Energy Efficient Resource Management and Task Scheduling for IoT Services in Edge Computing Paradigm

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Outline

- Background
- System Model
- Scheduling Scheme
- Real Data Based Evaluation
- Conclusion and Future Work

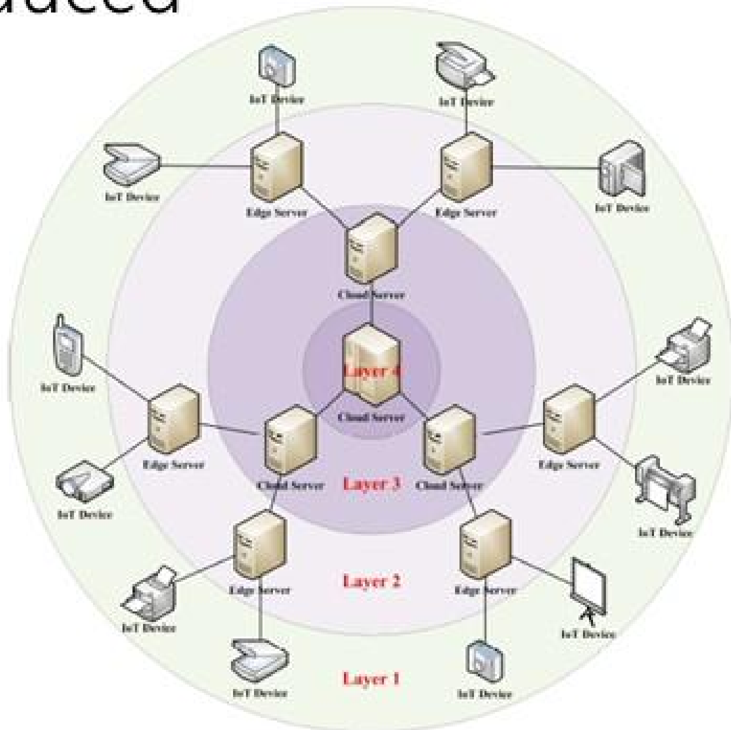
Background

❖Internet of Things (IoT)

- Connect interrelated devices over the network
- Cooperate with each other to reach common goals
- Wide application in several aspects
  - ✓Internet of Vehicles
  - ✓Smart home
  - ✓Transportation
  - ✓...

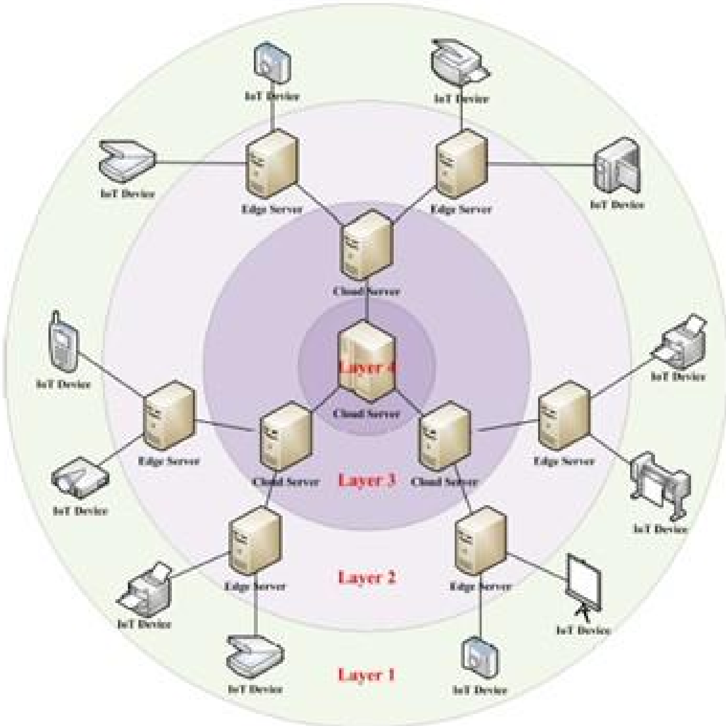
Background

- Edge Computing
  - Novel computing paradigm for IoT service implementation
  - Computation overload distributedly balanced
  - Communication delay reduced



Background

- Energy Efficiency Issues in Edge Computing
  - Resource management according to dynamic workload
  - Task assignment between layers



Background

❖ Our contribution

- Dynamic Formulation for IoT Services Under the Edge Computing Paradigm
- Quantitative Analyses for Performance and Energy Costs of IoT Services
- Joint Decision Process of Resource Management and Task Scheduling with High Efficiency
- Empirical Experiments Based on Real-World Data

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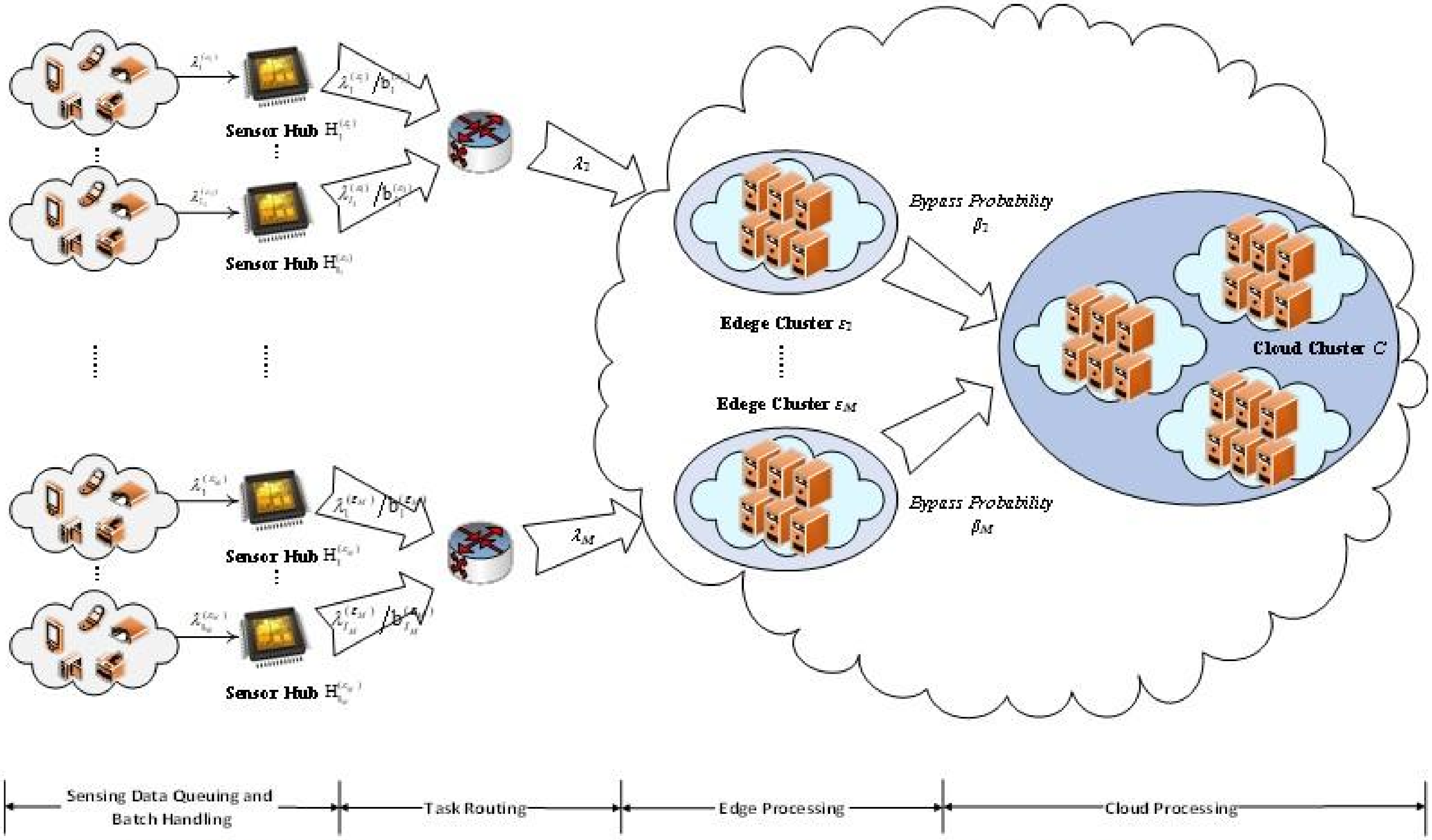
System Model

❖Overall Architecture



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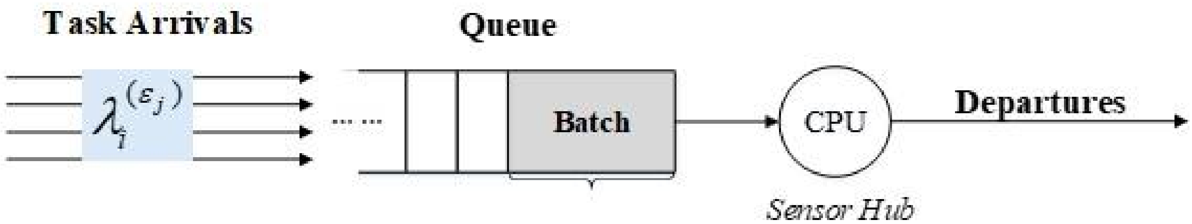
System Model

- Sensor Hub $H_i^{\varepsilon_j}$
  - M/M/1 Queue Model with Batch Service
  - Average Queue Length $E[q_i] = \dfrac{\rho_i}{1-\rho_i}$
  - Average Response Time $\mathrm{T}_i^{RS} = \dfrac{b_i \cdot E[q_i]}{\lambda_i}$
  - Power Consumption $\mathrm{P}_i^{\varepsilon_j} = \sigma_i \cdot \left(p_i^{(static)} + \rho_i \cdot p_i^{(dyn)} \right)$



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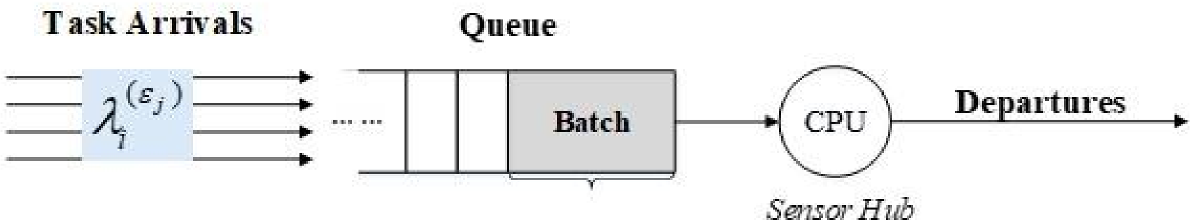
Batch Arrival Rate

$$\hat{\lambda}_i^{(\varepsilon_j)} = \lambda_i^{(\varepsilon_j)} \Big/ b_i^{(\varepsilon_j)}$$



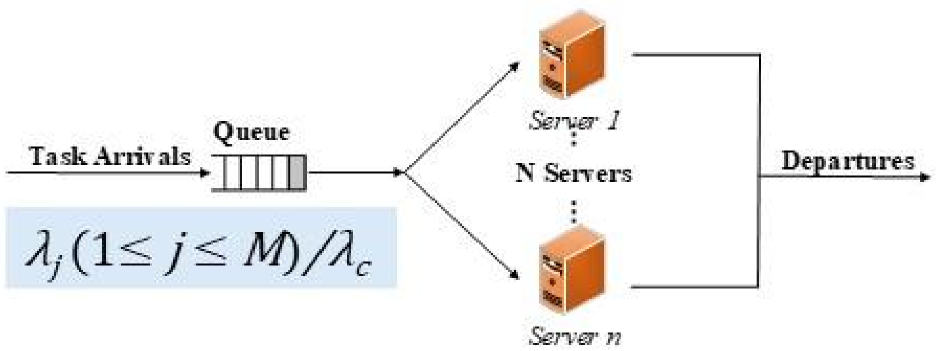
System Model

❖ Edge (ε_j) and Cloud (c) Server Cluster

- M/M/n Queue Model
- Average Queue Length

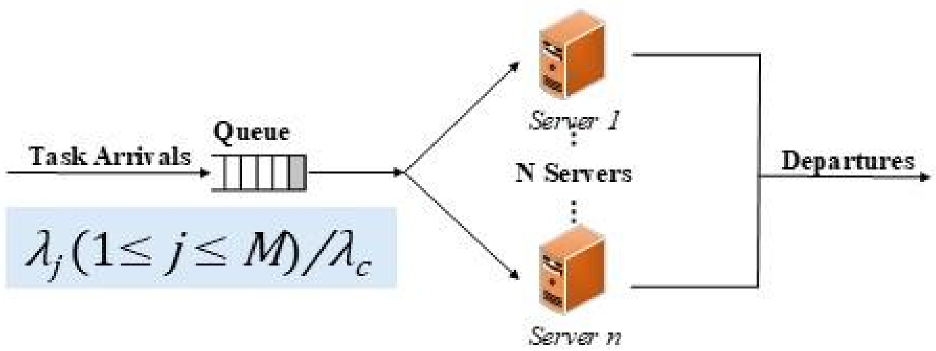
$$E\left[q_j\right]=n_j\rho_j+\frac{\rho_j\left(n_j\rho_j\right)^{n_j}}{n_j!\left(1-\rho_j\right)^2}\left[\sum_{k=0}^{n_j-1}\frac{\left(n_j\rho_j\right)^k}{k!}+\frac{\left(n_j\rho_j\right)^{n_j}}{n_j!\left(1-\rho_j\right)}\right]^{-1}$$

- Average Response Time $T_j^{RS}=\dfrac{E\left[q_j\right]}{\lambda_j}$



System Model

- Edge and Cloud Server Cluster ε_j
  - M/M/n Queue Model
  - Average Queue Length $E[q_j] = n_j\rho_j + \frac{\rho_j (n_j\rho_j)^{n_j}}{n_j!(1-\rho_j)^2}\left[\sum_{k=0}^{n_j-1}\frac{(n_j\rho_j)^k}{k!} + \frac{(n_j\rho_j)^{n_j}}{n_j!(1-\rho_j)}\right]^{-1}$
  - Average Response Time $T_j^{RS} = \frac{E[q_j]}{\lambda_j}$
  - Power Consumption $P_j = \sum_{k=1}^{N_j}\left(\sigma_k \cdot \left(p_k^{(static)} + \rho_k \cdot p_k^{(dyn)}\right)\right)$



$\lambda_j (1 \le j \le M) / \lambda_c$

System Model

❖Cross-Layer Transmission

- Bypass Transmission Probability $\beta_j \left(1 \le j \le M\right)$
- Power Consumption $T_j^{TR} = D_j \cdot t$
- Communication Delay $P_j^{TR} = p^{(dyn)} \cdot \lambda_j \cdot \beta_j + p^{(static)}$

System Model

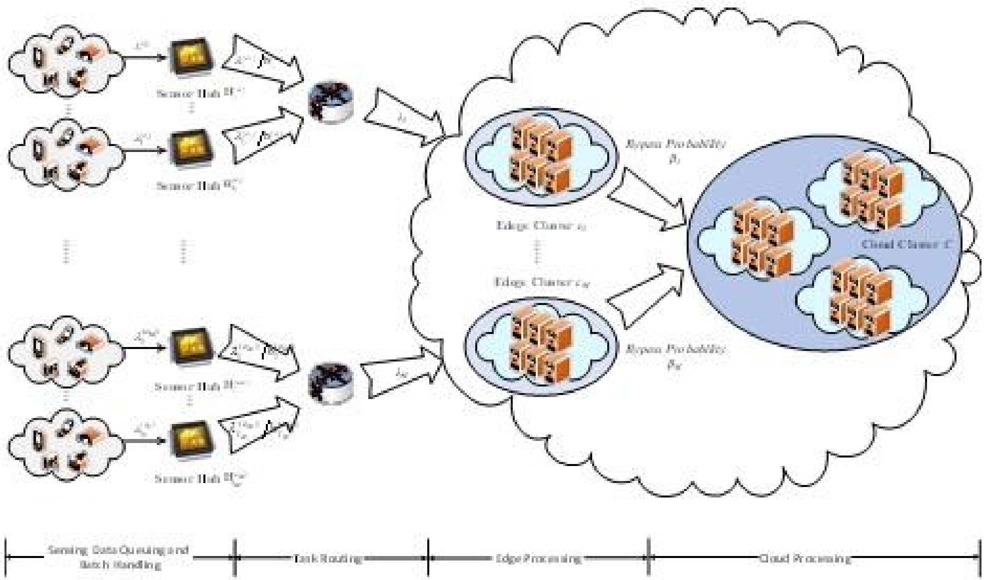
❖ Overall Architecture

- Central Cloud Cluster c
- Edge Clusters $\varepsilon_j \left(1 \le j \le M\right)$
- Sensor Hubs Subordinating to ε_j $H_i^{\varepsilon_j} \left(1 \le i \le I_j\right)$

Arrival Rate λ_c

Arrival Rate λ_j

Batch Arrival Rate $\hat{\lambda}_i^{(\varepsilon_j)}$



System Model

❖ Overall Architecture

- Central Cloud Cluster c
- Edge Clusters $\varepsilon_j \left(1 \le j \le M\right)$
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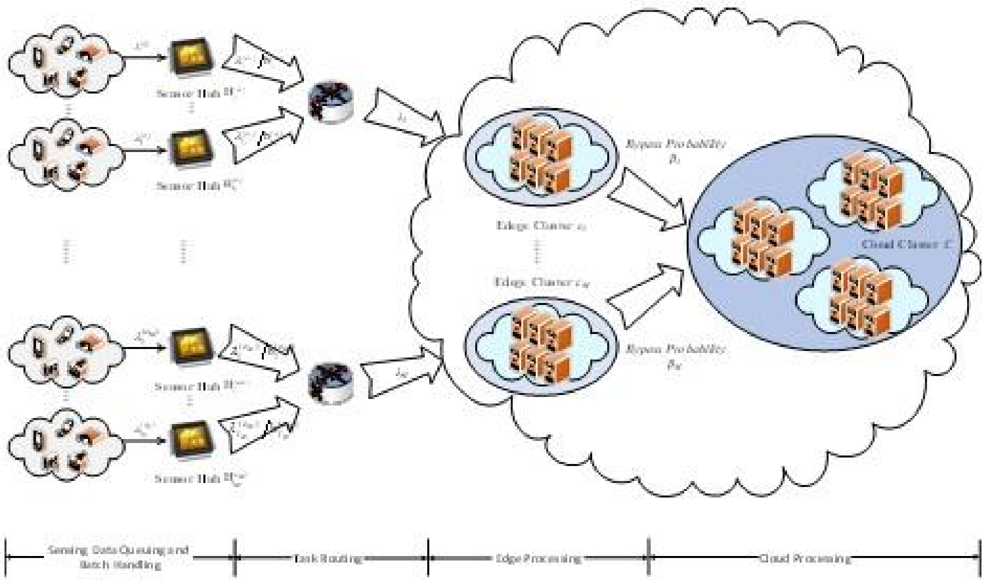


$$\lambda_j = \left(1 - \beta_j\right) \cdot \sum_{i=1}^{I_j} \hat{\lambda}_i^{(\varepsilon_j)}$$

$$\lambda_c = \beta_j \cdot \sum_{i=1}^{I_j} \hat{\lambda}_i^{(\varepsilon_j)}$$

System Model

❖Total System Power Consumption

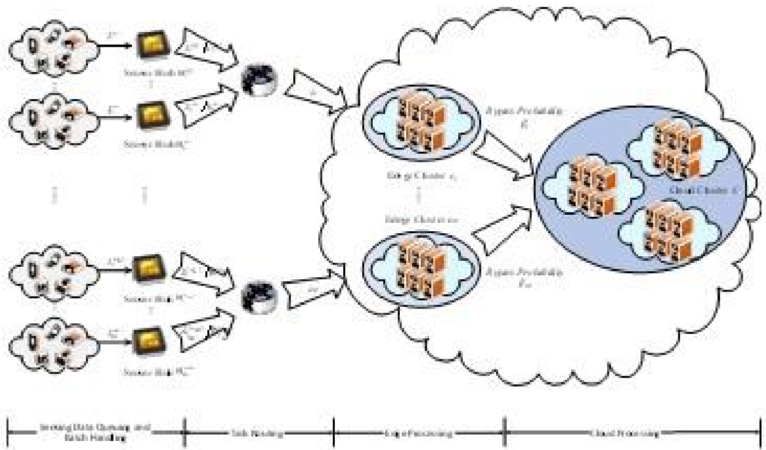
$$P^{sys} = \sum_{j=1}^{M}\left(P_j + P_j^{TR}\right) + P_{\mathrm{c}}$$

❖Total System Response Time

$$T^{sys} = \sum_{j=1}^{M} \lambda_j \cdot \left(\frac{q_j \cdot (1-\beta_j)}{n_j \cdot \mu_j} + \beta_j \cdot \left(T_j^{TR} + T_c\right) \right) \Bigg/ \sum_{j=1}^{M} \lambda_j$$

$$\lambda_j = \left(1-\beta_j\right) \cdot \sum_{i=1}^{I_j} \hat{\lambda}_i^{(\varepsilon_j)}$$

$$\lambda_c = \beta_j \cdot \sum_{i=1}^{I_j} \hat{\lambda}_i^{(\varepsilon_j)}$$



System Model

- Total System Power Consumption

$$P^{sys} = \sum_{j=1}^{M}\left(P_j + P_j^{TR}\right) + P_{\mathrm{c}}$$

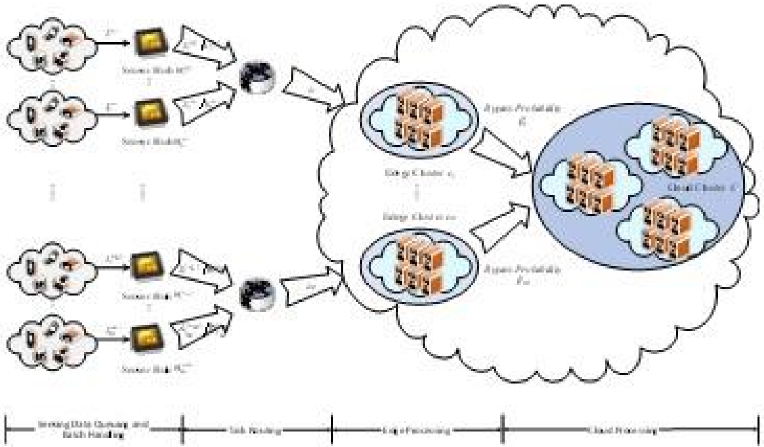
- Total System Response Time

Stationary Response Time at the Cloud Site

$$T^{sys} = \sum_{j=1}^{M}\lambda_j \cdot \left(\frac{q_j \cdot (1-\beta_j)}{n_j \cdot \mu_j} + \boxed{\beta_j \cdot \left(T_j^{TR} + T_c\right)}\right) \Big/ \sum_{j=1}^{M}\lambda_j$$

$$\lambda_j = \left(1-\beta_j\right) \cdot \sum_{i=1}^{I_j} \hat{\lambda}_i^{(\varepsilon_j)}$$

$$\lambda_c = \beta_j \cdot \sum_{i=1}^{I_j} \hat{\lambda}_i^{(\varepsilon_j)}$$



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Scheduling Scheme

Reward Model

- Total System Power Consumption

$$P^{sys} = \sum_{j=1}^{M}\left(P_j + P_j^{TR}\right) + P_c$$

- Total System Response Time

$$T^{sys} = \sum_{j=1}^{M}\lambda_j \cdot \left(\frac{q_j \cdot (1-\beta_j)}{n_j \cdot \mu_j} + \underbrace{\boxed{\beta_j \cdot \left(T_j^{TR} + T_c\right)}}_{\text{Stationary Response Time at the Cloud Site}}\right) \Big/ \sum_{j=1}^{M}\lambda_j$$

Stationary Response Time at the Cloud Site

- Service Level Agreement (SLA)

$$\boxed{T_{SLA}}$$

Upper Bound of the Response Time

Scheduling Scheme

❖ Reward Model

- Total System Power Consumption

$$P^{sys} = \sum_{j=1}^{M} \left(P_j + P_j^{TR} \right) + P_c$$

- Total System Response Time

Stationary Response Time at the Cloud Site

$$T^{sys} = \sum_{j=1}^{M} \lambda_j \cdot \left(\frac{q_j \cdot (1-\beta_j)}{n_j \cdot \mu_j} + \boxed{\beta_j \cdot \left(T_j^{TR} + T_c \right)} \right) \Bigg/ \sum_{j=1}^{M} \lambda_j$$

- Reward Function

$$R = \frac{T_{SLA} - T^{sys}}{T_{SLA}} \Bigg/ \frac{P^{sys}}{P_{\max}}$$

Scheduling Scheme

❖ MDP Formulation

- Decision Epoch $t = \tau, 2\tau, 3\tau, 4\tau, \ldots\ldots$
- State Space

Workload in M edge clusters

$$(q_1, \ldots, q_j, \ldots, q_M)$$

- Action Space
- Reward Function
- State Probability

Scheduling Scheme

MDP Formulation

- Decision Epoch $t = \tau, 2\tau, 3\tau, 4\tau, \dots \dots$
- State Space $(q_1, \dots, q_j, \dots, q_M)$
- Action Space

Cartesian Product for bypass transmission probability n_j and #of power-on machines β_j

$$(\beta_1, \dots, \beta_M) \times (n_1, \dots, n_M, n_c)$$

- Reward Function
- State Probability

Scheduling Scheme

MDP Formulation

- Decision Epoch $t = \tau, 2\tau, 3\tau, 4\tau, \ldots \ldots$
- State Space $(q_1, \ldots, q_j, \ldots, q_M)$
- Action Space $(\beta_1, \ldots, \beta_M) \times (n_1, \ldots, n_M, n_c)$
- Reward Function

$$R = \frac{T_{SLA} - T^{sys}}{T_{SLA}} \bigg/ \frac{P^{sys}}{P_{\max}}$$

- State Transition Probability

MDP Formulation

- State Transition Probability
  - Discrete Time Markov Chain

$$p_{q_j \to q_j+1} = \lambda_j \left(1-\beta_j\right)\left(1-e^{-\sum_{k=1}^{M}(\lambda_k+q_k\mu_k)\cdot\tau}\right) \Bigg/ \sum_{k=1}^{M}(\lambda_k+q_k\mu_k)$$

$$p_{q_j \to q_j+1} = q_j\mu_j \left(1-e^{-\sum_{k=1}^{M}(\lambda_k+q_k\mu_k)\cdot\tau}\right) \Bigg/ \sum_{k=1}^{M}(\lambda_k+q_k\mu_k)$$

$$p_{loop} = e^{-\sum_{k=1}^{M}(\lambda_k+q_k\mu_k)\cdot\tau} + \lambda_j\beta_j\left(1-e^{-\sum_{k=1}^{M}(\lambda_k+q_k\mu_k)\cdot\tau}\right) \Bigg/ \sum_{k=1}^{M}(\lambda_k+q_k\mu_k)$$

Scheduling Scheme

❖OO-Based Solution

- Ordinal Optimization (Edward et al.1997)
- Coarse Model
- Selection Rule

Scheduling Scheme

❖ OO-Based Solution

$$R = \frac{T_{SLA} - T^{sys}}{T_{SLA}} \bigg/ \frac{P^{sys}}{P_{\max}}$$

- Ordinal Optimization
- Coarse Model - Ignore the future earnings and simply focus on the current reward
- Selection Rule

Scheduling Scheme

❖OO-Based Solution

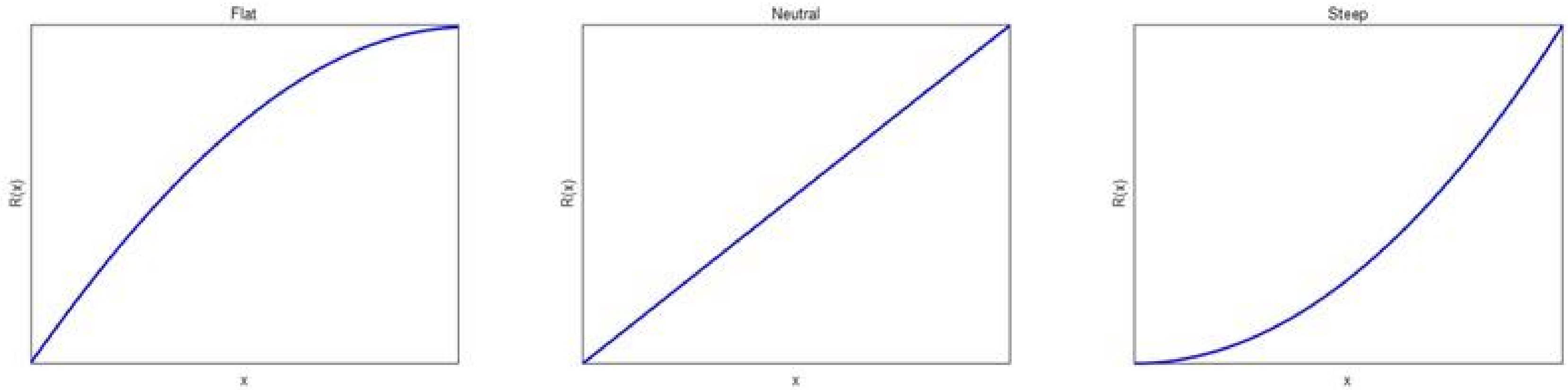
$$R = \frac{T_{SLA} - T^{sys}}{T_{SLA}} \Big/ \frac{P^{sys}}{P_{\max}}$$

- Ordinal Optimization
- Coarse Model - Ignore the future earnings and simply focus on the current reward
- Selection Rule
  - Ordered Performance Curve (OPC)
  - Error Level

Selection Rule

❖ Ordered Performance Curve (OPC)

$$r(x_i) = \frac{r_e^{[i]} - r_e^{[1]}}{r_e^{[N]} - r_e^{[1]}} \qquad x_i = \frac{i-1}{N-1}$$



- Non-decreasing sequence for estimated actions

$$\vec{R}_e = \left(r_e^{[1]}, r_e^{[2]}, \ldots\ldots, r_e^{[N]} \right)$$

Selection Rule

- Error Level

$$error = \max_{1\le k\le N}\left\{1-\frac{\vec{R}_e^{(k)^T}\cdot\vec{R}^{(k)}}{\left\|\vec{R}_e^{(k)}\right\|_2\times\left\|\vec{R}^{(k)}\right\|_2}\right\}$$

  - $0 \le error < 0.5$ (Small Level)
  - $0.5 \le error < 1$ (Medium Level)
  - $error \ge 1$ (Large Level)

Non-decreasing sequence for estimated actions

$$\vec{R}_e^{(k)} = \left(r_e^{[1]}, r_e^{[2]}, \ldots\ldots, r_e^{[N]}\right)$$

Non-decreasing sequence for evaluated actions

$$\vec{R}^{(k)} = \left(r^{[1]}, r^{[2]}, \ldots\ldots, r^{[N]}\right)$$

Scheduling Scheme

❖TSECS Algorithm

Algorithm 1 Task Scheduling of Edge-Cloud System (TSECS)

Input: Decision-making space of scheduling scenarios $\overline{S}$, the number of good enough solutions $\boldsymbol{g}$, alignment level $\boldsymbol{k}$

Output: Determined action $\boldsymbol{a_n}$.

1: Calculate the reward values of all the scheduling scenarios using coarse model

2: Estimate the OPC type based

3: Estimate the normalized error level

4: Calculate the number $\boldsymbol{s}$ of selected scenarios and the theory of OO ensures that $\boldsymbol{s}$ scheduling scenarios contains at least $\boldsymbol{k}$ good enough scheduling scenarios with probability no less than 0.95

5: Use the iterative algorithm for MDP optimization to obtain the determined action $\boldsymbol{a_n}$ within the selected $\boldsymbol{s}$ scheduling scenarios

6: Return the determined action $\boldsymbol{a_n}$.

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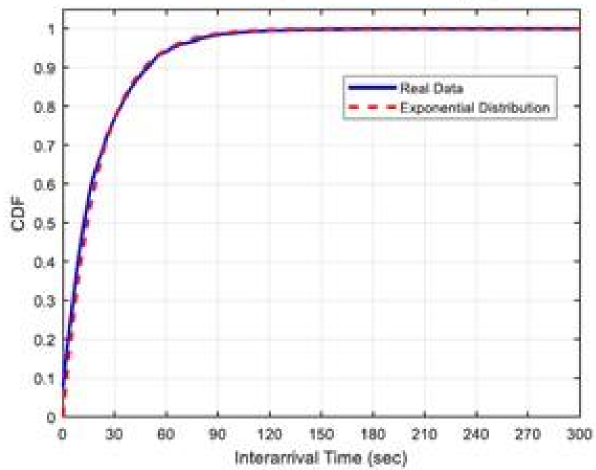
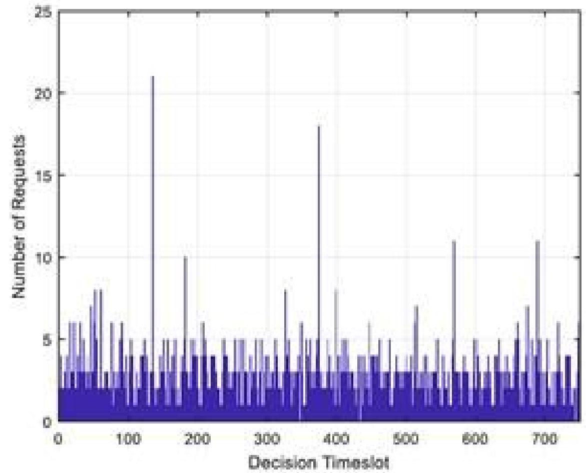
- ❖Conclusion and Future Work

Evaluation

- T-Drive Dataset
  - Released by Microsoft Research
  - GPS trajectories of 10,357 taxis within Beijing during a period of one week in 2008
  - 4 fields for each piece of data, including taxi id, timestamp, longitude and latitude





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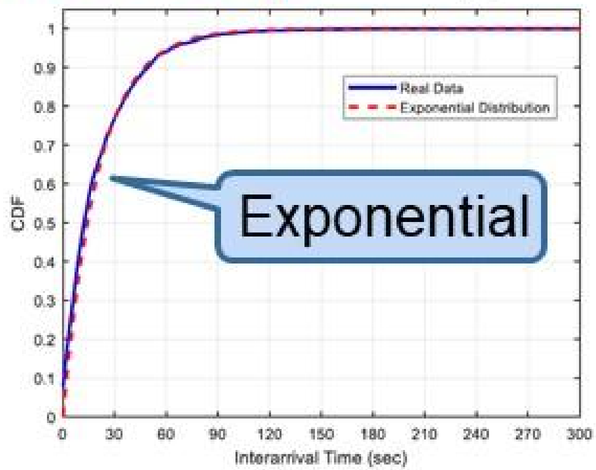
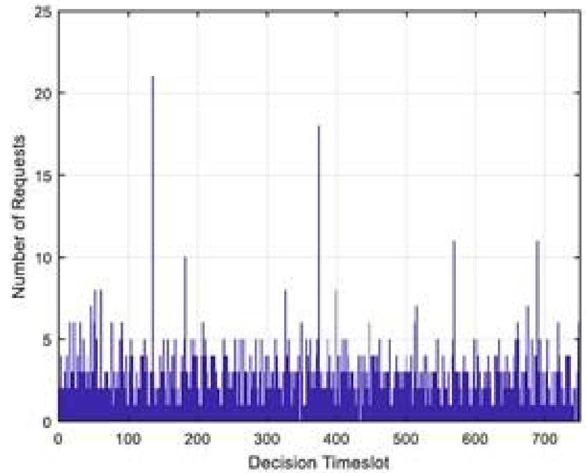
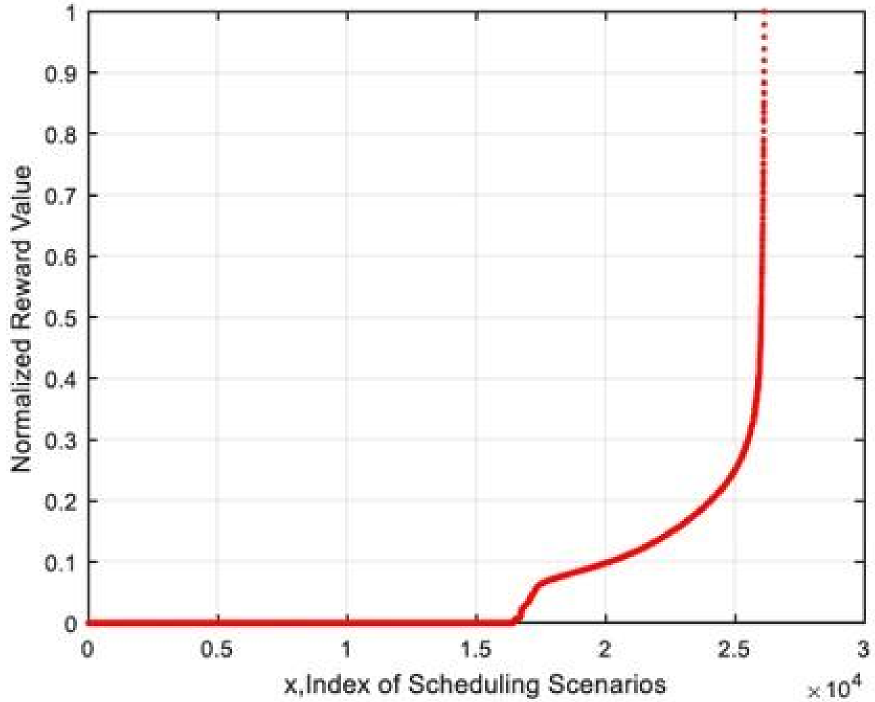




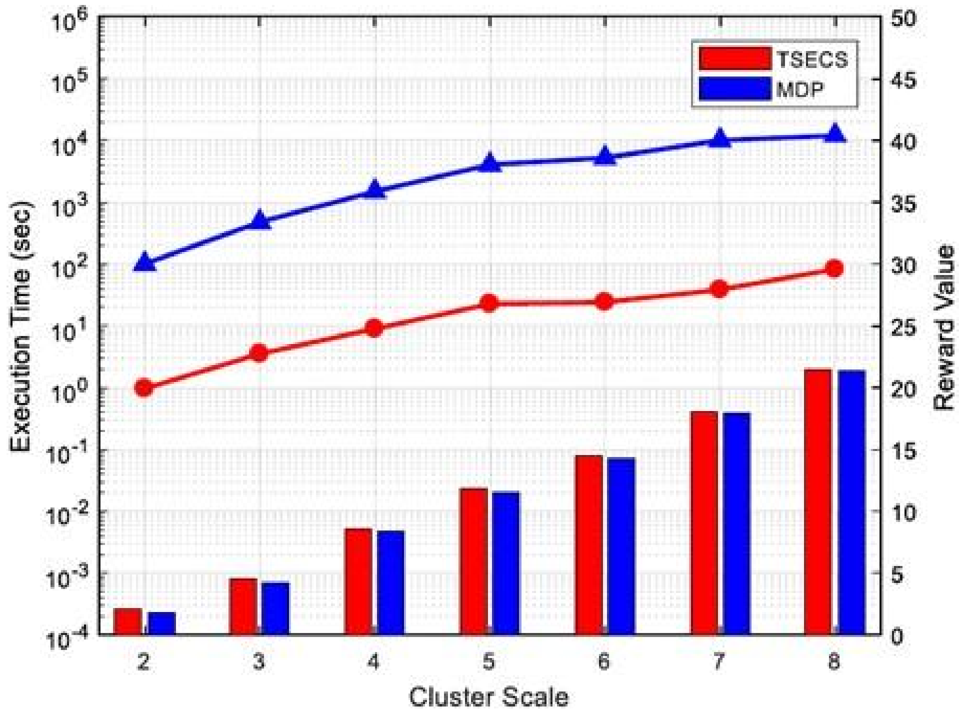
Evaluation

- Normalized Error= 0.5789 (Medium Level)
- Ordered Performance Curves (Steep)



Evaluation

❖TSECS(OO-Assisted) V.S. MDP(Classic)



Evaluation

❖ State-of-the-Art

- Load-Balanced Algorithm

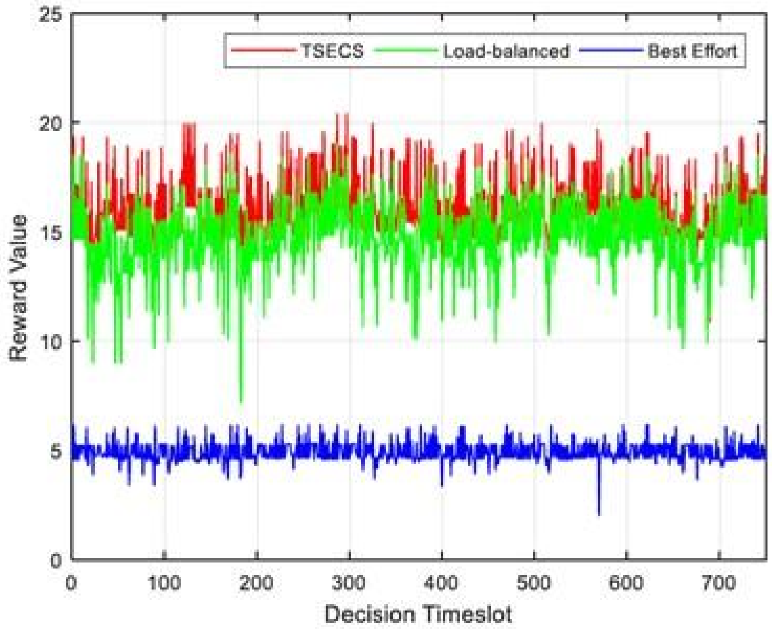
  \- Requests are dispatched to edge or cloud servers based on the serving capacity

- Best Effort Algorithm

  \- All of servers are switched on and keep constantly running

Evaluation

❖State-of-the-Art



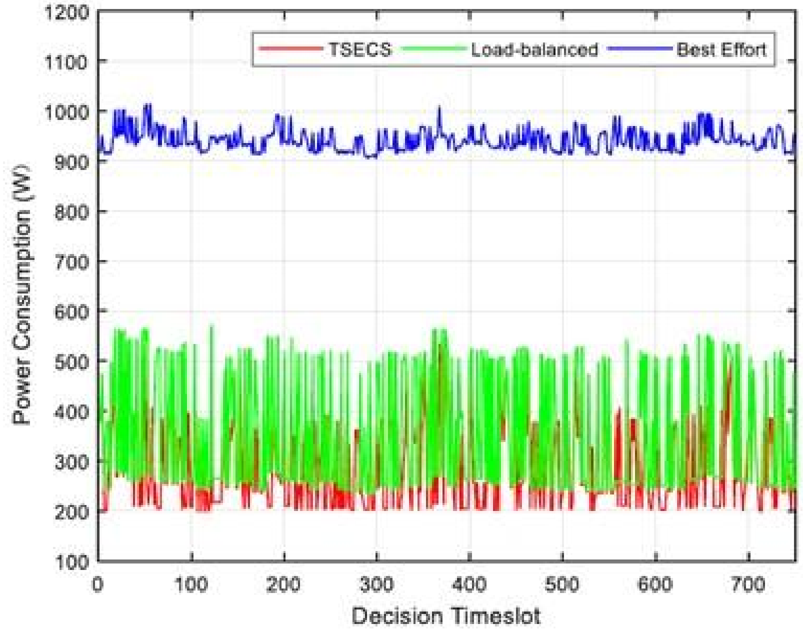


TABLE. AVERAGE RESPONSE TIME OF DIFFERENT ALGORITHMS

T_{SLA} (sec)	Algorithms Response Time (sec)		
	TSECS	Load-balanced	Best Effort
8.00	7.67	7.16	7.59

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Conclusion

- Modeling approach of energy-aware performance evaluation for an IoT system with edge computing paradigm
- Joint scheme for task scheduling and resource allocations with high efficiency
- Scheduling efficiency improvement with OO techniques applied
- Simulation experiments based on real-world data from IoT and cloud systems

Future Work

- Detailed specifications on models
  - More variety of real-life IoT systems
  - More adaptive to various task arrivals
- Elaborate algorithm design
  - Further theoretical validation of efficiency

Thank you!

Q&A

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