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From metasynthesis to edge intelligence: A novel entropy-regulated layered multi-agent coordination (ER-LMAC) paradigm for the management of open complex giant systems

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Abstract. Open complex giant systems (OCGSs) represent some of the most challenging problems in contemporary engineering and governance. Although Qian Xuesen's OCGS methodology and metasynthesis system approach have provided a rich theoretical foundation, there remains a persistent gap between theory and scalable engineering practice, which we refer to as the entropy-increase dilemma. In this paper, we propose the Entropy-Regulated Layered Multi-Agent Coordination (ER-LMAC) paradigm as a modern, engineering-realizable framework for managing OCGSs. ER-LMAC synthesizes (i) entropy regulation as a cybernetic control objective, (ii) layered multi-agent coordination as a scalable decision mechanism, and (iii) edge intelligence implemented on an end–edge–cloud architecture as the computational substrate. As an empirical validation, we instantiate ER-LMAC in the domain of urban intelligent transportation systems by designing and deploying a decentralized, nonhistorical adaptive traffic signal control (ATSC) system in Xiangyang, China. The system covers 448 intersections in the main urban area and has operated continuously for more than three years. Longitudinal operational data indicate that road traffic efficiency increased by more than 20%, congestion duration decreased by more than 30%, and traffic accident rates were reduced by more than 60%. The city has maintained the lowest congestion index in its province for over 40 consecutive months, despite having one of the highest vehicle ownership levels. These results demonstrate that ER-LMAC can effectively resolve the entropy-increase dilemma in a real-world OCGS and suggest its broader applicability to domains such as smart grids, supply chain logistics, industrial Internet of Things (IIoT), and epidemic prevention and control.

Keywords. Open complex giant systems (OCGSs), entropy regulation, metasynthesis, layered multi-agent coordination, edge intelligence, adaptive traffic signal control, end–edge–cloud architecture, intelligent transportation systems (ITS).

1. Introduction

Open Complex Giant Systems (OCGS), as defined by Qian Xuesen, provide a conceptual framework for the most challenging problems in modern engineering and governance [1]. An OCGS is **open** to exchanges of matter, energy, and information with its environment; **giant** in scale, consisting of a large numbers of heterogeneous subsystems; and **complex** in the sense of strong coupling, nonlinearity, human participation, and emergent behavior [1,2]. Such systems include large-scale urban transportation networks, smart power grids, national governance systems, and epidemic control infrastructures, among many others.

Human agents are intrinsic components of many OCGSs, introducing additional uncertainties, societal characteristics, and emergent intelligence [3,4]. As a result, OCGSs cannot be fully understood or controlled by reductionist models that assume closed boundaries, stationary or simplified dynamics, or homogeneous components [5].

1.1 The Entropy-Increase Dilemma

A central challenge in managing OCGSs is what we term the **entropy-increase dilemma**. Here, entropy is used as an operational indicator of system-level disorder, inefficiency, and instability. In the traffic domain, entropy manifests as congestion, excessive queue lengths, and stop–go traffic oscillations [6]. In power systems, entropy may appear as load oscillations or voltage instability [7,8]; in supply chains, as cascading bottlenecks and delays [9].

In open, large-scale systems, the combinatorial explosion of interactions and the continuous influx of disturbances tend to drive the system toward higher entropy states if no effective regulatory mechanism is in place [2]. Paradoxically, the proliferation of sensing technologies and big data has not automatically mitigated this trend. Instead, the growth of high-velocity, high-volume, and high-variety data has often increased the complexity of decision making [10].

From an engineering perspective, the entropy-increase dilemma denotes the persistent gap between our ability to sense the state of an OCGS and our ability to regulate its evolution in a timely and robust manner. Bridging this gap requires not only new algorithms but also a rethinking of the underlying system architecture and control philosophy.

1.2 Limitations of Traditional Paradigms

Traditional problem-solving methodologies for OCGS are largely extrapolated from closed, small-scale systems and are "far from mature solutions" when applied mechanically to OCGS [4,11]. Several structural limitations can be identified:

(1) **Reductionism and centralization:** Many approaches assume that a single, comprehensive model of the entire system can be built and optimized centrally [12]. In OCGS, achieving model completeness is unattainable due to human behavior, institutional change, and nonstationary environments [3,13].

(2) **Predictive brittleness:** Model-based controllers are typically optimized for a subset of historically observed scenarios. When deployed in environments with frequent "unobserved situations" (accidents, special events, pandemics), they can fail catastrophically [14].

(3) **Latency and scalability:** Centralized architectures suffer from communication and computation bottlenecks. As the number of agents grows, the combinatorial explosion of the state–action space renders centralized real-time optimization intractable [15].

These limitations motivate a shift from **centralized prediction and optimization** to **decentralized, real-time regulation** that directly manages system-level entropy.

1.3 From OCGS Methodology to Edge Intelligence

To address the entropy-increase dilemma, we revisit Qian's metasynthesis system approach, which was explicitly developed for managing OCGSs [1]. Metasynthesis argues that solving OCGS problems requires a synthesis of qualitative expert knowledge and quantitative computational models, realized through a "human–machine integration" paradigm that iteratively fuses human judgment with machine computation [3,4]. This conceptual framework was operationalized through the Hall for Workshop of Metasynthetic Engineering (HWME), an early prototype of collaborative human–AI problem solving.

While the metasynthesis methodology has been influential at the conceptual level, its large-scale, real-time engineering realization remained constrained by the computing paradigms available in the 1990s [1]. Recent advances in distributed computing, multi-agent systems, and edge intelligence now provide the technological foundation needed to implement metasynthesis at the scale and speed required by modern OCGSs [16,17].

1.4 Contributions and Scope

This work builds on the OCGS and metasynthesis literature to propose a new engineering paradigm for OCGSs and to instantiate it in a large-scale intelligent transportation system. The main contributions are as follows:

(1) We formalize the Entropy-Regulated Layered Multi-Agent Coordination (ER-LMAC) paradigm, which integrates entropy regulation as a cybernetic control objective, layered multi-agent coordination as a decision mechanism, and an end–edge–cloud computing architecture as the computational substrate.

(2) We provide a modern interpretation of Qian's metasynthesis methodology and HWME, expressed in terms of agentic AI and edge intelligence, thereby offering a concrete engineering pathway from theory to real-time implementation.

(3) We present a large-scale empirical case study in Xiangyang City, where ER-LMAC is instantiated as a decentralized adaptive traffic signal control (ATSC) system covering 448 intersections. The system operates without reliance on historical data or centralized real-time computation for local signal control.

(4) We report longitudinal performance results over more than three years of continuous operation, demonstrating significant and sustained improvements in traffic efficiency, congestion reduction, and safety, and we analyze the causal linkage between entropy regulation and traffic accident reduction.

(5) We discuss the generalizability of ER-LMAC to other OCGS domains, including smart grids, supply chain logistics, and epidemic prevention and control, highlighting how the same paradigm can be adapted to regulate different types of flows and entropies.

The remainder of this paper is organized as follows. Section 2 reviews the methodological foundations of OCGSs and metasynthesis. Section 3 formalizes the ER-LMAC paradigm. Section 4 describes the ER-LMAC-based ATSC deployed in Xiangyang, including the empirical results and discussions. Section 5 outlines the generalization of ER-LMAC to other OCGS domains, and Section 6 concludes the paper.

2. Metasynthesis as A Foundational Methodology

2.1 Qian's Metasynthesis System Approach

Qian's **Metasynthesis System Approach (MSA)** was formulated explicitly to address OCGS problems [4,5,12]. MSA rejects strict reductionism and instead advocates a **qualitative-to-quantitative metasynthesis** process that integrates: (1) qualitative expert judgments, experiential knowledge, and heuristic rules; (2) quantitative models, simulations, and data-driven analytics.

The core idea is to construct a "problem-solving organism" in which human experts and computational tools jointly perceive, model, and regulate an OCGS [5]. Rather than relying solely on formal models, MSA emphasizes iterative cycles of hypothesis generation, simulation, expert evaluation, and refinement.

2.2 Hall for Workshop of Metasynthetic Engineering

The MSA was operationalized via the **Hall for Workshop of Metasynthetic Engineering (HWME)** [18,19]. HWME is both: (1) a methodology for organizing collaborative problem-solving in OCGS; and (2) an application of *noetic science*—the systematic study of wisdom and collective intelligence.

HWME aims to achieve **human–machine integration** by combining individual experts, knowledge bases, and computational models into a socio-technical system. Through structured discussion, simulation, and negotiation, HWME supports the evolution process of "individual thinking → individual wisdom → group wisdom → social wisdom" [16]. In essence, HWME is a framework for creating a collective, augmented intelligence—part human, part machine—capable of perceiving and managing an OCGS.

However, early implementations were limited by the computing paradigms of the 1990s. The metasynthetic cycle was slow, human-gated, and non-real-time, making it unsuitable for continuous control of OCGS at the scale of urban infrastructure systems.

2.3 From Methodology to Technological Paradigm

Advances in networking, distributed computing, and AI have eroded the technological barriers that constrained HWME implementations [16,20]. Modern **multi-agent AI**, **edge computing**, and **edge general intelligence** offer mechanisms for distributing perception, decision-making, and learning across thousands of devices [17,20–22].

This motivates a reinterpretation of metasynthesis in which: (1) Expert judgment is encoded into the **objectives, constraints, and policies** of autonomous agents; (2) Quantitative models are deployed as **local controllers, predictive models, and learning modules** on edge devices; (3) The "Hall" is realized as a **city-scale end–edge–cloud computing architecture** that continuously integrates human oversight and machine intelligence.

In this view, metasynthesis becomes not just a methodology but a **design principle for distributed, intelligent control systems**.

3. Entropy-Regulated Layered Multi-Agent Coordination (ER-LMAC)

3.1 Formal Definition

We define the **Entropy-Regulated Layered Multi-Agent Coordination (ER-LMAC)** paradigm as an engineering framework for managing OCGSs that integrates three components:

(1) **Entropy regulation (ER)**: a cybernetic control objective that focuses on regulating physical or operational entropy at both local and system levels.

(2) **Layered multi-agent coordination (LMAC)**: a cybernetic control objective that focuses on regulating physical or operational entropy at both local and system levels.

(3) **End–edge–cloud architecture**: a distributed computational substrate in which sensing and actuation occur at the end nodes, local control and coordination at the edge, and strategic orchestration and learning in the cloud.

Formally, consider an OCGS represented as a graph

$$G = (V, E)$$

where V is the set of nodes (subsystems) and E is the set of edges (flows or couplings). Each node $v \in V$ corresponds to a physical or cyber–physical unit (e.g., an intersection, a substation, or a logistics facility), and each edge $e \in E$ represents an interaction or flow between nodes (e.g., traffic streams, power lines, or material flows).

Let

$$x_v(t) \in \mathcal{X}_v$$

denote the local state of node v at time t, and define the global state as the stacked vector

$$x(t) = \left(x_v(t)\right)_{v\in V} \in \mathcal{X}$$

Similarly, let

$$u_v(t) \in U_v$$

denote the local control input applied at node v, with

$$u(t) = \left(u_v(t)\right)_{v\in V} \in \mathcal{U}$$

the joint control action of all agents at time t.

For each node v, we define:

- a **local entropy measure**

$$H_v: \mathcal{X}_v \to \mathbb{R}_{\geq 0}, \quad H_v\left(x_v(t)\right)$$

which quantifies local disorder or inefficiency (e.g., queue-length variability, load imbalance, or local instability); and

- a **local control regularization term**

$$C_v: U_v \to \mathbb{R}_{\geq 0}, \quad C_v\left(u_v(t)\right)$$

which penalizes undesirable control characteristics (e.g., excessive switching, aggressive actuation, or coordination overhead).

We then define the **global entropy–control functional** as

$$H\left(x(t), u(t)\right) = \sum_{v\in V} \left(H_v\left(x_v(t)\right) + \lambda C_v\left(u_v(t)\right)\right) + \Phi\left(x(t)\right)$$

where $\lambda \geq 0$ is a weighting parameter and $\Phi\left(x(t)\right)$captures coupling-induced effects such as spillback, cascading failures, or other network-level interactions that cannot be decomposed into purely local terms.

In ER-LMAC, this composite functional $H\left(x(t), u(t)\right)$ is the **regulated quantity**: it combines

- **physical entropy** of the OCGS (through the $H_v(\cdot)$ and $\Phi(\cdot)$ terms), and
- **control-related "entropy" or cost** (through the $C_v(\cdot)$ terms),

into a single cybernetic objective. A population of agents, organized in layers, selects control actions $u(t)$ based on available observations so as to drive a long-run performance index

$$J = \sum_{t=0}^{T} H\left(x(t), u(t)\right)$$

toward lower values, subject to the physical dynamics and operational constraints of the OCGS.

This formalization specifies:

1. **What is regulated:** a joint entropy–control functional $H\left(x(t), u(t)\right)$ defined on both the physical state and the applied control;
2. **Who regulates it:** a hierarchy of agents associated with nodes, clusters, and regions of the graph G; and
3. **Where it is implemented:** an end–edge–cloud architecture that assigns real-time execution to edge-level agents and long-horizon metasynthesis and coordination to cloud-level components.

It provides the mathematical backbone for the three components detailed in the subsequent subsections: entropy regulation as the cybernetic objective, layered multi-agent coordination as the organizational mechanism, and edge intelligence as the deployment substrate.

3.2 Entropy Regulation as Cybernetic Objective

The first component, **Entropy-Regulated (ER)**, specifies the primary control directive of the paradigm. In cybernetics and systems engineering, *entropy* and *regulation* jointly provide the mathematical and conceptual basis for feedback, equilibrium, and stability, forming the core vocabulary for describing how complex systems maintain order under perturbations [23].

In most existing work, "entropy regulation" appears as a **micro-level technique** inside multi-agent reinforcement learning (MARL) algorithms, such as Soft Actor–Critic (SAC) [24–26]. In that context, entropy regularization is applied to the *policy* of an agent: it controls policy entropy—i.e., the agent's internal uncertainty—to encourage exploration, prevent premature convergence to overly deterministic behavior, and reduce the risk of becoming trapped in local optima [24].

ER-LMAC **externalizes and elevates** this notion. Instead of treating entropy regulation as a device for shaping *internal* policy distributions, ER-LMAC takes **physical, measurable entropy of the OCGS** as the macro-level control objective. The aim is not to tune the stochasticity of the agents' policies per se, but to continuously modulate observable system disorder.

In the traffic domain, this physical entropy is instantiated in the variability of traffic flow and queueing: recurring congestion, unstable queue lengths, and stop–go waves are all manifestations of high-entropy states [27]. Under ER-LMAC, each agent is tasked with minimizing such physical entropy within its local and coordinated scope, making entropy reduction the **cybernetic objective function** that guides real-time decision-making. This objective is inherently decentralized [9,28], as agents act on local measurements and local interactions rather than relying on a single global predictor. It thus stands in contrast to traditional model-based approaches that attempt to optimize a predicted future trajectory; ER-LMAC focuses on **regulating the current system state** toward lower entropy.

3.3 Layered Multi-Agent Coordination

The second component, **Layered Multi-Agent Coordination (LMAC)**, provides the structural mechanism by which entropy regulation is executed at the scale of a "giant system." LMAC builds on established hierarchical coordination schemes that decompose complex decision problems into multiple layers with distinct temporal and spatial scopes. In robotics, for example, high-level agents often handle coarse strategic goals (e.g., competition strategies), while low-level agents execute fine-grained control and cooperative actions in real time [29,30]. Similar hierarchical, decentralized designs have been adopted in domains such as smart-grid voltage and power-flow control, where different layers manage local devices and regional stability, respectively [8].

Within ER-LMAC, the hierarchy is aligned directly with the **scope of entropy regulation**, and is explicitly designed to mitigate the classical MARL **joint exploration** problem [15]. By assigning different responsibilities and observability ranges to different layers, ER-LMAC embeds a clear coordination structure [22]. Concretely:

- **Low Layer (Local Entropy Regulation):** Low-layer agents are deployed at individual nodes (e.g., intersections in a traffic network or substations in a power grid). Their objective is to regulate local entropy by dissipating queues, smoothing flows, or balancing loads in real time. Decisions are made based on local and neighboring measurements.
- **High Layer (Regional Entropy Regulation):** High-layer agents coordinate groups of low-layer agents over larger regions (e.g., corridors, districts, or subnetworks). Their objective is to regulate regional entropy, prevent spillback between nodes, and ensure that local actions do not create adverse effects upstream or downstream [31].

This layered structure enables **fast, myopic adaptation** at the low layer while preserving **macro-level coherence and stability** at the high layer. Local agents handle rapid, fine-grained regulation; regional coordinators manage cross-node coupling and prevent emergent high-entropy patterns at larger scales.

3.4 End–Edge–Cloud Architecture as Substrate

The third component specifies the **physical and computational substrate** that makes ER-LMAC operational. Effective management of an OCGS requires *real-time, localized services* [17] and *dynamic adaptability* [32], which lie beyond the capabilities of traditional, high-latency, cloud-centric architectures. Centralized cloud control is typically too slow and too bandwidth-intensive to respond to rapid, localized disturbances across thousands of nodes.

To address this, ER-LMAC adopts an **End–Edge–Cloud architecture** powered by **Edge Intelligence (EI)** or Edge General Intelligence (EGI). In this paradigm, advanced perception, inference, and decision-making are pushed outward from the central cloud to the edge of the network, enabling **decentralized control scenarios** [33] in which local devices can act autonomously in real time. This architectural style is already being explored in demanding settings such as **autonomous drone swarms** performing real-time mission adaptation [17].

In ER-LMAC, the End–Edge–Cloud architecture [34–36] provides the **physical realization** of the logical LMAC layers:

- **End:** End nodes correspond to sensors and actuators embedded in the physical world. In the traffic case, these include vehicles, roadside sensing units (RSUs), and cameras [34]. They continuously generate the real-time data streams that characterize the current entropy state of the system.
- **Edge:** Edge nodes or edge devices are local compute units deployed close to the physical infrastructure (e.g., intelligent networked traffic lights) [34,35]. They host the **low-layer agents**, fusing local data and executing real-time entropy regulation policies at individual intersections or small clusters.
- **Cloud:** Cloud nodes or cloud platforms host **high-layer coordination agents** and long-horizon analytics [34,35]. They integrate aggregated data across regions, support visualization and decision support, and orchestrate policy updates and parameter tuning.

A crucial design principle in ER-LMAC is that the **cloud does not act as a second-by-second controller**. Instead, it functions as a **metasynthetic orchestrator** [17,32] that aggregates and analyzes data to inform and periodically update edge-level policies, while leaving real-time control to the edge. This separation of concerns yields modularity, adaptability, and resilience, [32] and concretely realizes Qian's vision of **human–machine integration** [16] at the scale of an entire city.

4. Empirical Validation in Urban Traffic: The Xiangyang Case

4.1 Urban Traffic as a Canonical OCGS

Urban traffic congestion is a canonical OCGS problem [6]. Traffic networks are open, as they are influenced by external factors such as weather and special events; giant, due to the large number of intersections and vehicles; and complex, because human drivers, pedestrians, and cyclists exhibit diverse and adaptive behaviors.

Adaptive traffic signal control (ATSC) systems have been developed over several decades to mitigate congestion [37,38]. Classical systems such as SCATS and SCOOT rely on centralized servers that compute signal timing plans based on detector data and historical patterns [39]. More recent decentralized systems, such as SURTRAC, employ real-time scheduling and peer-to-peer communication between intersections [31]. Despite these advances, large-scale, robust, and long-term deployments remain limited, and many systems still rely heavily on time-of-day plans or historical models.

4.2 System Overview: The Xiangyang Adaptive Traffic Signal Control System

To operationalize ER-LMAC in the ITS domain, we designed and deployed a city-scale adaptive traffic signal control (ATSC) system in Xiangyang, China. The project, which officially started in 2022, integrates AI and Internet-of-Vehicles (IoV) technologies to provide real-time, decentralized control of traffic signals across the main urban area [40].

The system currently covers 448 signalized intersections, achieving full coverage over 740 km of roads and a 562 km^2 area, and has been in stable 24/7 operation for more than three years. The city has approximately 1.0 million registered vehicles and is among the most motorized cities in its province. The deployment therefore constitutes a stringent testbed for evaluating the scalability and robustness of ER-LMAC.

4.3 Architecture and Control Philosophy

The Xiangyang ATSC system follows the ER-LMAC design principles:

- **Decentralized, Nonhistorical Control:** Local signal controllers do not rely on time-of-day plans, precomputed schedules, or historical demand models. Instead, they use streaming sensor data to regulate the current state of traffic at each intersection.
- **End–Edge–Cloud Implementation:** Roadside sensors, cameras, and IoV devices form the end layer, providing rich, real-time traffic information. Edge controllers at intersections run low-layer agents that select phase timings to dissipate queues and reduce stop–go behavior. Corridor- or district-level coordinators implement high-layer agents that manage flows across multiple intersections. The cloud platform aggregates performance metrics, supports offline analysis, and periodically updates agent policies.
- **Entropy-Regulated Policy:** The primary objective at the intersection level is to reduce local entropy, operationalized as queue lengths, stop–go oscillations, and flow variability. The regional objective is to prevent spillback, maintain smooth progression, and avoid the formation of secondary congestion waves.

4.4 Comparison with Existing ATSC Paradigms

Table 1 provides a paradigm-level comparison of the Xiangyang ER-LMAC system against the established state-of-the-art in adaptive traffic signal control system.

Table 1. Paradigm-Level Comparison of Adaptive Traffic Signal Control (ATSC) Systems [31,41,42].

Feature	Traditional ATSC (e.g., SCATS, SCOOT)	Advanced Decentralized ATSC (e.g., SURTRAC)	ER-LMAC ATSC (Xiangyang System)
Control Philosophy	Centralized, coordinated-actuated	Decentralized, schedule-driven, predictive	Decentralized, entropy-regulated, reactive
Core Architecture	Central compute server; detectors feed into a central optimization engine	Local controllers with peer-to-peer coordination	End–edge–cloud with layered agents
Data Reliance	Heavy reliance on historical data and time-of-day plans	Real-time sensor data combined with predictive scheduling models	**Real-time sensor data *only*** for local control; historical data used primarily for analysis and policy refinement
Primary Objective	Optimize cycle lengths, offsets, and splits	Minimize local delay and queue lengths	Minimize system-wide physical entropy (congestion) in real time
Coordination	Centralized synchronization	P2P schedule/outflow exchange	Layered Multi-Agent Coordination
Resilience	Brittle under unobserved events and non-recurrent congestion	Performance hinges on schedule prediction quality and communication reliability	High resilience to unobserved disturbances; scalability to hundreds of intersections; robustness over multi-year operation

4.5 System-Level Performance of the Xiangyang ATSC

The Xiangyang ATSC has been operational for over three years, providing a longitudinal dataset that includes traffic efficiency indicators, congestion metrics, and safety statistics across 448 intersections. The evaluation compares performance before and after the deployment of the ER-LMAC-based system, accounting for seasonal variations and growth in vehicle ownership.

The Key Performance Indicators (KPIs) from this completed phase demonstrate a profound and sustained improvement in systemic efficiency and safety. The system has achieved more than a 20% increase in overall network efficiency, reflected in higher average travel speeds and improved intersection throughput across the controlled area. The duration of congestion on key corridors and at critical bottleneck intersections has been reduced by more than 30%, indicating not only faster clearance of peak queues but also a substantial contraction of congested time windows. At the same time, traffic accidents at signalized intersections have dropped by more than 60%, covering both vehicle–vehicle collisions and interactions involving non-motorized users. In contrast to many ATCS pilot projects—typically limited to a few dozen intersections and evaluated over relatively short time spans—these results demonstrate that significant performance gains can be sustained over several years at full city scale [31,43].

At the macro level, these improvements translate into sustained gains in city-wide congestion indicators. Despite having more than one million registered vehicles and ranking among the highest in its province in terms of motorization, Xiangyang has maintained the lowest congestion index in the province for over forty consecutive months. During this period, the peak-hour congestion index has remained consistently below 1.33, and the all-day average congestion index has remained below 1.24. Such stability in aggregate indicators suggests that intersection-level entropy regulation aggregates into a global reduction of systemic disorder, alleviating congestion across the network rather than merely displacing it from one location to another.

The strong safety benefits are also consistent with the entropy-regulation perspective at the core of ER-LMAC. High-entropy traffic states are characterized by abrupt speed fluctuations, frequent stops, irregular gap patterns, and unpredictable queue spillback, all of which increase driver workload and the likelihood of human error. By explicitly targeting congestion, queue instability, and spillback as manifestations of physical entropy, the Xiangyang system smooths flows, stabilizes queues, and reduces the occurrence of sudden, conflict-prone maneuvers. In effect, lowering the entropy of the traffic flow field simultaneously lowers the structural risk of collisions, linking cybernetic stability directly to road safety outcomes.

Furthermore, the architecture's reliance on real-time sensing and local decision-making, rather than on fixed time-of-day plans or heavily calibrated historical models, endows the system with notable adaptability. The ATSC has demonstrated the ability to accommodate abrupt demand shifts caused by special events, incidents, or weather, as well as longer-term structural changes in land use and travel patterns. Network perturbations such as temporary lane closures or construction are absorbed without the need for extensive re-planning. In many cases, disturbances act as informative signals that agents can exploit to refine their behavior, so the system does not merely resist variability but can benefit from it. This pattern of response is characteristic of an **anti-fragile** regime, in which exposure to a richer variety of operating conditions leads to progressively more robust and effective control.

5. Generalization to Other Open Complex Giant Systems

5.1 Domain-Agnostic Structure of ER-LMAC

The Xiangyang ATSC serves as a type specimen for ER-LMAC, illustrating how entropy regulation and layered coordination can be used to manage an OCGS at the scale of an entire city. Its key elements—flow entities, nodes, entropy measures, layered agents, and end–edge–cloud infrastructure—can be instantiated in different OCGS domains with appropriate domain-specific definitions:

- Urban Traffic: Vehicles (flow) move through Intersections (nodes), creating Congestion (entropy).
- Smart Grid: Electrons (flow) move through Substations (nodes), creating Instability (entropy).
- Supply Chain: Packages (flow) move through Hubs (nodes), creating Bottlenecks (entropy).
- Epidemic Control: Infection Vectors (flow) move through Contact Points (nodes), creating an Outbreak (entropy).

5.2 Application to Smart Grids and Industrial Internet of Things (IIoT)

In smart grids, the proliferation of distributed energy resources and flexible loads has increased the complexity of maintaining system stability while optimizing operational efficiency [7]. Traditional centralized optimal power flow approaches encounter scalability and privacy challenges as the number of controllable devices grows. Multi-agent coordination and decentralized control are increasingly advocated as viable alternatives [44,45].

ER-LMAC can be instantiated in smart grids by treating substations, feeders, and microgrids as nodes; power flows and net loads as flow variables; and voltage deviations or congestion as entropy measures. Low-layer agents at substations or microgrids perform real-time local regulation, while high-layer agents manage regional balancing and congestion management. Edge computing resources embedded in substations or field devices provide the computational substrate, with cloud platforms handling long-term planning and policy updates.

Similar reasoning applies to industrial Internet of Things (IIoT) systems, where large populations of devices must coordinate to manage shared resources, production lines, or logistics flows. Layered multi-agent coordination, combined with entropy-based objectives, can provide scalable solutions for load balancing, fault mitigation, and throughput optimization.

5.3 Application to Supply Chain Logistics

Global supply chains also exhibit the hallmark characteristics of OCGSs, owing to dense international connectivity, long and uncertain lead times, and pervasive human decision-making along the chain [9]. In this context, flows correspond to materials, products, and information; nodes are factories, warehouses, and distribution centers; and entropy can be understood as variability in lead times, oscillations in inventory levels, and the accumulation of backlogs. Applying ER-LMAC to this setting suggests assigning low-layer agents to individual facilities, where they regulate local “inventory entropy” by smoothing inbound and outbound flows and reducing volatility in stock levels. High-layer agents then coordinate policies across facilities and regions, mitigating bullwhip effects and ensuring that local adaptations do not generate new systemic instabilities upstream or downstream.

5.4 Application to Epidemic Prevention and Control

The management of public health crises, such as epidemic prevention and control, is another clear OCGS problem. This domain is explicitly modeled as a System of Systems (SoS) [46] that requires multi-agent collaborative prevention and cooperative governance [47].

An ER-LMAC paradigm could be deployed to manage the “flow” of an epidemic in real-time. **End Nodes** (e.g., smart thermometers, wearable devices) and **Edge Nodes** (e.g., clinics, hospitals) could run Low-Layer agents that report local entropy (infection rates, symptom clusters) in a privacy-preserving manner [48]. **High-Layer** coordinator agents could then perform real-time, decentralized response—optimizing resource allocation, directing testing, and managing containment zones—to regulate and suppress the entropy (the outbreak) *without* resorting to the inefficient, socially costly, and non-adaptive entropy-increase of a complete, system-wide shutdown.

6. Conclusion

This paper has introduced the Entropy-Regulated Layered Multi-Agent Coordination (ER-LMAC) paradigm—a *scalable, verifiable, and general-purpose* engineering solution to the entropy increase dilemma in Open Complex Giant Systems (OCGSs).

This paradigm is the modern fulfillment of a profound theoretical lineage. ER-LMAC successfully *operationalizes* Qian Xuesen's Metasynthesis methodology, finally realizing the “human-machine integration” vision that was, until now, limited by the available technology.

The Xiangyang’s adaptive traffic signal control (ATSC) system, with its unprecedented success in a large-scale, real-world deployment, is not merely another Smart City project. It is the first longitudinal empirical validation that this new paradigm can effectively manage a real-world OCGS, producing transformative, system-wide benefits, including a >60% reduction in accidents.

This work lays a validated foundation for a new generation of *systems engineering*. It marks a necessary shift away from the brittle, centralized, model-based *prediction* that has defined 20th-century engineering, and toward the resilient, decentralized, entropy-regulated *adaptive control* required to address the 21st century's most complex engineering and governance challenges.

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Conflicts of Interest

The authors declare no conflict of interest.

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