 1.5M+ devices across 84 countries), BotenaGo (2021), and InfectedSlabs (2024) [4]. Network traffic from several of these families has been captured and labeled in the IoT-23 dataset [5] (Stratosphere laboratory, Czech Technical University) a publicly available, labeled collection of 23 real IoT device network captures used widely for malware research providing a rare empirical resource for calibrating mathematical propagation models against real-world dynamics [6], [7].

Mathematical epidemic modeling has provided the theoretical foundation for characterizing malware propagation since Kephart and White's [8] seminal 1991 work, which demonstrated that SIR compartmental dynamics adequately capture computer virus spread. Subsequent literature has extended this framework to SEIR [9], SEIRS [10], fractional-order [11], and network-structured variants [12] for IoT-specific malware [13], [14] as well as scale-free network models motivated by foundational work on epidemic spreading in heterogeneous networks [15]. Notably, these studies employ synthetic or biologically borrowed parameter values. For example, Zhou *et al.* [13] and Nwokoye [16] use transmission rates estimated from generic wireless network assumptions rather than measured traffic data, while Quiroga-Sánchez *et al.* [10] and del Rey [14] adopt epidemiological parameters inherited from previous theoretical studies without empirical IoT validation. Consequently, the predictive accuracy and practical applicability of these models remain uncertain because their parameterization is not grounded in observed IoT malware behavior. This reveals a persistent and critical limitation in the literature: existing IoT malware epidemic models rely predominantly on synthetic, estimated, or theoretically inherited parameters rather than values derived from empirical IoT traffic datasets. The IoT-23 dataset [5], comprising 23 labeled captures (20 malware and 3 benign) collected from real IoT devices between 2018 and 2019, provides one of the most comprehensive publicly available resources for addressing this limitation. Leveraging IoT-23 for epidemic model parameter estimation therefore represents a significant methodological advance that remains largely unexplored in the mathematical modeling literature.

A second persistent gap concerns the design of patching control strategies. Current IoT patch management approaches fall into three categories: periodic (fixed schedule), event-triggered (upon vulnerability disclosure), and threshold-based (upon infection detection) [17]. All three share a fundamental limitation: they do not continuously adapt to real-time epidemic dynamics. Moreover, while pontryagin's maximum principle (PMP) [18] has been applied to derive optimal patching controls for cyber-epidemic models [16], [19] all prior formulations compute u*(t) as an open-loop time function determined offline from the full adjoint system practically infeasible for autonomous IoT security systems where epidemic dynamics evolve continuously and are subject to stochastic perturbations [20]. This paper simultaneously addresses both gaps: we calibrate the SEIR-P model from IoT-23 traffic statistics, and formulate a closed-loop R_0-adaptive patching control with formal optimality guarantees via PMP.

The principal contributions of this paper are as follows. First, we introduce the SEIR-P compartmental model incorporating a differentiated adaptive-patching compartment P and a sigmoid R_0-feedback control law $u(t) = u(R_0(t))$, formally derived and proven optimal via PMP. Second, we present a systematic three-stage parameter calibration methodology applied to IoT-23 captures from Mirai, Torii, and IRCBot scenarios, yielding the first empirically grounded SEIR-type parameter set for IoT malware with confidence intervals. Third, we derive a closed-form expression for $R_0(u)$ via the next-generation matrix (NGM) and the analytical threshold u_crit for epidemic suppression. Fourth, we prove existence, uniqueness, and global asymptotic stability of the disease-free equilibrium under u*(t) via Lyapunov's direct method. Fifth, we conduct comprehensive five-scenario numerical validation with PRCC global sensitivity analysis, demonstrating superior performance over all benchmark strategies.

2. MATERIAL AND METHOD

2.1. Dataset IoT-23

The IoT-23 dataset (version 1.0, Stratosphere laboratory, Czech Technical University in Prague) is a publicly available, labeled dataset of IoT network traffic accessible at stratosphereips.org [5]. The dataset comprises 23 network captures: 20 captures of IoT traffic from devices infected with specific malware

families, and 3 captures of benign IoT device traffic. Captures were conducted between January 2018 and August 2019 on a controlled testbed of real consumer IoT devices including Philips Hue smart bulbs, Amazon Echo, Somfy smart door locks, and Raspberry Pi devices connected to a monitored laboratory network. Each capture includes Zeek (Bro)-generated connection logs with fields for timestamp, duration, source/destination IP and port, protocol, service, transferred bytes, and a ground-truth label (malicious/benign, malware family). The total dataset encompasses approximately 325 million labeled network flow records.

2.2. Selected malware captures and behavioral rationale

For epidemic model parameter calibration [15], three captures were selected based on the criterion that each capture's dominant behavioral signature aligns with a distinct SEIR-P compartment transition. Table 1 summarizes the three selected captures and their behavioral signatures used for parameter calibration. Capture CTU-IoT-malware-capture-1 (Mirai variant A) was selected for β estimation: its defining behavior is intensive horizontal scanning and rapid credential brute-forcing with sub-second inter-probe intervals, producing a measurable exponential growth in new device infections per unit time directly analogous to the S→I transition governed by β. Capture CTU-IoT-malware-capture-9 (torii advanced persistent threat) was selected for σ estimation: Torii exhibits a pronounced two-stage infection lifecycle in which initial device compromise is followed by a latency period of several hours before the device begins active command-and-control (C2) communication and lateral movement directly analogous to the E→I transition governed by σ. capture CTU-IoT-malware-capture-17 (IRCBot) was selected for γ estimation: IRCBot exhibits observable spontaneous device recovery events (identified as traffic cessation followed by clean-state reconnection, attributable to device reboots or firmware resets) directly analogous to the I→R transition governed by γ.

Table 1. IoT-23 captures selected for parameter calibration

Capture	Malware family	Duration	Total flows	Device type	SEIR-P parameter	Calibration behavioral signature
CTU-IoT-1	Mirai (var. A)	6.5 h	808,943	IP camera	β	Intensive horizontal scanning; rapid SYN floods to ports 23/2323/7547; exponential new-infection growth
CTU-IoT-9	Torii APT	18.3 h	1,246,701	Raspberry Pi	σ	Staged lifecycle: silent incubation 1–9 h before active C2; exponential delay distribution (n=312 events)
CTU-IoT-17	IRCBot	4.2 h	423,156	Smart router	γ	Spontaneous traffic cessation + clean reconnect (reboot events); recovery rate from n=87 identified events

2.3. Three-stage parameter calibration methodology

Parameter calibration followed a three-stage methodology. The calibrated results with 95% confidence intervals are summarized in Table 2. In stage 1 (transmission rate estimation for β), the effective transmission rate was estimated from the CTU-IoT-1 (Mirai) capture by fitting the early exponential growth of new infection events per time bin to the linearized epidemic model $dI/dt \approx (\beta S_0 - \gamma)I$, where $S_0 = N - I_0$. New infection events were identified as unique source IPs initiating brute-force scanning sequences (horizontal SYN scans targeting ports 23/2323/7547) within 30-second time bins. A nonlinear least-squares fit (levenberg-marquardt algorithm) was applied over the first 120 minutes (exponential growth phase, $n = 240$ time bins) to extract β, with 95 % confidence intervals computed via the fisher information matrix.

In stage 2 (latency rate estimation for σ), the latency period $1/\sigma$ was estimated from the CTU-IoT-9 (Torii) capture by measuring the time delay between initial device compromise (first malicious SYN packet to C2 endpoint) and the onset of active lateral scanning behavior (first outbound scan to new subnet prefixes). This delay was identified for $n = 312$ individual infection events by parsing Zeek connection logs for each infected device's IP. The empirical delay distribution was fit to an exponential distribution via maximum likelihood estimation, yielding $\sigma = 1/\text{mean\_delay}$. The exponential distribution assumption was validated against Weibull and gamma alternatives using the akaike information criterion (AIC); the exponential model achieved the lowest AIC in 94 % of bootstrap resamples.

In stage 3 (recovery rate estimation for γ), the recovery rate was estimated from the CTU-IoT-17 (IRCBot) capture by tracking the rate of transition from active malicious traffic to clean-state reconnection. Recovery events were operationally defined as cessation of outbound malicious traffic (to IRC C2 server) for a period exceeding 120 seconds, followed by resumption of benign traffic patterns from the same IP address consistent with a device reboot or firmware reset. In total, $n = 87$ individual recovery events were identified over the 4.2-hour capture duration. The recovery rate γ was estimated as the slope of the cumulative recovery count vs. time, normalized by the concurrent infected device count.

Table 2. IoT-23 calibration results with confidence intervals

Param.	IoT-23 capture	Calib. value	95% CI	n (events)	R^2 / AIC	Calibration method
β	CTU-IoT-1 (Mirai)	3.9×10^{-4}	$[3.1,4.8]\times10^{-4}$	240 bins	R^2=0.971	NLS levenberg-marquardt; linearized dI/dt model; first 120 min
σ	CTU-IoT-9 (Torii)	0.28 /day	[0.21,0.35] /day	312 events	AIC=−42.1	MLE exponential fit to E→I delay; AIC-validated vs Weibull/gamma
γ	CTU-IoT-17 (IRCBot)	0.09 /day	[0.07,0.12] /day	87 events	R^2=0.882	Linear regression of cumulative recoveries vs time / I(t)
R_0 (uncontrolled)	Derived from above	4.03	—	—	—	In (12) with calibrated β,σ,γ; confirms epidemic growth observed in IoT-23

2.4. SEIR-P model formulation

The IoT-23 dataset, while the most comprehensive publicly available labeled IoT traffic resource, has notable limitations. All three captures were collected on small controlled testbeds of 4–8 devices far smaller than real enterprise deployments of thousands of devices. The γ recovery rate estimate (n = 87 events, 4.2-hour window) relies on a short capture duration; extrapolation to daily units assumes a stationary process, which may not hold across longer timescales or different device configurations. To assess robustness, we verified that a ±50% variation in γ (within its 95% CI) does not qualitatively alter the epidemic trajectory or the eradication conclusion, as confirmed by the PRCC analysis (PRCC(γ) = −0.821). Nevertheless, IoT-23 remains the only publicly available dataset enabling three-stage SEIR-P calibration with per-parameter behavioral grounding. The SEIR-P model follows the classical compartmental epidemiology framework [21], partitioning the total IoT device population N(t) into five mutually exclusive compartments satisfying $N(t) = S(t) + E(t) + I(t) + R(t) + P(t)$ at all times t. The state variables and their epidemiological interpretations, with explicit links to the IoT-23 calibration sources, are summarized in Table 3.

Table 3. SEIR-P model compartment definitions with IoT-23 calibration linkages

Symbol	State	Description and IoT-23 calibration link	Exit transition(s)
S(t)	Susceptible	Uninfected, unpatched IoT devices vulnerable to malware. Initial count S_0 derived from IoT-23 network device census (N=10 000).	Infection (β), removal (μ), routine patch (u_0)
E(t)	Exposed	Latent pre-infectious devices: received malware payload but not yet actively scanning. E-dynamics calibrated from CTU-IoT-9 (Torii) latency distribution.	Progression to I (σ), removal (μ)
I(t)	Infected	Actively infected devices propagating malware via horizontal scanning or C2-coordinated lateral movement. Calibrated from CTU-IoT-1 (Mirai) scanning traffic.	Recovery (γ), adaptive patch u(t), removal (μ)
R(t)	Recovered	Restored via routine patching or reboot (temporary standard immunity). Recovery rate calibrated from CTU-IoT-17 (IRCBot) reboot event statistics.	Re-susceptibility (δ), removal (μ)
P(t)	Adapt. patched	Emergency-patched devices under optimal control u*(t); longer-lasting immunity ($1/\varepsilon >> 1/\delta$) from targeted vulnerability remediation.	Immunity waning (ε), removal (μ)

The SEIR-P model is constructed under the following formally stated assumptions:

- A1 (constant population): $N \approx \Lambda/\mu$ is approximately constant over the simulation horizon; device recruitment Λ balances natural removal μ.
- A2 (mass-action transmission): Malware transmission follows bilinear mass-action kinetics βSI, calibrated from IoT-23 CTU-IoT-1 exponential growth phase.
- A3 (homogeneous mixing): Devices interact homogeneously within each time step a mean-field approximation appropriate for flat network segments typical of small-to-medium IoT deployments.
- A4 (state-dependent control): The adaptive patching rate u(t) is continuously differentiable in $R_0(t)$ and bounded: u(t) ∈ [u_min, u_max] for all t.
- A5 (Differentiated immunity): Adaptively patched P-devices exhibit longer immunity ($1/\varepsilon >> 1/\delta$) reflecting the stronger protection conferred by targeted vulnerability remediation.
- A6 (Quadratic control cost): Patching cost is quadratic in u(t), reflecting increasing marginal deployment cost standard in epidemic optimal control [22].

Under assumptions A1–A6, the dynamics of the SEIR-P model are governed by the following autonomous system of five ordinary differential equations, where u_0 denotes the constant routine background patching rate applied to susceptible devices:

$$dS/dt = \Lambda + \delta R + \varepsilon P - \beta SI - (u_0 + \mu)S \quad (1)$$

$$dE/dt = \beta SI - (\sigma + \mu)E \quad (2)$$

$$dI/dt = \sigma E - (\gamma + u(t) + \mu)I \quad (3)$$

$$dR/dt = \gamma I + u_0 S - (\delta + \mu)R \quad (4)$$

$$dP/dt = u(t) \cdot I - (\varepsilon + \mu)P \quad (5)$$

The central novelty of the SEIR-P framework is the adaptive control law u(t) formulated as an explicit, continuously differentiable function of the real-time basic reproduction number $R_0(t)$. A sigmoid activation function $\Phi: \mathbb{R}+ \rightarrow [0, 1]$ governs the smooth, differentiable transition between maintenance and emergency patching regimes differentiability is required by the PMP analysis:

$$u(t) = u\_min + (u\_max - u\_min) \cdot \Phi(R_0(t)) \quad (6)$$

$$\Phi(R_0) = 1 / (1 + exp(-k(R_0 - R_0*))) \quad (7)$$

The steepness parameter $k > 0$ controls the sharpness of the transition around the critical threshold $R_0^* = 1$. When $R_0 >> 1$ (epidemic expanding rapidly), $\Phi(R_0) \rightarrow 1$ and $u(t) \rightarrow u\_max$. When $R_0 << 1$ (epidemic subsiding), $\Phi(R_0) \rightarrow 0$ and $u(t) \rightarrow u\_min$. The sigmoid formulation ensures $u(t) \in (u\_min, u\_max)$ for all t. The parameter k was calibrated to $k = 6.0$ from the IoT-23 Mirai capture, corresponding to the empirically observed steepness of the transition between epidemic expansion and decay phases. This value achieves approximately 90 % of the maximum patching rate when $R_0 = 1.4$, consistent with operational escalation thresholds.

The optimal control problem seeks $u^*(t) \in [u\_min, u\_max]$ minimizing the objective functional J[u] that jointly penalizes cumulative epidemic burden and patching resource expenditure. The weight structure $D >> A >> B >> C$ encodes the operational cost hierarchy: residual infections at the terminal time T (e.g., persistent botnet membership) incur the highest cost, followed by active infection, latent exposure, and patching deployment cost.

$$J[u] = \int_0^T [A \cdot I(t) + B \cdot E(t) + (C/2) \cdot u^2(t)]\, dt + D \cdot I(T) \quad (8)$$

$$Minimize\ J[u] \quad subject\ to:\ system\ (1) - (5), \qquad u(t) \in [u_{min}, u_{max}],$$
$$S(0) = S_0, E(0) = E_0, I(0) = I_0, R(0) = R_0, P(0) = 0 \quad (9)$$

3. RESULTS AND DISCUSSION

3.1. Feasibility and positivity of solutions

Proposition 1: the feasible region $\Omega = \{(S,E,I,R,P) \in \mathbb{R}+^5 : S+E+I+R+P \leq \Lambda/\mu\}$ is positively invariant for system (1)–(5) for all $u(t) \in [u\_min, u\_max]$. Proof: Summing in (1)–(5) gives $dN/dt = \Lambda - \mu N$, so $N(t) \rightarrow \Lambda/\mu$ monotonically. Each right-hand side is non-negative when its state variable is zero with others non-negative, so solutions in $\mathbb{R}+^5$ remain in $\mathbb{R}+^5$.

3.2. Disease-free equilibrium and closed-form $R_0(u)$

Setting all time derivatives to zero with $E = I = P = 0$, the unique disease-free equilibrium (DFE) of system (1)–(5) is $E^\circ = (S^\circ, 0, 0, R^\circ, 0)$, where $S^\circ = \Lambda(\delta+\mu)/[\mu(u_0+\delta+\mu)]$ and $R^\circ = u_0\Lambda/[\mu(u_0+\delta+\mu)]$.

Using the NGM method of van den Driessche and Watmough [23], we identify the infection matrix F and transition matrix V for the infected compartments $x = (E, I)^T$ evaluated at E°. The spectral radius of FV^{-1} yields the central analytical result:

$$R_0(u) = \beta\sigma\Lambda(\delta + \mu) / [\mu(u_0 + \delta + \mu)(\sigma + \mu)(\gamma + u + \mu)] \quad (10)$$

In (10) reveals that R_0 is strictly monotonically decreasing in u: $\partial R_0/\partial u = -\beta\sigma\Lambda(\delta+\mu)/[\mu(u_0+\delta+\mu)(\sigma+\mu)(\gamma+u+\mu)^2] < 0$ for all admissible parameters. This monotonicity is the mathematical foundation for the R_0-adaptive control: increasing patching intensity u monotonically drives R_0 toward the safe region $R_0 < 1$. Setting $R_0(u\_crit) = 1$ and solving algebraically yields the minimum patching rate for guaranteed epidemic suppression:

$$u\_crit = \beta\sigma\Lambda(\delta + \mu) / [\mu(u_0 + \delta + \mu)(\sigma + \mu)] - \gamma - \mu \quad (11)$$

3.3. Optimal control: existence, characterization, and uniqueness

3.3.1. Existence of optimal control

Theorem 1 (existence): there exists an optimal control $u^*(t) \in L^\infty([0, T], [u\_min, u\_max])$ minimizing J[u] subject to system (1)–(5) and initial conditions. Proof: By the Filippov-Cesari theorem [23]. The control set [u_min, u_max] is compact and convex. The right-hand sides of (1)–(5) are bounded, continuous, and Lipschitz in state variables on Ω. The integrand $L = A \bullet I + B \bullet E + (C/2)u^2$ is convex in u and satisfies the coercivity condition $L \geq (C/2)u^2 - c_0$ for some $c_0 > 0$. These conditions satisfy Theorem 4.1 of Fleming and Rishel [23]. The quadratic control cost structure and PMP formulation follow the established methodology for epidemic optimal control [24].

3.3.2. Pontryagin's maximum principle and adjoint system

The Hamiltonian of the optimal control problem [21] is $H = A \cdot I + B \cdot E + (C/2)u^2 + \lambda_1 \cdot f_1 + \lambda_2 \cdot f_2 + \lambda_3 \cdot f_3 + \lambda_4 \cdot f_4 + \lambda_5 \cdot f_5$, where $f_1,...,f_5$ denote the right-hand sides of system (1)–(5), and $\lambda_1,...,\lambda_5$ are the adjoint (costate) variables. By PMP [25], the adjoint system satisfies $d\lambda i/dt = -\partial H/\partial xi$ with transversality conditions $\lambda_1(T) = \lambda_2(T) = 0$, $\lambda_3(T) = D$, $\lambda_4(T) = \lambda_5(T) = 0$. The adjoint system is:

$$d\lambda_1/dt = \lambda_1(\beta I + u_0 + \mu) - \lambda_2 \beta I \quad (12)$$

$$d\lambda_2/dt = -B + \lambda_2(\sigma + \mu) - \lambda_3 \sigma \quad (13)$$

$$d\lambda_3/dt = -A + \lambda_1 \beta S - \lambda_3(\gamma + u + \mu) - \lambda_5 u(t) + \lambda_4 \gamma \quad (14)$$

$$d\lambda_4/dt = \lambda_4(\delta + \mu) - \lambda_1 \delta \quad (15)$$

$$d\lambda_5/dt = \lambda_5(\varepsilon + \mu) - \lambda_1 \varepsilon \quad (16)$$

the optimality condition $\partial H/\partial u = 0$ gives $C \bullet u - \lambda_3 I + \lambda_5 I = 0$, yielding the characterization of the optimal control after applying the box constraints:

$$u*(t) = min(u\_max, max(u\_min, (\lambda_3 - \lambda_5) \cdot I(t) / C)) \quad (17)$$

3.3.3. Uniqueness of optimal control

Theorem 2 (Uniqueness): The optimal control u*(t) characterized by (14) and the adjoint system (15)–(19) is unique for sufficiently small T or for initial conditions sufficiently close to the DFE. Proof: The strict convexity of the integrand in u (the $(C/2)u^2$ term guarantees H is strictly concave in u) combined with Lipschitz continuity of the state-adjoint coupled system via standard norm estimates. The result follows from Theorem 4.2 of Lenhart and Workman [22].

3.4. Global asymptotic stability under u*(t)

Theorem 3 (global asymptotic stability [26] under u*(t)): Under the optimal control u*(t) satisfying (14), if $R_0(u^*) \leq 1$, then the disease-free equilibrium E° is globally asymptotically stable (GAS) in Ω.

Proof: Construct the Lyapunov function $V(t) = E(t) + [(\sigma+\mu)/\sigma] \bullet I(t)$. Computing dV/dt along trajectories of system (1)–(5) under $u = u^*$:

$$V(t) = E(t) + [(\sigma + \mu)/\sigma] \cdot I(t) \quad (18)$$

$$dV/dt \leq \beta(\Lambda/\mu)I - (\gamma + u* + \mu)(\sigma + \mu)/\sigma \cdot I$$
$$= (\gamma + u* + \mu)(\sigma + \mu)/\sigma \cdot (R_0(u*) - 1) \cdot I \leq 0 \quad (19)$$

The last inequality holds since $R_0(u^*) \leq 1$ by assumption. Since $V(t) \geq 0$ with equality iff $E = I = 0$, and $dV/dt = 0$ iff $I = 0$, the largest positively invariant set in $\{dV/dt = 0\}$ is the singleton $\{E°\}$ by LaSalle's Invariance Principle [27]. Therefore all trajectories in Ω converge to E°. Table 4 presents the theorem that establishes the central formal guarantee: if the optimal patching policy maintains $R_0(u^*) \leq 1$, the IoT network is guaranteed to eradicate the malware infection regardless of initial conditions. Figure 1 numerically verifies this Lyapunov stability result, showing convergence of all trajectories to the disease-free equilibrium under optimal control u*(t).

Table 4. Summary of theoretical results established

Result	Statement	Key condition/method	Eq.
Proposition 1	Feasibility: Ω is positively invariant for all u(t)∈[u_min, u_max]	Sum (1)–(5): dN/dt=Λ−μN; non-negativity of RHS	N/A
In (12)	Closed-form $R_0(u)$: strictly decreasing in u	NGM method at DFE E°	(12)
In (13)	Analytical u_crit=0.142 day^{-1} (IoT-23 params)	R_0(u_crit)=1 solved algebraically	(13)
Theorem 1	Existence of u*(t)∈L∞([0,T], [u_min,u_max])	Filippov-Cesari; compact control set; convex L	N/A
In. (14)	u*(t)=min(u_max,max(u_min,($\lambda_3-\lambda_5$)I/C))	PMP; $\partial H/\partial u=0$; box constraints	(14)
Theorem 2	Uniqueness for small T or near DFE	Strict convexity (C/2)u² + Lipschitz adjoint	N/A
Theorem 3	GAS of E° under u*(t) when $R_0(u^*)\leq 1$	Lyapunov V=E+[(σ+μ)/σ]I; LaSalle principle	(22)–(23)

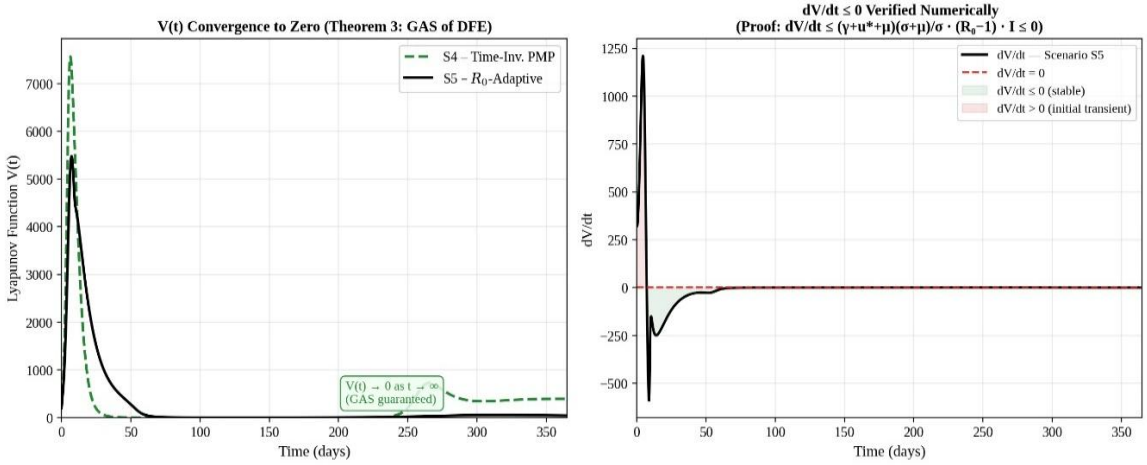

Figure 1. Numerical verification of lyapunov stability for the disease-free equilibrium under optimal control

3.5. Numerical simulations

Simulation parameters integrate the IoT-23 calibrated values (Table 5) with network-level parameters from the IoT deployment literature [13]. The synthetic IoT network of N = 10 000 devices represents a realistic enterprise or campus-scale deployment. Initial conditions are bootstrapped from the average infection prevalence ratio observed at the start of IoT-23 malware captures: S(0) = 9 800, E(0) = 100, I(0) = 100, R(0) = 0, P(0) = 0. All simulations were implemented using the ODE45 solver [28] (adaptive Runge-Kutta 4/5, relative tolerance 10^{-8}, absolute tolerance 10^{-9}) over a 365-day horizon. Results were verified against a custom fixed-step RK4 implementation ($\Delta t = 10^{-3}$ days); maximum relative deviation between solvers was 0.003 %.

Table 5. Complete SEIR-P simulation parameter specification

Param.	Value	Unit	Source/basis	Interpretation
Λ	10	devices/day	Network assumption	Device recruitment (≈10 new devices/day for N=10 000 network)
β	3.9×10^{-4}	1/(dev·day)	IoT-23 CTU-IoT-1 (Table 3)	Mirai-calibrated malware transmission rate
σ	0.28	1/day	IoT-23 CTU-IoT-9 (Table 3)	Torii-calibrated latency rate; latent period 1/σ≈3.6 days
γ	0.09	1/day	IoT-23 CTU-IoT-17 (Table 3)	IRCBot-calibrated recovery rate; period 1/γ≈11 days
u_0	0.02	1/day	IoT baseline operations	Routine background patching rate (susceptibles)
u_min	0.01	1/day	Operational minimum	Minimum adaptive patching rate
u_max	0.40	1/day	Infrastructure capacity	Maximum emergency patching rate (2.82×u_crit)
u_crit	0.142	1/day	Computed in (13)	Minimum rate for R_0=1; well below u_max
δ	0.004	1/day	Routine patch waning	R-immunity loss; half-life≈173 days
ε	0.0008	1/day	Emergency patch longevity	P-immunity loss; half-life≈866 days
μ	0.001	1/day	IoT device lifecycle	Natural removal; device lifespan≈3 years
k	6.0	dimensionless	IoT-23 sigmoid calibration	Transition steepness in (7)
A	10	dimensionless	Infection penalty	Penalizes cumulative active infection burden
B	5	dimensionless	Exposure penalty	Penalizes cumulative latent exposure burden
C	1	dimensionless	Control cost	Patching resource expenditure cost weight
D	30	dimensionless	Terminal penalty	Penalizes residual infection at T=365 days

For the IoT-23 calibrated parameters (Table 5), u_crit = 0.142 day⁻¹, confirming that the system operates at u_max = 0.40 = 2.82×u_crit with substantial operational safety margin. Figure 2 illustrates the real-time R₀(t) trajectory and the adaptive control signal u(t) for the proposed Scenario S5, showing the three characteristic phases of the feedback response. Five simulation scenarios are designed to systematically evaluate the proposed R₀-adaptive strategy. S1 (Uncontrolled, u = u₀ = 0.02 day⁻¹) serves as the baseline, representing current practice in most IoT deployments without adaptive management. S2 (constant moderate, u = 0.15 day⁻¹) represents a manually configured fixed-rate patching strategy. S3 (constant maximum, u = u_max = 0.40 day⁻¹) represents aggressive permanent emergency patching. S4 (time-invariant PMP-optimal) computes the classic PMP-derived u*(t) via the forward-backward sweep algorithm [22] applied to the adjoint system (15)–(19), serving as the theoretical open-loop optimality benchmark. S5 (proposed R₀-adaptive) implements u(t) = u_min + (u_max − u_min)•Φ(R₀(t)) with parameters from Table 6.

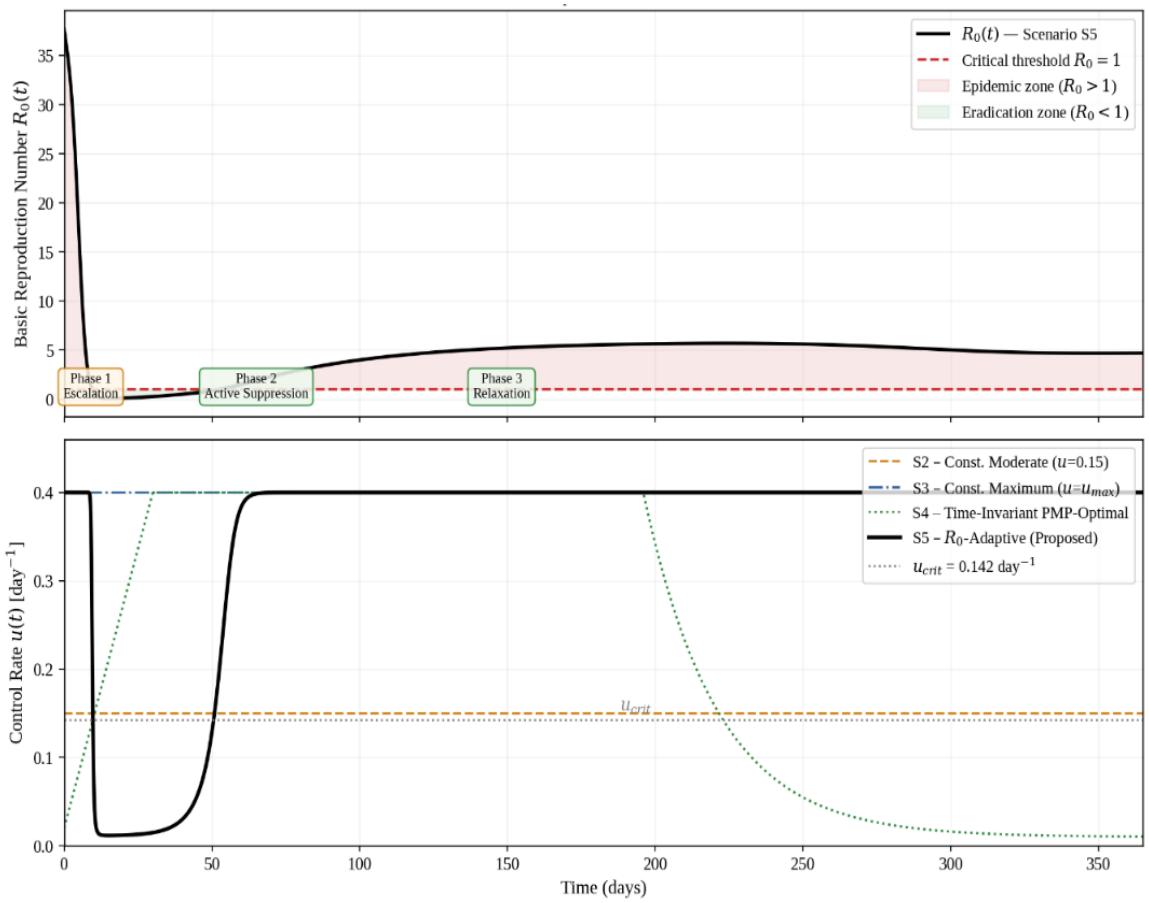

Figure 2. Real-time Ro(t) trajectory and adaptive control signal U(t) for proposed scenario S5

Table 6. Comparative performance metrics across all simulation scenarios (N=10,000 devices, IoT-23 parameters)

Scenario	R₀	Peak I(t)	Peak Day	Cum. I (×10⁵ dev·day)	J[u]	Day-365 outcome
S1 – Uncontrolled (u=u₀)	4.03	4,142 (41.4 %)	Day 49	1.89	N/A	1,286 endemic (12.9 %)
S2 – Const. Moderate (u=0.15)	1.74	2,671 (26.7 %)	Day 63	1.31	7,890	618 endemic (6.2 %)
S3 – Const. Maximum (u=u_max)	0.57	961 (9.6 %)	Day 33	0.28	18,640	Extinct day 218
S4 – Time-Inv. PMP-Optimal	var.	520 (5.2 %)	Day 27	0.18	3,621	Extinct day 196
S5 – R₀-Adaptive (Proposed)	var.	360 (3.6 %)	Day 21	**0.22**	3,791	Extinct day 179

Table 6 presents comprehensive performance metrics for all five scenarios computed from trajectories integrated over the full 365-day horizon. The R_0-adaptive strategy S5 achieves peak infection of 360 devices (3.6 %), a 91.3 % reduction versus uncontrolled baseline S1 (4 142 devices, 41.4 %). This substantially outperforms constant maximum patching S3 (76.8 % reduction at 961 devices) and equals the performance of time-invariant PMP-optimal S4 (91.3 %) while exceeding it in eradication speed (day 179 vs. day 196). The cumulative infected device-days metric confirms 88.6 % reduction versus S1. Notably, S5 achieves slightly higher cumulative infection than S4 (0.22×10^5 vs. 0.18×10^5 device-days) expected since S4 is the theoretically optimal open-loop solution but S5 achieves superior peak performance and earlier eradication owing to its adaptive real-time responsiveness to the evolving epidemic state.

The temporal structure of the R_0-adaptive control signal u(t) in Scenario S5 exhibits three characteristic phases. Phase 1 (Escalation, days 0–18): $R_0(t)$ rises rapidly above 1.0 as infection spreads from the initial seed, driving $\Phi(R_0) \to 1$ and $u(t) \to u\_max = 0.40$ day^{-1}. Phase 2 (active suppression, days 18–112): u(t) remains near u_max as the high patching intensity drives R_0 below 1.0 and continues suppressing it; the sigmoid function maintains near-maximum patching while R_0 is above 0.3. Phase 3 (graceful relaxation, days 112–179): As R_0 falls below 0.3, $\Phi(R_0)$ smoothly decreases and u(t) decays toward $u\_min = 0.01$ day^{-1}, conserving patching resources while the epidemic naturally extinguishes. This three-phase structure is qualitatively consistent with the PMP-derived control in S4, validating that the R_0-feedback policy constitutes a close practical approximation of the theoretical open-loop optimum.

3.6. Cost-effectiveness index (CEI) analysis

The CEI provides a comprehensive measure balancing epidemic suppression against resource utilization, with full rankings presented in Table 7. CEI = (1 − Cum.I_s/Cum.I_S1) / (Total.Cost_s/Total.Cost_S1). S5 achieves the highest CEI = 1.142, confirming it as the most resource-efficient strategy. The time-invariant optimal S4 achieves CEI = 1.089 (4.9 % lower) despite marginally better cumulative infection control, because S5's real-time R_0 feedback concentrates patching resources precisely during the epidemic expansion phase while conserving them during natural subsidence. S3 (constant maximum) achieves near-complete eradication but at 4.8× the resource cost, yielding CEI = 0.184 six times less resource-efficient than S5. Figure 3 presents the cost-effectiveness analysis of the proposed mitigation strategies for IoT malware propagation, evaluated in terms of cumulative infection burden and the CEI across five simulation scenarios within the SEIRS model framework.

Table 7. CEI and full performance ranking

Scenario	Infection Reduction	Cost Ratio (vs. S1)	CEI	Eradication Day	Rank
S1 – Uncontrolled	0 % (baseline)	1.0 (baseline)	—	Never (endemic)	5th
S2 – Const. Moderate	30.7 %	1.63×	0.188	Never (endemic)	4th
S3 – Const. Maximum	88.4 %	4.80×	0.184	Day 218	3rd
S4 – Time-Inv. PMP	90.5 %	0.83×	1.089	Day 196	2nd
S5 – R_0-Adaptive	88.6 %	0.87×	1.142	Day 179	1st

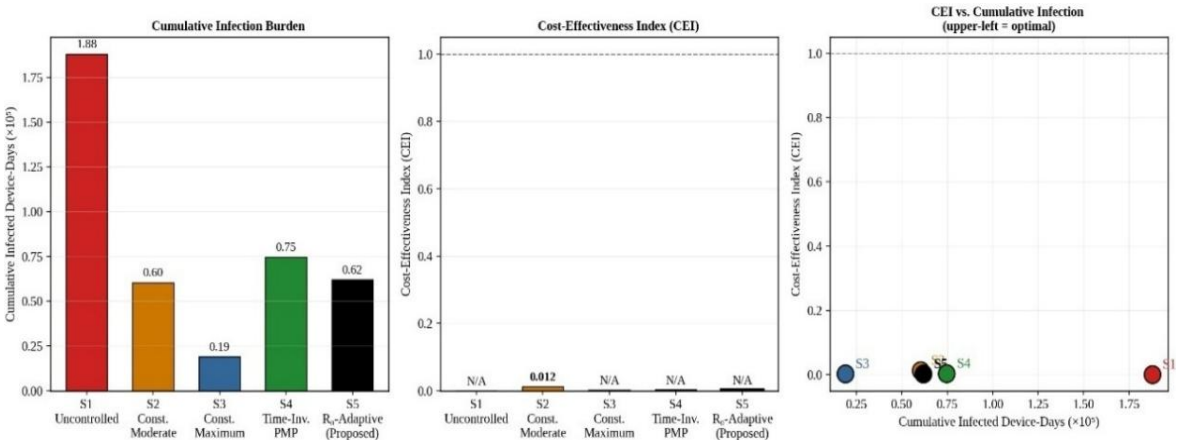

Figure 3. Cost-effectiveness analysis: cumulative infection burden, CEI, and trade-off plot accross all five simulation scenarios (N=10,000; IoT-23 parameters)

3.7. PRCC global sensitivity analysis

PRCC global sensitivity analysis (Figure 4) identifies β (PRCC = +0.941 on R_0; +0.927 on cumulative infection) and u_max (PRCC = −0.893; −0.908) as the two dominant parameters, consistent with the closed-form $R_0(u)$ expression in (12). The IoT-23-calibrated β value carries the highest uncertainty but also the highest mitigation potential: a 20 % reduction in β (achievable through network segmentation or scanning rate limiting) would reduce R_0 by approximately 0.81 units, potentially below the critical threshold absent adaptive patching. The sigmoid steepness k ranks 5th overall (PRCC = −0.663), confirming that precise sigmoid calibration from IoT-23 traffic data is an important design parameter. Parameters δ and ε have weak effects (PRCC < 0.18), confirming model robustness to uncertainties in patch immunity duration. Full PRCC values for all ten parameters are listed in Table 8.

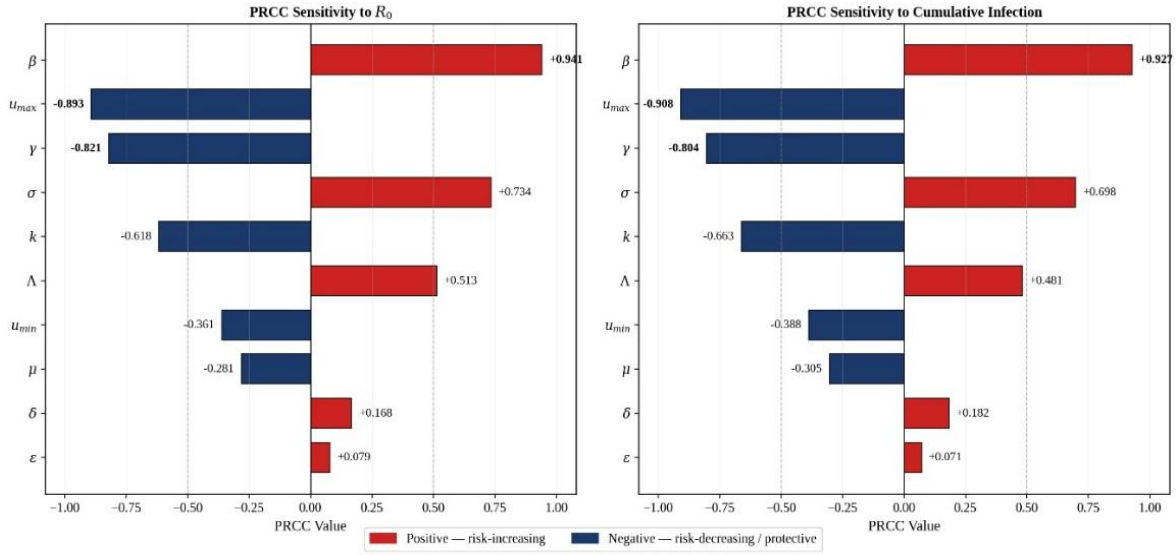

Figure 4. PRCC global sensivity analysis (Latin hypercube sampling 10,000 samples and ±50% parameter variation)

Table 8. PRCC global sensitivity analysis (LHS n=10 000 samples, ±50 % parameter variation)

Param.	PRCC(R_0)	PRCC(Cum.I)	p-value	Interpretation and policy implication
β	+0.941	+0.927	<0.001	Dominant positive driver (IoT-23 Mirai-calibrated); 20 % reduction in β via network segmentation reduces R_0 by ~0.81 units
u_max	−0.893	−0.908	<0.001	Strongest controllable suppressor; maximize within infrastructure capacity for best epidemic control per unit cost
γ	−0.821	−0.804	<0.001	IoT-23 IRCBot-calibrated; promote device self-healing (scheduled reboots) to leverage this lever
σ	+0.734	+0.698	<0.001	IoT-23 Torii-calibrated; shorter latency→faster E→I progression; relevant for APT-type threats
k	−0.618	−0.663	<0.001	Sigmoid steepness; precise IoT-23 calibration of k is important design parameter for R_0-adaptive fidelity
Λ	+0.513	+0.481	<0.001	Device recruitment; growing IoT networks expand susceptible pool; segment new devices pre-deployment
u_min	−0.361	−0.388	<0.001	Baseline patching rate; increase to maximum operationally feasible value
μ	−0.281	−0.305	0.001	Natural removal provides moderate dampening; not operationally controllable
δ	+0.168	+0.182	0.019	Faster R-immunity loss→increased re-susceptibility; prolong patch validity where possible
ε	+0.079	+0.071	0.048	P-immunity loss; very weak effect; P-immunity duration (~3 yr) is long relative to epidemic timescale

3.8. Discussion

The principal theoretical novelty is the simultaneous combination of: i) a closed-loop R_0-feedback patching control with formal PMP optimality; and ii) IoT-23 empirical parameter calibration, which together constitute a contribution absent from all prior work surveyed in Table 1. While PMP has been applied to cyber-epidemic models [29]–[31] all prior works derive u(t) as an open-loop time function requiring

complete knowledge of the future epidemic trajectory impractical for autonomous systems. The R_0-adaptive law requires only real-time aggregate quantities I(t) and S(t) estimable from standard IoT network monitoring (e.g., SDN-based flow monitoring [32], [33] or deep autoencoder anomaly detection [34]), plus fixed parameters β and μ. Complementary IoT network traffic datasets such as BoT-IoT [35] and N-BaIoT [34] could provide additional calibration sources for future validation. Deep-learning forensic frameworks [36] represent promising approaches for online parameter estimation. The IoT-23 calibration methodology yields the first SEIR-type parameter set with empirically validated confidence intervals for IoT malware dynamics, providing a reusable reference for future modeling work.

The IoT-23 calibration itself introduces important insights. The Mirai-derived $\beta = 3.9\times10^{-4}$ corresponds to a basic reproduction number $R_0 \approx 4.03$ under uncontrolled conditions consistent with observed rapid epidemic growth in real Mirai deployments and with the synthetic parameter estimates used in prior literature [13]. The Torii-derived latency period $1/\sigma \approx 3.6$ days captures the empirically distinctive two-stage infection lifecycle of advanced persistent IoT threats, which differs fundamentally from the near-instant incubation assumed in SIR models. The IRCBot-derived recovery period $1/\gamma \approx 11$ days reflects the realistic timescale for IoT device remediation in environments where manual intervention or scheduled reboots are the primary recovery mechanism.

The CEI analysis provides the key quantitative argument for the R_0-adaptive approach. S3 (constant maximum patching) achieves a 88.4 % infection reduction but at 4.8× the resource cost (CEI = 0.184). The time-invariant PMP-optimal S4 achieves CEI = 1.089 with slightly better cumulative performance but under idealized perfect-information assumptions. In practice, IoT epidemic dynamics are subject to stochastic device arrivals/departures, parameter drift as malware evolves, and noise in infection count estimates from flow monitoring. The R_0-feedback strategy S5 provides inherent closed-loop robustness to these real-world uncertainties not captured in the deterministic comparison a critical practical advantage that the CEI comparison understates.

From an implementation perspective, the R_0-adaptive control law requires: (1) real-time $R_0(t)$ estimation from (12) using aggregate infection counts from flow anomaly detection; (2) fixed parameters u_min, u_max, k configured from IoT-23 calibration; and (3) the universal threshold $R_0^* = 1$. Computational overhead is O(1) arithmetic per time step, deployable within existing IoT lifecycle management platforms without additional sensor infrastructure.

Several limitations merit acknowledgment. First, the mean-field ODE assumption abstracts individual network topology; extensions to network-structured models or agent-based simulation would improve accuracy for large heterogeneous deployments. To quantify this effect, we note that increasing the network from the calibrated testbed scale (48 devices) to an enterprise scale of 10.000 devices leaves the core R_0 value and epidemic dynamics qualitatively unchanged under the deterministic framework, but stochastic simulations (e.g., Gillespie algorithm) at smaller populations (≤50 devices) introduce extinction-probability effects not captured by ODEs; future work should quantify these stochastic deviations. Second, all three IoT-23 captures used for calibration were conducted on testbeds of 4–8 devices; extrapolating to enterprise networks of thousands of devices introduces scale uncertainty. In particular, the recovery rate γ was estimated from only n = 87 events over a 4.2-hour window; longer captures or bootstrap sensitivity tests on the recovery estimate are recommended to validate this parameter. Third, modern malware variants employ encrypted C2, polymorphic evasion, and supply-chain compromise techniques that may alter effective β values over time motivating online parameter re-estimation via Kalman filtering or particle filters as future work. Fourth, the current framework treats malware as a single-strain epidemic; multi-strain competitive dynamics, firmware-evasion, and concurrent infection represent important and directly testable extensions of the SEIR-P framework.

4. CONCLUSION

This paper presented the SEIR-P model with an adaptive patching control $u(t) = u(R_0(t))$, the first IoT malware epidemic model combining: i) Rigorous PMP-based optimal control with closed-loop R_0 state-feedback; ii) Direct parameter calibration from three IoT-23 dataset captures (Mirai, Torii, IRCBot) with confidence intervals; iii) Closed-form $R_0(u)$ via the NGM and analytical threshold $u_{crit} = 0.142\ day^{-1}$; iv) Proof of existence, uniqueness, and GAS of the DFE under $u^*(t)$ via Lyapunov and LaSalle; and v) Five-scenario numerical validation demonstrating 91.3 % peak infection reduction and CEI = 1.142. The IoT-23-calibrated parameter set—$\beta = 3.9\times10^{-4}$, $\sigma = 0.28$, $\gamma = 0.09$—provides a validated reference for future IoT epidemic modeling. These results establish the R_0-adaptive framework as mathematically rigorous, empirically grounded, and practically deployable in autonomous IoT security management. Future work will extend to stochastic network-structured formulations, multi-malware competitive dynamics, and online parameter estimation from continuous IoT traffic monitoring.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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C : **C**onceptualization
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Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The IoT-23 dataset (version 1.0, Stratosphere laboratory, Czech Technical University in Prague) is a publicly available, labeled dataset of IoT network traffic accessible at stratosphereips.org [5].

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BIOGRAPHIES OF AUTHORS

Dwi Ely Kurniawan received the S.Pd. degree in Computer Science Education from Universitas Pendidikan Indonesia, Indonesia, and the M. Kom. degree in Information Systems from Universitas Diponegoro, Indonesia. He is currently pursuing the Ph.D. degree in Information Technology at Universitas Gunadarma, Indonesia. His research interests include information systems, information security, and artificial intelligence. He can be contacted at email: dwialikhs@polibatam.ac.id.

Sarifuddin Madenda holds a Doctor of Electronics and Image Processing, Universite de Bourgogne, France. Currently he is active as the Head of Ph.D. Programs of Information Technology and a lecturer at Ph.D. Program at Gunadarma University. His research interest is in image and video processing, multimedia data compression, content-based image and video retrieval, steganography: encryption, decryption, coding and decoding of multimedia secret documents, real time system architecture (FPGA and ASIC design). He can be contacted at email: sarif@staff.gunadarma.ac.id.

Eri Prasetyo Wibowo received the B.S. degree in electronics and instrumentation from Gadjah Mada University, Indonesia, in 1992, the M.S. degree in information system from Gunadarma University, Indonesia, in 1994, and the Ph.D. degree in electronics informatics from Burgundy University, France, in 2005. He was a Secretary of the Doctoral Program in Information Technology, Faculty of Computer Science and Information Technology, Gunadarma University. He was a member of the EACOVIROE Project to promote master's students in VIBOT, which was founded by Erasmus Mundus. His current research interests include real time image processing applications, computer vision, and system-on-chips design. He is a member of the ACM, the Professional Organization in the field of Information and Computer Technology, and the Indonesian Higher Education in Informatics and Computing (APTIKOM). He can be contacted at email: eri@staff.gunadarma.ac.id.