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Strategies for mitigating detrimental effects in cyber-physical multiplex networks

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Detrimental effects, such as widespread epidemics or rumors, can inflict significant damage on society in a remarkably short time [1]. Various studies have focused on mitigating these effects independently within single-layer networks [2]. This study focuses on the coupling effects between information dissemination and epidemic spread, aptly represented within a novel multiplex topology: the cyber-physical/online-offline network, $G := \langle C, P\rangle$.

As illustrated in Figure 1(a), our study delves into the dynamics of epidemic spread within a community-structured layer P, alongside information propagation in layer C, which comprises: (i) positive messages, like awareness campaigns, that bolster individuals' perception of epidemic risk and promote protective behaviors; (ii) negative messages, like rumors, which proliferate particularly when epidemics emerge. The amalgamation of epidemics with these positive and negative items engenders the emergence of two innovative mechanisms: the epidemic-awareness coupling mechanism (EACM) and the epidemic-rumor spreading mechanism (ERSM), each presenting unique and complex challenges.

Discussions about EACM. A seminal contribution in EACM researching was made by [3], which unveiled the pivotal role of awareness diffusion in mitigating the scale of epidemic outbreaks. Ref. [4] identified a meta-critical point where the initiation of an epidemic is intricately governed by the spread of awareness. Ref. [5] categorized prevention awareness into positive and negative paradigms. These foundational investigations paved the way for further inquiry into EACM. Yet, the physical contact network frequently manifests a community structure, wherein localized awareness exerts a profound impact on immunity campaigns. Inspired by this phenomenon, the present study endeavors to enhance the EACM framework by integrating community consciousness within the physical network. As demonstrated in Figure 1(b), which employs a combination of active and passive immunity mechanisms to mitigate epidemic spread, presenting a coupled immunity model and elucidating the impact of both awareness and community outreach on individuals.

The active-passive immunity can be defined mathematically as

$$\beta_i^{\mathrm{A}} = \beta_i^{\mathrm{U}} \cdot k_i^{-c_i} \cdot \exp\left(-\lambda \frac{\sum_{v\in\Gamma_i} I(v)+1}{|\Gamma_i|}\right), \quad (1)$$

where β_i^{A} and β_i^{U} denote infection rates for node v_i that are aware and unaware of epidemics, respectively. It is noted that when $c_i = 0$, β_i^{U} is degraded by only active immunity; while when $\lambda = 0$, it is degraded by only passive immunity.

Definition 1 (APEI). The active-passive based epidemic immunity (APEI) problem within the EACM concentrates on identifying an epidemic threshold β_c^{U}, essential for controlling the epidemic's spread by adjusting its relevant parameters.

In the EACM framework, the integration of node states across online (unaware, aware) and offline (susceptible, infected) layers yields composite states: US, AS, and AI. The absence of a UI state underscores the premise that infection prompts immediate awareness of the epidemic. This model facilitates the development of the microscopic Markov chain approach (MMCA) through the first discrete transition probability tree (FDTPT) methodology, which quantifies the likelihood of a node transitioning to a specific state at time $t+1$, based on its state at the preceding time t:

$$\begin{aligned} p_i^{\mathrm{US}}(t+1) = {}& p_i^{\mathrm{AI}}(t)\delta(1-c_i)\mu + p_i^{\mathrm{US}}(t)r_i(t)(1-c_i)q_i^{\mathrm{U}}(t) \\ & + p_i^{\mathrm{AS}}(t)\delta(1-c_i)q_i^{\mathrm{U}}(t), \end{aligned} \quad (2)$$

$$\begin{aligned} p_i^{\mathrm{AS}}(t+1) = {}& p_i^{\mathrm{AI}}(t)[\delta c_i\mu + (1-\delta)\mu] \\ & + p_i^{\mathrm{US}}(t)\left[r_i(t)c_i q_i^{\mathrm{A}}(t) + (1-r_i(t))\,q_i^{\mathrm{A}}(t)\right] \\ & + p_i^{\mathrm{AS}}(t)\left[\delta c_i q_i^{\mathrm{A}}(t) + (1-\delta)q_i^{\mathrm{A}}(t)\right], \end{aligned} \quad (3)$$

$$\begin{aligned} p_i^{\mathrm{AI}}(t+1) = {}& p_i^{\mathrm{AI}}(t)[\delta c_i(1-\mu) + \delta(1-c_i)(1-\mu) \\ & + (1-\delta)(1-\mu)] \\ & + p_i^{\mathrm{US}}(t)[r_i(t)c_i(1-q_i^{\mathrm{A}}(t)) + r_i(t)(1-c_i) \\ & \cdot (1-q_i^{\mathrm{U}}(t)) + (1-r_i(t))(1-q_i^{\mathrm{A}}(t))] \\ & + p_i^{\mathrm{AS}}(t)[\delta c_i(1-q_i^{\mathrm{A}}(t)) + \delta(1-c_i)(1-q_i^{\mathrm{U}}(t)) \\ & + (1-\delta)(1-q_i^{\mathrm{A}}(t))], \end{aligned} \quad (4)$$

where $p_i^{\mathrm{US}}(t+1)$ denotes the probability of node v_i being in the US state at time $t+1$, contingent upon its own states and transition parameters at the preceding time t.

Then, consider two foundational assumptions: (i) in the vicinity of the stationary state, where $t\to\infty$, it holds that $p_i(t+1) = p_i(t)$; (ii) in proximity to the onset of an epidemic, the proportion of infected individuals approaches to

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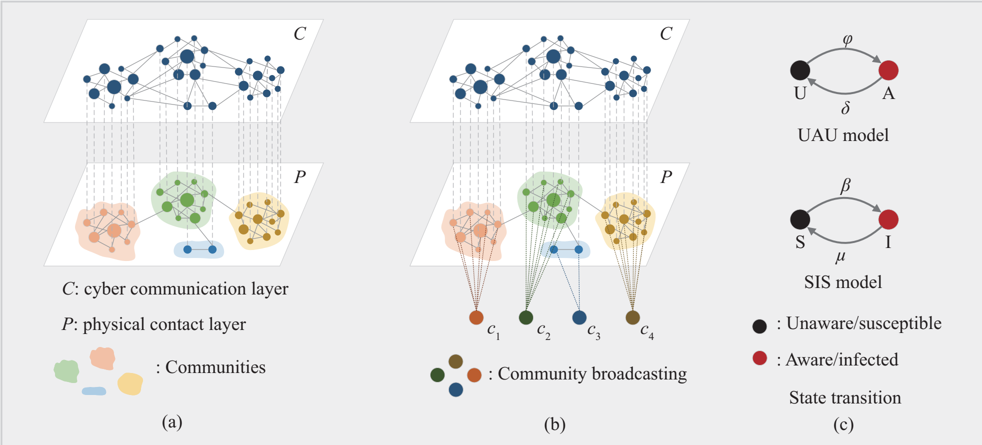

Figure 1 (Color online) Schematic diagram of the coupled propagation model. (a) Cyber-physical multiplex network; (b) multiplex network with community broadcasting; (c) state transition dynamics in each layer.

0. It becomes possible to derive the threshold of β^{U} as

$$\beta_c^{\mathrm{U}} = \frac{\mu}{\Lambda_{\max}(H)}, \tag{5}$$

which is a brief result, and is contingent upon parameters φ, δ, c_i, γ_i, μ, r_i, and structural configurations $\{a_{ij}\}_{n\times n}$ and $\{b_{ij}\}_{n\times n}$. Please see Appendix B for detailed proofs.

Discussions about ERSM. The ERSM concentrates on concurrently mitigating the spread of epidemics and rumors. The present study frames this challenge as a multi-objective optimization (MOO) problem, focusing on the development of containment strategies that not only reduce the prevalence of infection and rumors, but also ensure cost-effectiveness. Instead of addressing them separately, the MOO model offers two principal benefits: (i) flexible budgeting and (ii) multiple strategies.

The entire MOO function is constructed as follows:

$$\begin{aligned} \text{Minimize } & F(S) = (F_1(S), F_2(S), F_3(S))^{\mathrm{T}} \\ \text{where } & F_1(S) = \beta pwc(V\backslash S), \\ & F_2(S) = \sigma_R(S), \\ & F_3(S) = c_1(S) + c_2(S), \end{aligned} \tag{6}$$

where $F_1(\cdot)$, $F_2(\cdot)$ and $F_3(\cdot)$ correspond to the connectivity of the epidemic network, number of rumor-adopters, and associated costs, respectively. See Appendix C for details.

Then, we adapt the non-dominated sorting genetic algorithm II into a discrete form, named NSGAII-D, utilizing the Pareto front to provide a broad set of solutions that efficiently balance the competing objectives.

Experiments and results. The experimental analysis on six synthetic multiplex networks yields significant insights.

Within the EACM, (i) the active-passive immunity strategy significantly outperforms the single active immunity approach in curbing epidemic spread; (ii) parameter c_i effectively regulates epidemic proliferation; (iii) a higher λ indicates greater community responsiveness to epidemic threats, encouraging the uptake of preventive measures; (iv) parameter μ is pivotal in influencing both the evolution of epidemic and the calculation of its threshold; (v) although parameters φ, δ and τ exert minimal impacts on the threshold β_c^U, they still affect the epidemic spread at non-threshold levels. In conclusion, the findings derived from the MMCA (5) are consistent with the phase transitions observed in numerical simulations, affirming the accuracy and applicability of the MMCA in forecasting epidemic dynamics.

Within the ERSM, the modified NSGAII-D algorithm is adept at resolving (6) and achieves convergence. It outperforms the greedy algorithm by producing a diverse set of Pareto optimal solutions, thereby providing a nuanced and adaptable approach for addressing intricate containment challenges. For an in-depth exploration of the experimental results, please refer to Appendix D.

Conclusion. This study unveils two innovative mechanisms (EACM and ERSM) for mitigating detrimental items such as epidemics and rumors, both meticulously devised for coupling cyber-physical multiplex networks. The EACM elucidates the synergistic interplay between the physical spread of epidemics and the cyber-facilitated dissemination of awareness, employing the MMCA methodology to delineate epidemic thresholds and devise control strategies. Meanwhile, the ERSM targets the simultaneous mitigation of epidemic and rumor proliferation, employing an MOO model to minimize their impacts while maintaining cost-effectiveness. This framework leverages a refined NSGAII-D algorithm to thoroughly explore Pareto optimal solutions, facilitating effective management of these intertwined challenges.

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Supporting information Appendixes A–E. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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