STPer: Task Scheduling and Traffic Routing with Spatiotemporal Dynamic Perception in Green CPNs

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Motivation: Why Computing Power Networks Need New Scheduling?

- **Compute-intensive Workloads Rapidly Increase**

AI models, video rendering, and other compute-intensive applications are growing exponentially, creating unprecedented demand for efficient resource allocation.

- **CPN Integrates Cloud-Edge-Device Resources**

Computing Power Networks unify cloud, edge, and device computing into a single network, enabling seamless resource sharing across distributed environments.

- **Green CPN Reduces Cost via Hydropower Nodes**

Green CPN leverages hydropower to provide cost-effective and eco-friendly computing, significantly reducing operational costs and carbon footprint.

- ✨**Key Challenge: Dual Spatiotemporal Dynamics**

•Task arrival variation (work – rest cycles)
•Energy price & green power fluctuation
>>>Traditional optimization cannot handle real-time, large-scale dynamic systems.

Problem Definition

✨Goal : Maximize Platform Profit Under Dynamic Conditions

Profit = task revenue − energy & computation cost. The goal is to optimize this balance while meeting service quality requirements.

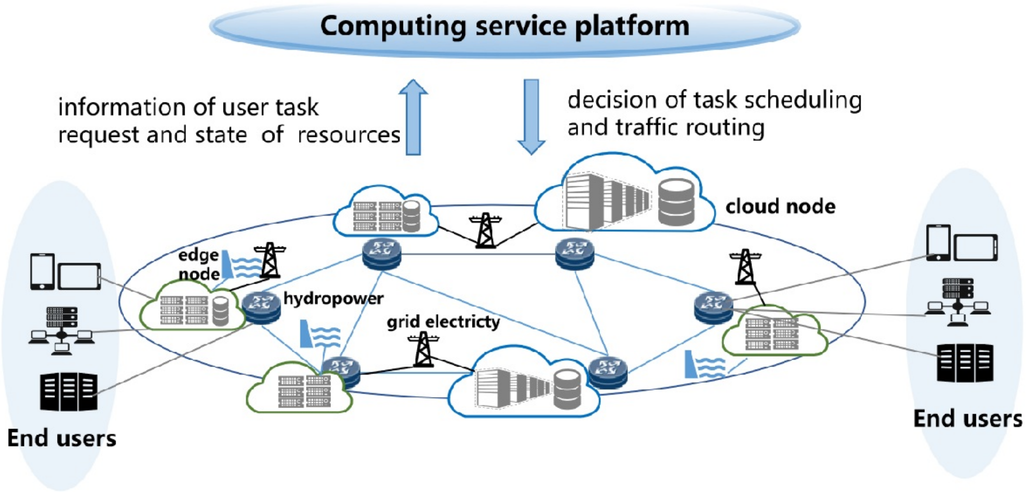
Joint Decision: Scheduling & Routing

- Task scheduling → select computing node
- Traffic routing → select network path

Formulated as NP-hard INLP

The problem is modeled as an Integer Nonlinear Programming (INLP) problem with constraints on **throughput, delay, and routing validity**, which is computationally intractable for large-scale systems.

System Architecture



Green Computing Power Network Architecture

Heterogeneous nodes: cloud & edge, with different computing power.

Green energy (hydropower) provides dynamic price discounts.

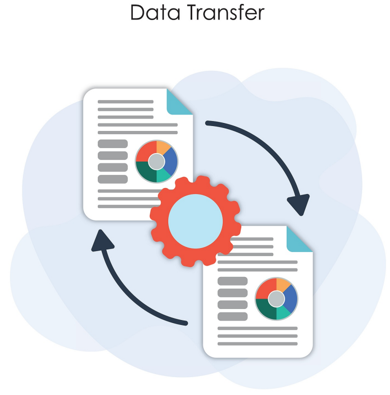
Users submit tasks with latency constraints.

Dual spatiotemporal dynamics shown across nodes & workloads.

Task & Delay Model

Delay Components in Task Completion

- Transmission delay: sum of link transmission + switching delay.
- Dispatching offset: avoid link conflicts by scheduling later slots.
- Computation delay: workload / node computing power.



Revenue Decreases with Longer Delay

Task revenue follows an exponential decay function as delay increases beyond user-specified thresholds, creating a direct incentive for minimizing latency.

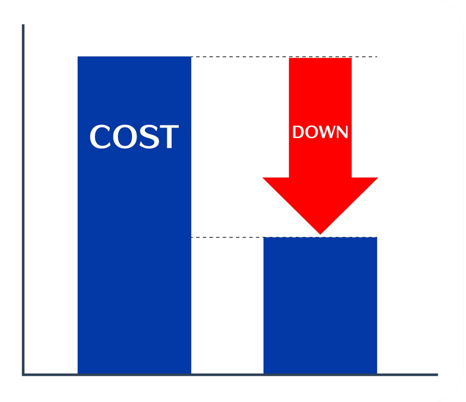
Energy Cost Model

Dynamic Energy Cost Structure

- Energy cost depends on electricity price $i_e(t)$.
- Hydropower discount $\alpha(t)$:

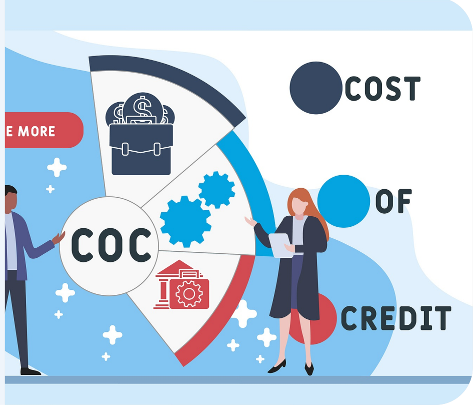
  $\alpha=0 \rightarrow$ full hydropower supply

  $\alpha=1 \rightarrow$ full grid electricity



Computing Cost Factors

- Computing cost:
  - Power consumption $\propto f^2$
  - Time-related cost $\propto$ workload / f



Optimization Challenges

01

High-Dimensional Decision Space

Binary variables multiply across task routing, time slots, and network edges, creating an exponentially large solution space that is computationally infeasible.

02

Dynamic Correlations Hard to Capture

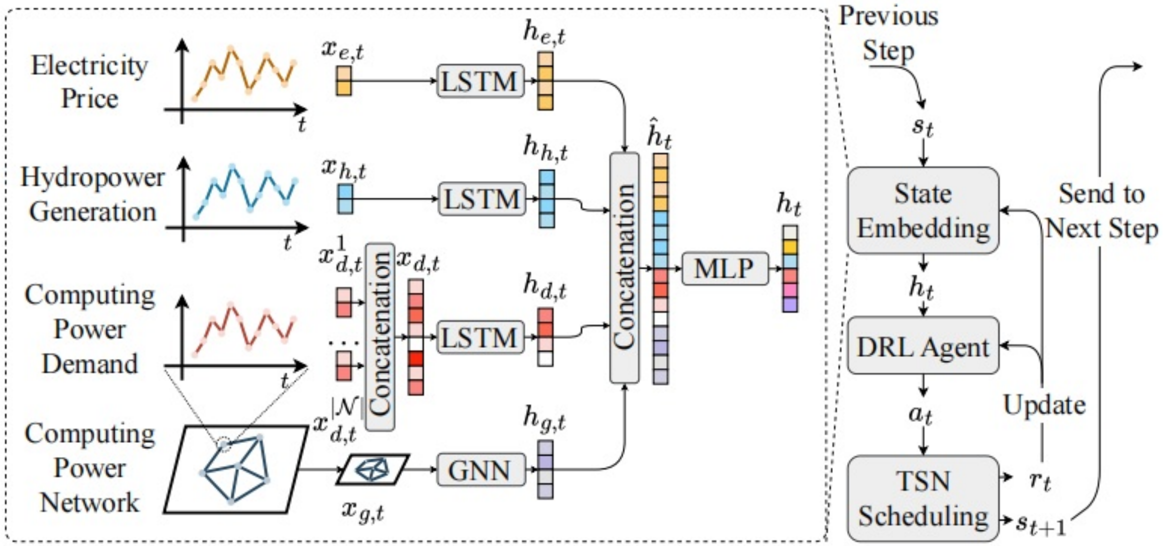
Static optimization methods cannot model the complex temporal dependencies between task arrival patterns and resource availability.

03

Need for Scalable & Adaptive Solution

Real-time decision-making in CPN requires a solution that can adapt to changing conditions. Deep reinforcement learning provides the necessary scalability and adaptability.

STPer Framework Overview



GNN + LSTM + PPO for Spatiotemporal Dynamic Perception

Graph Neural Network (GNN) Function

GNN captures spatial relationships among computing nodes.

Long Short - Term Memory (LSTM) Application

LSTM models temporal dynamics of energy & task demand.

Proximal Policy Optimization (PPO) Outcome

PPO reinforcement learning outputs task scheduling decisions.

Traffic Routing Solution

Traffic routing is solved by optimized mathematical module.

Spatial Modeling via GNN

01

Graph Structure Representation

Green CPN is abstracted as an undirected graph G=(E,N), where nodes represent computing resources/users and edges represent network links.

02

Graph Convolution Operation

GCN layers aggregate neighbor features through multiple convolutions: $H(l+1)=\sigma(D^{-1}AD^{-1}H(l)W)$, capturing spatial correlations across the network.

03

Spatial Feature Output

Inputs node workload and computing power. Outputs node-level spatial embeddings hg(t) that encode resource distribution patterns and network topology.

Temporal Modeling via LSTM

Time Series Inputs

Electricity price $i_e(t)$, hydropower generation $\alpha(t)$, and task/workload sequence $m(t)$ serve as inputs to capture temporal dynamics.

Multivariate Temporal Dependency

Three independent LSTM branches process different time series, modeling long-term dependencies of electricity prices, green energy supply, and task loads.

Temporal Feature Output

Outputs $h_i(t)$, $h_\alpha(t)$, $h_r(t)$ representing temporal patterns of energy prices, green power availability, and task demand respectively.

Feature Fusion & Policy Network

Spatiotemporal Feature Fusion

Combine spatial + temporal features: $h_f(t) = h_g(t) \mathbin{/\!/} h_i(t) \mathbin{/\!/} h_\alpha(t) \mathbin{/\!/} h_r(t)$. MLP transforms fused features into policy representation.

Policy Network Architecture

Fused features are fed into PPO's policy and value networks, which learn to map environmental states to optimal scheduling decisions.

State Representation

The state vector includes node computing power, energy prices, task queue lengths, and network link status, providing a comprehensive view of the system.

PPO Reinforcement Learning

State Space Definition

State includes spatiotemporal environment features: node status, energy prices, task queues, and network conditions.

Action Space Design

Action = choose computing node for each task. The action space is defined as the set of all possible task-node assignments.

Reward Function Construction

Reward = task revenue − computation/energy cost. The reward function directly aligns with the platform's profit maximization goal.

PPO Advantages

Clipped policy updates ensure stability. Generalized Advantage Estimation reduces variance. Suitable for large-scale, online CPN scheduling.

Traffic Routing Optimization

Iterative Routing Algorithm After Scheduling

- Given task → node assignment from RL.
- Routing solved via fractional programming → quadratic transform.
- Auxiliary variable $y_{u,n}$ has closed form:
    - y* = sqrt(benefit / delay)
- Remaining routing solved via ILP (CVX).
- Ensures feasible, non-loop, delay-bounded routing.

Experimental Setup

Real-world Datasets

- Electricity market prices
- Hydropower generation curves

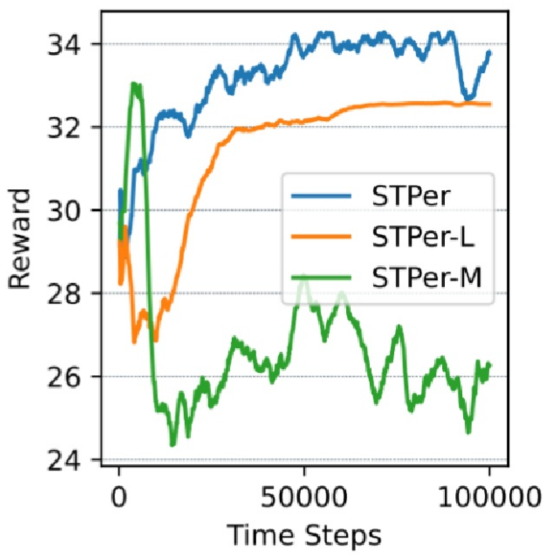
Simulation Environment

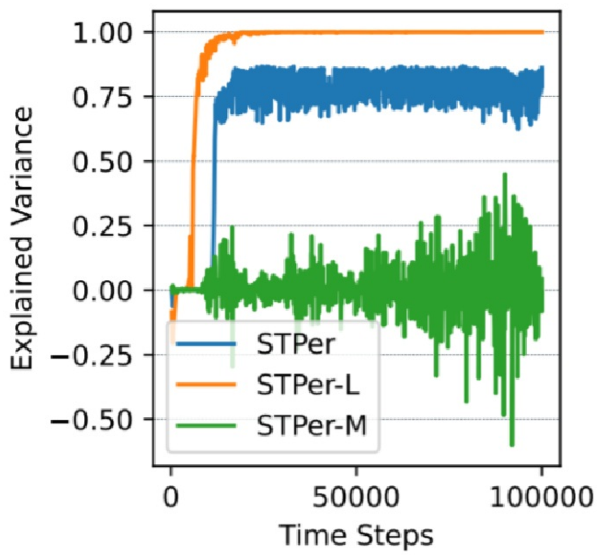
- Python-based simulation with Gymnasium for RL environment.
- Node computing capacity: 1-10 TFLOPs.
- Link bandwidth: 10-50 Mb/s.

Baseline Algorithms

- STPer (full model),
- STPer-L (no GNN),
- STPer-M (no GNN/LSTM),
- Random (random scheduling/routing)

Training Performance

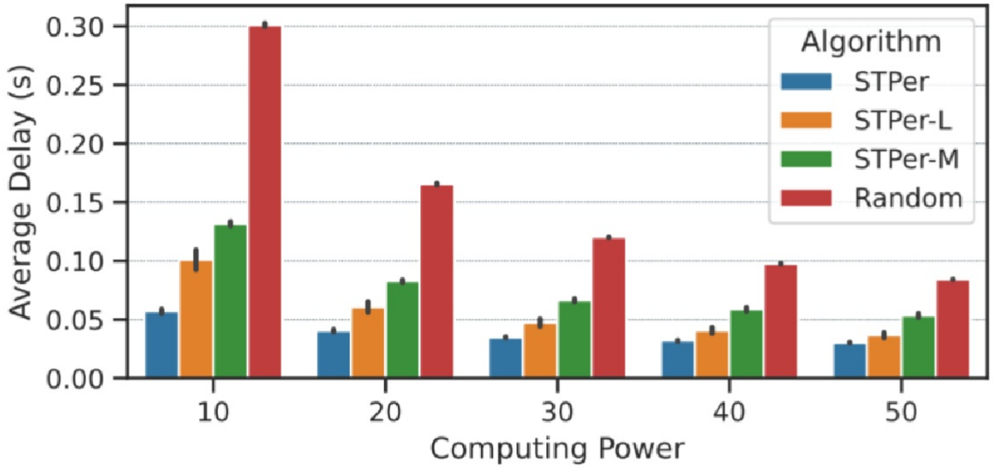


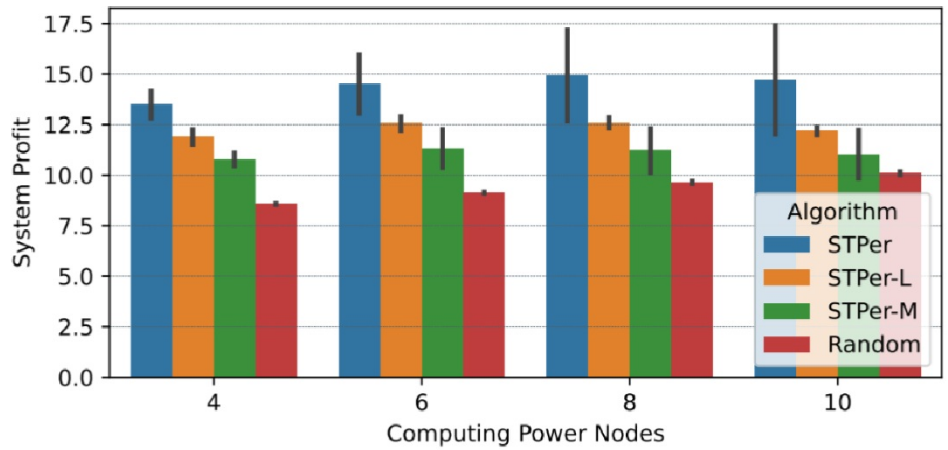


STPer Achieves Fast & Stable Convergence

- STPer has the highest cumulative reward.
- STPer-L has high explained variance (overfitting).
- GNN + LSTM improves representation → better generalization.

Delay & Profit vs Computing Power





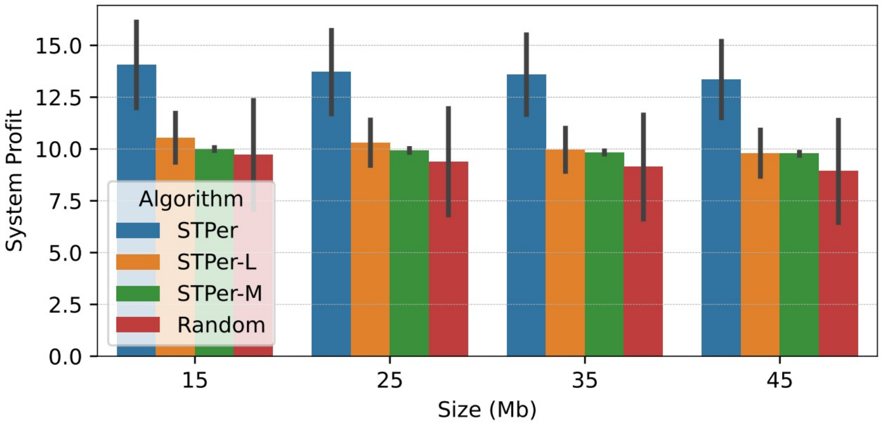
Increasing Node Power Reduces Delay

- All methods show decreasing delay as computing power increases.
- STPer achieves the lowest average delay across all settings.
- STPer-M only slightly better than random → proves spatiotemporal necessity.

STPer Maximizes Profit Across All Settings

- Higher computing power → higher profit (delay ↓).
- STPer consistently outperforms baselines.
- Demonstrates joint scheduling-routing advantage.

Profit vs Data Size



Profit Trend with Data Size

Larger task size increases transmission delay, leading to lower profit for all methods. The trend is consistent across data sizes from 15 to 45 Mb.

Algorithm Robustness

STPer remains most robust under heavy traffic, maintaining higher profits than baselines even with large data sizes. The spatiotemporal modeling helps adapt to varying workloads.

Conclusion

01 First Joint Optimization of Scheduling & Routing

STPer is the first comprehensive solution addressing dual spatiotemporal dynamics in green CPNs, integrating scheduling and routing decisions.

02 Novel STPer Framework

The framework combines GNN spatial perception, LSTM temporal modeling, and PPO reinforcement learning to handle dynamic environments effectively.

03 Significant Performance Improvements

STPer achieves substantial gains in delay reduction and profit maximization compared to state-of-the-art methods, demonstrating practical value for real-world green CPNs.

Thank you—questions are welcome.

Q&A