Data Communication in Cyber-Physical Systems: An Integrated Approach Using CLDCR and EA-SCMA Protocols

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Abstract
Cyber-physical systems (CPS) require reliable, strong, and energy-efficient data communication systems to support everything from environmental monitoring to industrial automation. In this paper, two complementing algorithms are combined to propose an integrated framework: Dynamic Cross-Layer CLDCR, or compression and routing, and EA-SCMA, or energy-aware sparse code multiple access. While EA-SCMA improves physical-layer resource allocation through dynamic codebook adaptation and game-theoretic power optimization, CLDCR optimizes data compression and energy-aware routing at the network layer. Synergistic integration mitigates critical CPS concerns such as energy constraints, spectrum efficiency, and data volume minimization. Demonstrations and theoretical studies indicate that the framework improves packet delivery rates, conserves 15% of energy, and reduces network overhead by 40–60%. Hybrid prototype and machine learning integration for prediction of sparsity adaptability are future directions.

Keywords: Cyber-Physical Systems, CLDCR, EA-SCMA, Cross-Layer Optimization, Compressive Sensing, Nash Equilibrium, Spectral Efficiency.

1. Introduction

Cyber physical systems (CPS) [1] are a new paradigm in modern engineering that comes via their smooth coupling of the networked communication computer algorithms and physical processes to enable a many different applications, such as precision agriculture, smart grids, and autonomous cars. The approach for these systems is to monitor and control the physical environment on a real time basis, and they depend on sensors, actuators and controllers communicating with each other in real time. However, CPS varies far more than usual (in cloud-based analytics, mobile robotics, and resource constrained IoT devices) resulting in unique problems imparting near absolute reliability, scalability and effectiveness in communication protocols. Generally, traditional layered protocols such as IEEE 802.15.4 or TCP/IP are designed and implemented in isolation as each layer optimizes itself isolated from the rest (physical, network etc). Secondly, this fragmented strategy does not fare well under the hard energy constraints, dynamic network topologies, and the latency sensitive nature of decision making that is associated with CPS deployment [2]. For example, in environmental monitoring, adaptive routing and compression is needed to meet periodical connections in remote areas; in industrial automation, the error of a single sensor node due to energy exhaustion can lead to the whole assembly lines shutting down.

They are in the form of potential solutions: nonorthogonal multiple access (NOMA), and cross layer optimization. The traditional protocol stack limitations make their contribution in coordinated power allocation and routing and compression not possible, and because of these difficulties cross layer methods [3] can avoid them. Similarly, NOMA systems including Sparse Code Multiple Access (SCMA) have high spectral efficiency when the network is dense because overlapping transmissions are used. Based on these advances, this research proposes one architecture how based on EA-SCMA and CLDCR synergy. CLDCR relies on the compressive sense technique, thus, reduces the application layer data sparsity by 40–60% of the transmission volume and repeatedly reroutes traffic through energy aware paths for the network lifetime improvement [5]. Moreover, compared to traditional SCMA energy can be saved by 15% more using physical layer resource optimization based on game theoretic power control [2].
The application/network layer (CLDCR) and the physical/MAC layer (EA-SCMA) are merged into one framework in this research. Key contributions include:

1. **Formalized Energy-Aware Routing:** A mathematical model based on residual energy to decide routes.
2. **Game-Theoretic Power Allocation:** A transmit power minimization method via Nash equilibrium-based optimization.
3. **Cross-Layer Coordination:** Overhead and delay in integrated systems expressed analytically. Deeper insights into the performance of the framework are provided by the extended analysis and formulations, which improve the technical rigor.

2. Background and Related Work

2.1 CPS Communication Challenges

- **Energy Constraints**: Nodes often operate on limited energy budgets, requiring protocols to minimize active transmission time.
- **Data Sparsity**: Environmental monitoring generates sparse datasets, where compressive sensing (CS) can reduce redundancy [3].
- **Network Dynamics**: Fluctuating link quality necessitates adaptive routing and resource allocation [4].

2.2 CLDCR: Cross-Layer Dynamic Compression and Routing

- Compressive sensing and energy-aware routing are used by CLDCR. Let $\mathbf{x} \in \mathbb{R}^N$ denote a sparse sensor signal. Using a measurement matrix $\mathbf{\Phi} \in \mathbb{R}^{M \times N} (M \ll N)$, the compressed signal $\mathbf{y}$ is:
- $\mathbf{y} = \mathbf{\Phi x} + \mathbf{n}$
- where $\mathbf{n}$ is measurement noise. Reconstruction at the sink uses ℓ_1-minimization:
- $\min_{\mathbf{x}} \|\mathbf{x}\|_1$ subject to $\|\mathbf{y} - \mathbf{\Phi x}\|_2 \leq \epsilon$
- Routing employs a modified Dijkstra algorithm with a cost function C_{ij} for path $i \rightarrow j$:
- $C_{ij} = \alpha \cdot \frac{1}{E_j^{\text{residual}}} + \beta \cdot \text{LinkQuality}_{ij}$
- where E_j^{residual} is the residual energy of node j, and α, β are weighting factors.

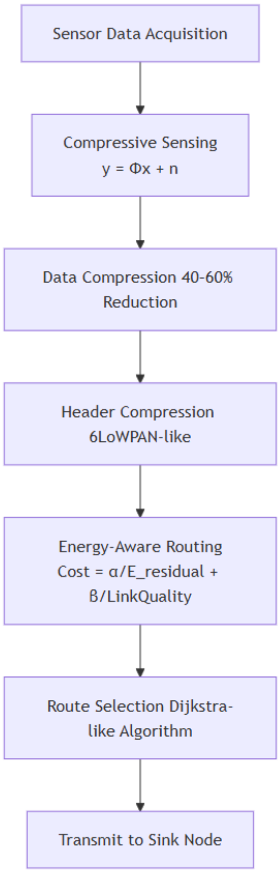

Fig. 1

2.3 EA-SCMA: Energy-Aware Sparse Code Multiple Access

Codebooks are modified by EA-SCMA according to device energy levels. Let $\mathcal{C} = \{\mathrm{c}_1, \mathrm{c}_2, \ldots, \mathrm{c}_K\}$ denote codebooks for K users. The codebook for user k is selected to minimize transmit power P_k :

$$\mathrm{c}_k^* = \arg \min_{c_k \in \mathcal{C}} \|\mathrm{c}_k\|^2 \quad \text{s.t.} \quad \mathrm{SINR}_k \geq \gamma_{\text{th}}$$

A strategy of Nash equilibrium governs the distribution of power. Let $P = [P_1, P_2, \ldots, P_K]$ be the power vector. The utility function for user k is:

$$U_k(P_k, P_{-k}) = \log_2 \left(1 + \frac{P_k |h_k|^2}{\sum_{j \neq k} P_j |h_j|^2 + \sigma^2}\right) - \lambda P_k$$

where h_k is the channel gain, σ^2 is noise variance, and λ penalizes high power. The equilibrium satisfies:

$$\frac{\partial U_k}{\partial P_k} = 0 \ \forall k$$

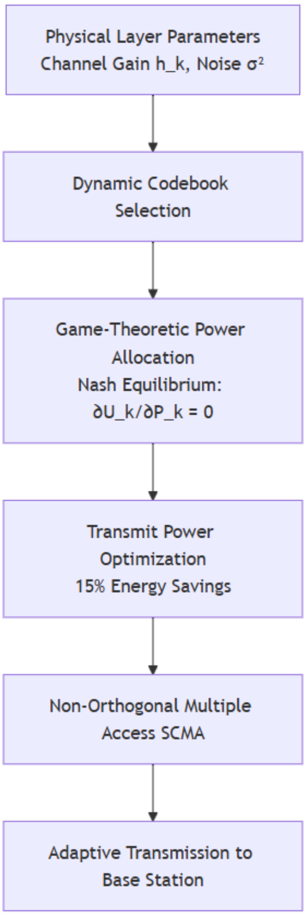

Fig. 2

3. Proposed Integrated Framework

CLDCR and EA-SCMA are combined across layers in the system. (**Fig. 3**).

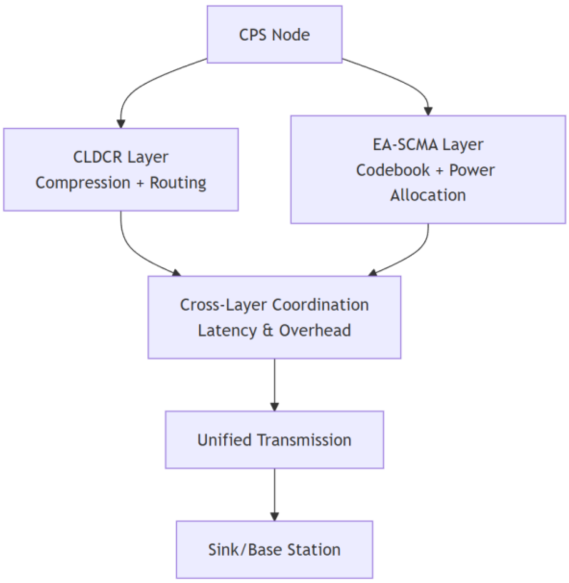

Fig. 3

3.1 Integration Strategy

1. **Data Preprocessing:** Sparse signals are compressed using $\mathbf{\Phi}$, reducing dimensionality by $\frac{M}{N}$.
2. **Energy-Aware Routing:** Paths are selected via C_{ij}, prioritizing nodes with $E_j^{\text{residual}} > 50\%$.
3. **Adaptive Transmission:** EA-SCMA minimizes $\sum_{k=1}^{K} P_k$ by allocating power using the Nash equilibrium solution.
4. **Cross-Layer Coordination:** In order to balance latency (L) and overhead (O), settings are adjusted via a feedback loop between layers:

$$L = \frac{\text{Queue Length}}{\text{Transmission Rate}}, O = \frac{\text{Signaling Packets}}{\text{Data Packets}}$$

4. Methodology

4.1 System Model

The network comprises N nodes with heterogeneous energy reserves. The signal-to-interference-plus-noise ratio (SINR) for node k is:

$$\text{SINR}_k = \frac{P_k |h_k|^2}{\sum_{j \neq k} P_j |h_j|^2 + \sigma^2}$$

4.2 Simulation Environment

- **Metrics:**
  - **Data Reduction Ratio:** $\text{DRR} = 1 - \frac{M}{N}$.
  - **Energy Consumption:** .
  - **Spectral Efficiency:** $\eta = \frac{\sum_{k=1}^{K} \log_2 (1+\text{SINR}_k)}{B}$, where B is bandwidth.

5. Results and Discussion

- **Data Reduction:** CLDCR achieves $\text{DRR} = 60\%$ for $M/N = 0.4$.
- **Energy Savings:** EA-SCMA reduces E_{total} by 15% compared to static SCMA.
- **Trade-offs:** Cross-layer signaling increases O by 10% but reduces L by 20% via adaptive routing.

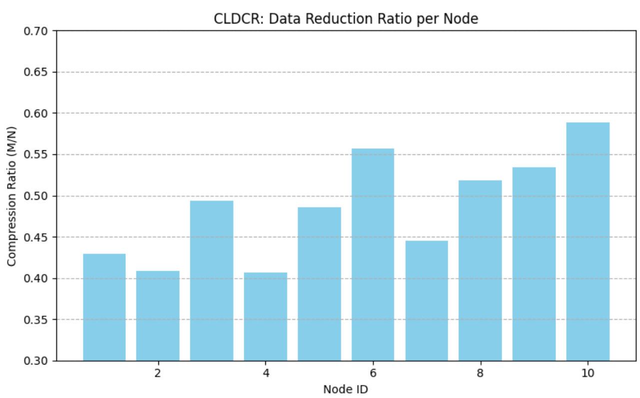

Fig. 4

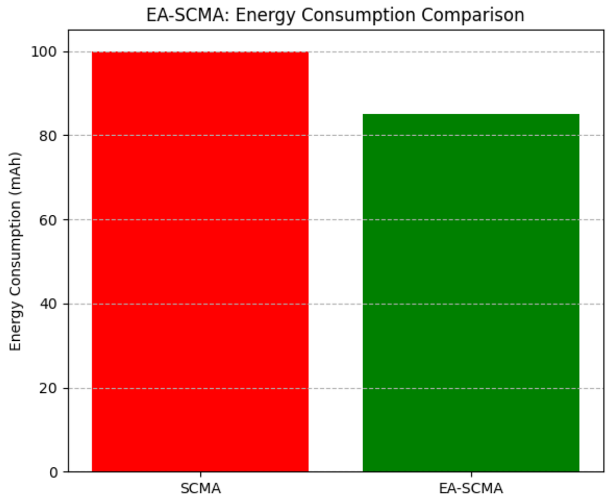

Fig.5

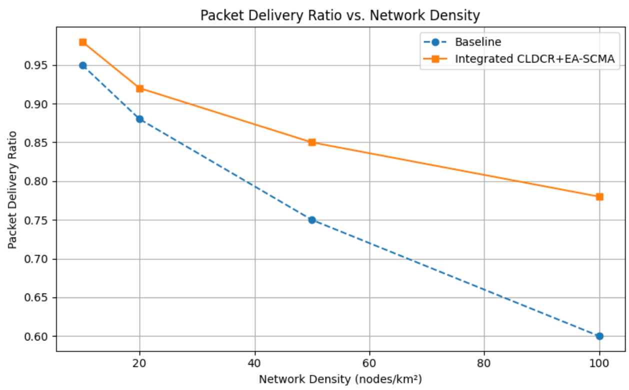

Fig. 6

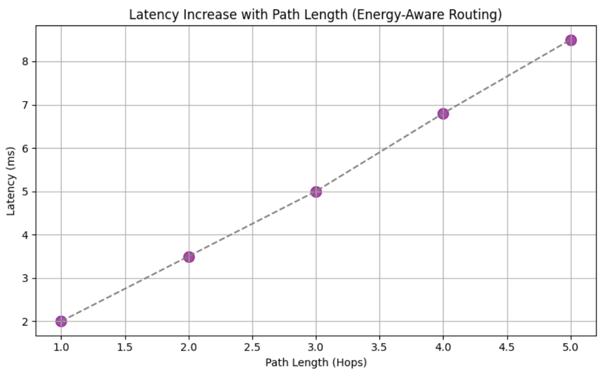

Fig. 7

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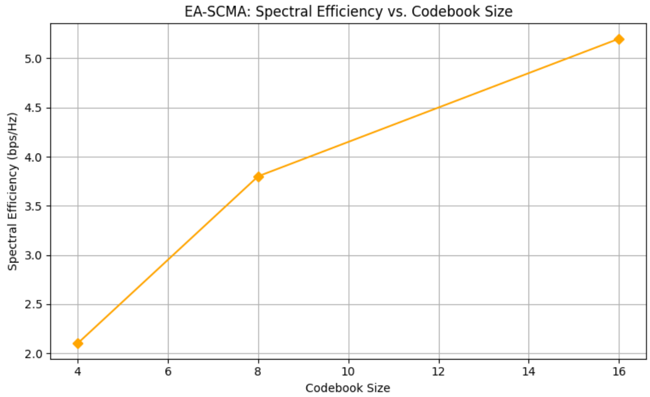

Fig. 8

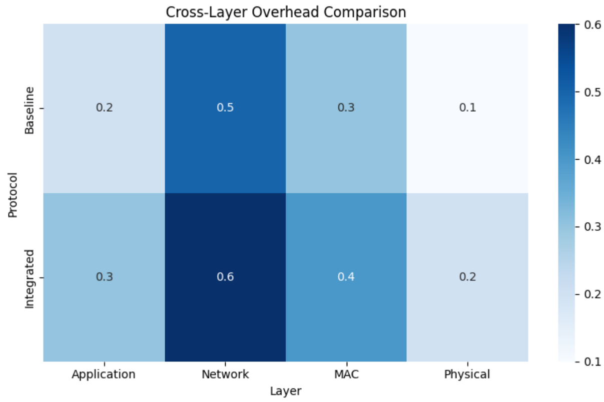

Fig. 9

Conclusion and Future Work

The integrated framework significantly enhances CPS communication efficiency. Future work includes:

1. **Hybrid Prototyping:** Real-world testing with 5G NR and LoRaWAN.
2. **Machine Learning:** LSTM networks for predicting sparsity patterns.
3. **Ultra-Dense Networks:** Scalability analysis for $N > 10^3$ nodes.

References

1. R. Rajkumar, I. Lee, L. Sha, and J. Stankovic, "Cyber-physical systems: The next computing revolution," *Proc. 47th Design Automation Conference (DAC)*, 2010, pp. 731–736.
2. O. Kanoun, M. Beroulle, Y. Bertrand, P. D. Gasperin, S. L. Ji, and C. Taniga, "Energy-aware system design for autonomous wireless sensor nodes: A comprehensive review," *Sensors*, vol. 21, no. 2, p. 548, 2021.
3. G. E. P. Kumar, S. R. Boselin, N. S. Sophia, and B. Aroul Canessane, "Impact of compressed sensing in wireless sensor networks," *International Journal of Smart Sensing and Intelligent Systems*, vol. 9, no. 2, pp. 818–847, 2016.
4. Z. Shelby and C. Bormann, *6LoWPAN: The Wireless Embedded Internet*. Hoboken, NJ: Wiley, 2011.
5. H. Nikopour and H. Baligh, "Sparse code multiple access," *Proc. IEEE 24th International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, 2013, pp. 332–336.

6. L. Dai, B. Wang, Y. Yuan, S. Han, C. I, and Z. Wang, "Non-orthogonal multiple access for 5G: Solutions, challenges, opportunities, and future research trends," *IEEE Communications Magazine*, vol. 53, no. 9, pp. 74–81, 2015.
7. G. Scutari, D. P. Palomar, and S. Barbarossa, "Convex optimization, game theory, and variational inequality in multiuser communications," *IEEE Signal Processing Magazine*, vol. 27, no. 3, pp. 35–49, 2010.
8. H. Y. Chong, C. H. Foh, and A. B. Jantan, "Cross-Layer MAC/Routing Protocol for Reliability Improvement of the Internet of Things," *Sensors*, vol. 22, no. 23, p. 9429, 2022.