Advanced Algorithms: Research Problem Statements (PS–1 to PS–17)

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PS–1: Energy-Aware IoT Task Scheduling in Edge-Cloud Systems

Background and Motivation

With the rapid proliferation of Internet of Things (IoT) devices, the demand for efficient task scheduling across heterogeneous edge–cloud architectures has become critical. IoT applications, such as smart surveillance or health monitoring, involve data-intensive tasks that need to be processed under energy and latency constraints. Centralized cloud computation often introduces high latency, while edge nodes suffer from limited computational resources. Optimizing task offloading and scheduling is thus an NP-hard problem that requires efficient heuristics or approximation models.

Problem Definition

Consider a set of IoT tasks $T = \{t_1, t_2, \ldots, t_n\}$ with computational requirements C_i and data size D_i. Each task can be executed on either an edge node E_j or the cloud C. The objective is to minimize total energy consumption and latency:

$$\min \alpha \sum_{i,j} E_{ij} x_{ij} + \beta \sum_{i,j} L_{ij} x_{ij}$$

subject to:

$$\sum_{j} x_{ij} = 1, \quad \forall i; \quad x_{ij} \in \{0, 1\}.$$

Here, E_{ij} and L_{ij} denote the energy and latency cost for assigning task t_i to node E_j, and α, β are weighting parameters.

Suggested Solution Approach

This problem can be solved using integer linear programming (ILP), but for large-scale deployments, heuristic or meta-heuristic techniques such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), or Energy-Aware Greedy Allocation are more effective. Machine learning models may also be incorporated to predict workload and adapt scheduling dynamically.

Expected Outcomes and Research Potential

The outcome should be an adaptive scheduling algorithm that optimizes energy and latency trade-offs for heterogeneous IoT environments. The work can be extended toward real-time workload prediction or multi-objective formulations incorporating reliability.

References

1. Li, X. et al., “Energy-efficient task offloading for IoT applications in edge–cloud environments,” *IEEE Internet of Things Journal*, 2024.

2. Sharma, R. & Gupta, P., “Adaptive edge computing framework for latency-aware scheduling,” *Future Generation Computer Systems*, 2023.

PS–2: Volunteer Allocation Optimization in Crowdsourcing for Emergency Response

Background and Motivation

Crowdsourcing-based emergency response systems rely on dynamic allocation of volunteers during medical or disaster events. However, assigning appropriate volunteers while minimizing response time and ensuring fairness is computationally challenging. The problem becomes more complex when volunteers have heterogeneous skills, availability, and travel times.

Problem Definition

Given a set of emergency requests $R = \{r_1, r_2, \ldots, r_m\}$ and volunteers $V = \{v_1, v_2, \ldots, v_n\}$, each request requires certain skills $S(r_i)$, and each volunteer has a skill set $S(v_j)$ and travel cost C_{ij}. The objective is to minimize overall response time and cost:

$$\min \sum_{i=1}^{m} \sum_{j=1}^{n} C_{ij} x_{ij}$$

subject to:

$$x_{ij} = 0 \text{ if } S(r_i) \not\subseteq S(v_j), \quad \sum_{j} x_{ij} = 1,\ x_{ij} \in \{0, 1\}.$$

This represents a variant of the assignment problem with skill and distance constraints.

Suggested Solution Approach

Possible solution methods include heuristic-based matching, Hungarian algorithm extensions, or meta-heuristic optimization such as GA and Ant Colony Optimization (ACO). Real-time constraints may be addressed using reinforcement learning for adaptive matching.

Expected Outcomes and Research Potential

The research can lead to a framework for intelligent volunteer dispatching in emergency networks, potentially integrating predictive modeling of incidents and dynamic routing.

References

1. Zhao, L. et al., "Crowdsourcing-based emergency response optimization under spatio-temporal uncertainty," *IEEE Transactions on Intelligent Transportation Systems*, 2023.

2. Singh, D. & Kumar, A., "AI-driven volunteer matching for emergency crowdsourcing," *Applied Soft Computing*, 2024.

PS–3: AI-Driven Energy Trading Optimization in Smart Grids

Background and Motivation

The integration of renewable energy sources into smart grids has led to dynamic peer-to-peer (P2P) energy trading mechanisms. Balancing local demand, production, and market pricing while maintaining grid stability requires intelligent optimization. This problem has economic, environmental, and computational significance.

Problem Definition

Let $B = \{b_1, b_2, \ldots, b_n\}$ be a set of buyers and $S = \{s_1, s_2, \ldots, s_m\}$ be sellers. Each seller s_i offers energy E_i at a minimum price $P_i^{\min}$, and each buyer b_j demands D_j. The goal is to maximize total utility:

$$\max \sum_{i,j} (P_j - P_i^{\min}) y_{ij}$$

subject to:

$$\sum_j y_{ij} \le E_i, \quad \sum_i y_{ij} = D_j, \quad y_{ij} \ge 0.$$

This is a constrained optimization problem similar to a transportation model with dynamic pricing.

Suggested Solution Approach

Methods include ILP for small systems and heuristic approaches (GA, PSO) for scalability. Reinforcement learning can be employed for adaptive pricing policies in stochastic environments.

Expected Outcomes and Research Potential

The project can explore fairness-based or carbon-footprint-aware trading models, enhancing renewable integration and sustainability.

References

1. Awasthi, A. & Zhang, L., "Reinforcement learning for dynamic energy trading in smart microgrids," *IEEE Access*, 2024.

2. Patel, M. et al., "Multi-agent optimization for decentralized energy markets," *Sustainable Energy, Grids and Networks*, 2023.

PS–4: QoS-Aware Flow Routing in Software-Defined Networks (SDN)

Background and Motivation

Software-Defined Networking (SDN) enables programmable control over network routing but optimizing Quality of Service (QoS) while reducing congestion remains NP-hard. Multi-commodity flow optimization with latency and bandwidth constraints is central to improving SDN performance.

Problem Definition

Let $G = (V, E)$ be a network graph with capacity c_{ij} and delay d_{ij} on edge (i, j). For each flow $k \in K$, with demand f_k and source-destination pair (s_k, t_k), the objective is:

$$\min \sum_{(i,j)\in E} d_{ij} \sum_{k\in K} x_{ij}^k$$

subject to:

$$\sum_{j:(i,j)\in E} x_{ij}^k - \sum_{j:(j,i)\in E} x_{ji}^k = \begin{cases} f_k, & \text{if } i = s_k, \\ -f_k, & \text{if } i = t_k, \\ 0, & \text{otherwise.} \end{cases}$$

and $\sum_k x_{ij}^k \leq c_{ij}$.

Suggested Solution Approach

Propose ILP formulations for smaller networks and heuristic/meta-heuristic methods like Genetic Algorithms, Tabu Search, or Reinforcement Learning-based routing policies for scalability.

Expected Outcomes and Research Potential

This project enables developing QoS-optimized routing protocols suitable for SDN controllers, improving latency, throughput, and fault tolerance in dynamic network environments.

References

1. Ahmed, S. & Reddy, V., "Heuristic QoS optimization in SDN-based routing," *IEEE Transactions on Network and Service Management*, 2024.
2. Li, Z. et al., "Reinforcement learning-based traffic engineering in SDN," *Computer Networks*, 2023.

PS-5: Smart Irrigation Scheduling for Smallholder Farms

Background and Motivation: Sustainable water management in Indian agriculture remains a key challenge, especially for smallholder farmers with limited resources. Recent advances in IoT and AI-enabled precision agriculture have shown promise in optimizing irrigation schedules to minimize water waste and energy use while maintaining crop yield. Government initiatives such as the "Pradhan Mantri Krishi Sinchai Yojana" emphasize micro-irrigation and automation for water efficiency, making this problem nationally relevant.

Problem Definition: Given a set of fields $F = \{1, \ldots, n\}$, each with initial soil moisture m_i, crop water demand $d_i(t)$ for time slots $t = 1, \ldots, T$, irrigation cost c_i, and moisture target M_i^{target}, allocate water volumes $x_{i,t}$ to minimize total irrigation cost under capacity limits.

$$\min \sum_{i=1}^{n} \sum_{t=1}^{T} c_i x_{i,t}$$

Subject to:

$$\sum_{t=1}^{T} x_{i,t} \geq M_i^{\text{target}} - m_i, \quad \sum_{i=1}^{n} x_{i,t} \leq W_{\max}(t), \quad x_{i,t} \leq X_{i,\max}$$

Suggested Solution Approach: Formulate as an Integer Linear Program (ILP) or dynamic programming model. Heuristic solutions can include greedy scheduling based on demand priority, genetic algorithms, or reinforcement learning for adaptive control under varying weather conditions.

Expected Outcomes and Research Potential: Students can analyze trade-offs between cost, yield, and water efficiency. Research extensions include predictive scheduling using rainfall forecasts, multi-crop field optimization, and blockchain-based smart irrigation contracts.

References:

1. S. Kumar et al., "Precision Agriculture System with IoT: An Approach to Increase Production and Efficiency," *IJSECS*, 2024.

2. Government of India, "Pradhan Mantri Krishi Sinchai Yojana," Ministry of Agriculture, 2023.

PS-6: Solar-Plant Maintenance and Generation Scheduling Under Uncertainty

Background and Motivation: Solar energy systems in India face issues of equipment degradation, uncertain generation, and maintenance delays. Optimal scheduling of maintenance and power generation is crucial to ensure continuous operation and maximize energy output.

Problem Definition: Given solar modules $j = 1, \ldots, N$ with predicted generation $g_j(t)$, maintenance cost m_j, and downtime d_j, determine activation $y_j(t) \in \{0, 1\}$ and storage scheduling $s(t)$ to maximize delivered generation:

$$\max \sum_{t=1}^{T} \left(\sum_{j=1}^{N} y_j(t) g_j(t) - \sum_{j=1}^{N} \mathbf{1}\{y_j(t-1) = 1, y_j(t) = 0\} m_j \right)$$

Subject to downtime, capacity, and storage constraints.

Suggested Solution Approach: Model as mixed-integer optimization or use metaheuristics such as Genetic Algorithms or Particle Swarm Optimization for scalable scheduling. Incorporate solar irradiance prediction using ML.

Expected Outcomes: Efficient maintenance scheduling and resilience improvement. Students can simulate uncertainty and measure generation stability improvement.

References:

1. Li et al., "Real-Time Solar Power Generation Scheduling," *Energies*, vol. 17, no. 13, 2024.
2. MNRE India, "National Solar Mission Progress Report," 2023.

PS-7: E-Commerce Last-Mile Delivery Hub Location and Vehicle Routing

Background and Motivation: The rise in e-commerce demand in Indian cities has led to logistical inefficiencies in last-mile delivery. Optimizing hub placement and routing reduces both delivery time and emissions, aligning with India's sustainable logistics mission.

Problem Definition: Given demand nodes $D = \{1, \ldots, d\}$ and candidate hubs $H = \{1, \ldots, h\}$, choose hubs $x_h \in \{0, 1\}$ and assignments $z_{i,h} \in \{0, 1\}$ minimizing:

$$\min \sum_{h} C_h^{open} x_h + \sum_{i,h} z_{i,h} w_i t_{\ell_i, h}$$

Subject to:

$$\sum_{h} z_{i,h} = 1, \quad z_{i,h} \leq x_h, \quad \sum_{h} x_h \leq p$$

Suggested Solution Approach: Formulate as a p-median or capacitated facility location problem. Apply greedy heuristics, GA, or Ant Colony Optimization. Extend to time-dependent travel using real traffic data.

Expected Outcomes: Reduction in delivery cost and emissions; applicability for smart logistics startups.

References:

1. Faisal and Khalid, "Distribution Hub Optimization for Urban Logistics," *arXiv*, 2024.
2. NITI Aayog, "National Logistics Policy 2022: Last-Mile Efficiency," 2023.

PS-8: Intelligent Traffic Signal Timing Optimization in Indian Cities

Background and Motivation: Congestion in Indian cities like Delhi and Mumbai causes major energy and productivity losses. AI-based adaptive traffic control can mitigate congestion without costly infrastructure expansion.

Problem Definition: For intersections $I = \{1, \ldots, n\}$, with variable arrival rates $\lambda_i(t)$, find signal green times $g_i(t)$ minimizing total waiting time:

$$\min \sum_{i,t} \lambda_i(t) \cdot W_i(g_i(t))$$

subject to cycle length and coordination constraints.

Suggested Solution Approach: Model as an optimization problem using Reinforcement Learning (RL) or heuristic adjustment (hill climbing, simulated annealing). Benchmark on real traffic data (e.g., OpenTraffic India).

Expected Outcomes: Reduced congestion and emissions. Students can prototype with SUMO traffic simulator.

References:

1. S. Das et al., "Deep Reinforcement Learning for Urban Traffic Control," *IEEE Access*, 2024.

PS-9: Smart Microgrid Energy Scheduling with Demand Response

Background and Motivation: Microgrids are key to India's decentralized renewable goals. Scheduling renewable generation and storage to balance demand is a growing research area.

Problem Definition: Given power sources (solar, diesel, grid) and loads, minimize total cost of energy:

$$\min \sum_t (C_{grid} P_{grid}(t) + C_{diesel} P_{diesel}(t)) - \alpha P_{solar}(t)$$

subject to power balance and capacity constraints.

Suggested Solution Approach: Mixed-Integer Linear Programming or evolutionary algorithms (PSO, GA). Explore edge-based control for real-time adaptation.

Expected Outcomes: Efficient scheduling, reduced fuel use, and grid resilience.

References:

1. Sharma et al., "IoT-Based Energy Management in Microgrids," *IEEE Transactions on Smart Grid*, 2024.
2. MNRE, "Decentralized Renewable Energy Policy," 2023.

PS-10: Crowdsourced Air-Quality Monitoring and Data Fusion

Background and Motivation: Urban air-quality monitoring networks are sparse. Crowdsourcing data from citizen sensors can enhance spatial resolution for AQI estimation.

Problem Definition: Given multiple low-cost sensor readings x_i with bias b_i, estimate true pollutant level y minimizing:

$$\min_y \sum_i w_i(x_i - (y + b_i))^2$$

under network communication and reliability constraints.

Suggested Solution Approach: Weighted regression or Kalman filtering for data fusion; apply heuristics for sensor placement optimization.

Expected Outcomes: Improved air quality maps, low-cost monitoring framework.

References:

1. Gupta et al., "Citizen Sensing for Air Quality Mapping," *IEEE Sensors Journal*, 2024.

PS-11: Drone-Assisted Oil Pipeline Inspection Scheduling

Background and Motivation: Regular inspection of oil and gas pipelines is critical to prevent leaks. Drone scheduling can reduce cost but needs optimized routing under battery constraints.

Problem Definition: Given pipeline segments $S = \{1, \ldots, n\}$ and drones D, assign routes r_d to minimize inspection time:

$$\min \sum_{d} T(r_d)$$

subject to flight range, recharge, and coverage constraints.

Suggested Solution Approach: Model as Vehicle Routing Problem (VRP) with energy constraints. Solve via Ant Colony or Tabu Search.

Expected Outcomes: Efficient inspection scheduling, improved safety.

References:

1. R. Singh et al., "Autonomous UAV-Based Pipeline Surveillance," *IEEE Access*, 2025.

PS-12: Optimizing Cold Chain Logistics for Perishable Goods

Background and Motivation: India loses nearly 30% of perishable produce due to inefficient cold chain systems. Optimizing vehicle routing and cooling capacity can significantly reduce loss.

Problem Definition: Given nodes N with temperature-sensitive goods, minimize transport cost subject to temperature and time limits:

$$\min \sum_{i,j} c_{ij} x_{ij}$$

subject to capacity and thermal decay constraints.

Suggested Solution Approach: Heuristic optimization using PSO or Simulated Annealing. Integrate IoT sensor data for predictive rerouting.

Expected Outcomes: Reduced wastage, improved food security.

References:

1. NITI Aayog, "India Cooling Action Plan," 2023.
2. K. Patel et al., "Optimization of Cold Supply Chains," *IEEE IoT Journal*, 2024.

PS-13: Electric Vehicle (EV) Charging Station Placement Optimization

Background and Motivation: Rapid EV adoption requires efficient placement of charging stations to minimize travel detours and grid load imbalance.

Problem Definition: Given potential locations L, minimize driver detour and grid stress:

$$\min \sum_i d_i(x) + \beta \sum_j G_j(x)$$

subject to coverage and capacity constraints.

Suggested Solution Approach: Formulate as facility location or multi-objective optimization. Use heuristic or GA-based solutions.

Expected Outcomes: Balanced spatial coverage and reduced congestion at charging points.

References:

1. A. Yadav et al., "Optimizing EV Charging Infrastructure," *IEEE Access*, 2024.

PS-14: Predictive Maintenance Scheduling for Oil Refineries

Background and Motivation: Unplanned shutdowns in refineries cause heavy financial losses. Predictive maintenance can reduce downtime if scheduled optimally.

Problem Definition: For each equipment e, with failure probability $p_e(t)$, decide maintenance time t_e minimizing:

$$\min \sum_e (C_{maint}(t_e) + C_{fail} p_e(t_e))$$

Suggested Solution Approach: Use ML for failure prediction, then optimize schedule using heuristic search or ILP.

Expected Outcomes: Reduced maintenance cost and downtime.

References:

1. S. Verma et al., "AI-Based Predictive Maintenance for Oil Plants," *IEEE Transactions on Industrial Informatics*, 2024.

PS-15: Smart Waste Collection Routing for Urban Municipalities

Background and Motivation: Smart cities require efficient waste collection to minimize fuel and manpower. Route optimization with dynamic bins reduces cost and emissions.

Problem Definition: Given bins with fill levels $f_i(t)$, design daily routes r_k minimizing:

$$\min \sum_k C(r_k)$$

subject to bin capacity, vehicle limits, and time windows.

Suggested Solution Approach: Apply greedy or evolutionary routing algorithms. Integrate real-time IoT bin data.

Expected Outcomes: Cost reduction and cleaner cities.

References:

1. P. Ghosh et al., "IoT-Enabled Smart Waste Management," *IEEE Sensors Journal*, 2024.

PS-16: Dynamic Task Allocation in Crowdsourced Emergency Response Systems

Background and Motivation: Crowdsourced volunteer systems for emergencies (e.g., accidents or medical aid) require dynamic task assignment under uncertainty of volunteer availability.

Problem Definition: Given volunteers V with skill s_v and tasks T with requirement r_t, assign volunteers to tasks maximizing coverage:

$$\max \sum_{v,t} a_{v,t} \delta(s_v, r_t)$$

subject to availability and location constraints.

Suggested Solution Approach: Use Hungarian Algorithm, GA, or multi-objective heuristic balancing distance and skill match.

Expected Outcomes: Efficient coordination and faster response.

References:

1. Yadav et al., "AI-Based Volunteer Mobilization in Emergencies," *IEEE Access*, 2024.

PS-17: Agricultural Supply Chain Price Forecasting and Optimization

Background and Motivation: Price volatility affects farmers' profits. Predicting and optimizing logistics can reduce losses.

Problem Definition: Forecast market price p_t using time-series data, and optimize shipment x_i to maximize profit:

$$\max \sum_i (p_t - c_i) x_i$$

Suggested Solution Approach: Combine ML-based forecasting (LSTM) with optimization of transport and storage costs.

Expected Outcomes: Better market planning and income stability for farmers.

References:

1. A. Sharma et al., "AI for Agri-Supply Optimization," *IEEE Access*, 2025.