Spatially Partitioned Robust Optimization for Energy-Efficient Underwater Wireless Sensor Networks under Simulation-Informed Network Conditions

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Özhan EREN received his bachelor’s degree in Naval Architecture and Marine Engineering from Turkish Naval Academy and master’s degree in Defense Resource Management from the Institute of Strategic Studies at the Turkish War College (National Defense University). He is currently a doctoral student majoring in industrial engineering at the Department of Industrial Engineering, TOBB University of Economics and Technology.

His research interests include the application of optimization techniques to model and analyze problems in underwater wireless networks, with a focus on robust optimization.

Aim of our paper

Our primary aim is:

1. designing an event-driven UWSN capable of monitoring a designated underwater area through a robust optimization approach,
2. assessing the robustness of the proposed model against the deterministic formulation, with consideration of key metrics influencing system behavior.

Contributions of our paper

Contributions of our study are threefold:

1. A simulation framework integrating vehicle mobility, sensor deployment, and real-world bathymetry to realistically estimate sensing rates.
2. A robust optimization model with balanced 3D K-means partitioning to better capture localized uncertainty and traffic variations.
3. Computational tests indicating that small sensing-rate deviations degrade deterministic designs, while the robust design sustains performance and prolongs lifetime.

Table for notation used in our paper

TABLE SETS, PARAMETERS, AND DECISION VARIABLES.

Sets	
N	Set of sensor nodes
N_G	Set of all nodes in the network, i.e., $N \cup \{BS\}$, where BS denotes the base station
$\mathscr{R}$	Set of sensor subsets (regions), i.e., $\mathscr{R} = \{R_1, R_2, \dots\}$ with $R_j \subseteq N$
R_j	A subset of sensors forming region R_j, i.e., $R_j \in \mathscr{R}$
$\mathscr{J}$	Index set of regions, i.e., $\mathscr{J} = \{1, 2, \dots, \lvert\mathscr{R}\rvert\}$
$\mathscr{S}$	Set of sensing rate vectors within feasible intervals satisfying regional sum constraints
A	Set of directed one-hop connections: $A = \{(i,j) : i \in N, j \in N_G \setminus \{i\}, d_{ij} \leq R\}$
G	Directed graph representing the network, i.e., $G = (N_G, A)$
$\mathscr{U}$	Uncertainty set of feasible sensing rate vectors
Parameters	
d_{ij}	Euclidean distance between $i \in N$ and $j \in N_G$
T	Default network lifetime in configuration
R	Transmission range for sensors (m)
e_{ij}^{TX}	Energy cost of transmission from $i \in N$ to $j \in N_G$ per bit (mJ/bit)
e_{ji}^{RX}	Energy cost of reception by $i \in N$ from $j \in N$ per bit (mJ/bit)
s_k	Sensing rate of sensor $k \in N$ (bit/s)
s_{nom}^k	Nominal sensing rate of sensor $k \in N$ (bit/s)
s_{dev}^k	Sensing rate deviation of sensor $k \in N$ (bit/s)
α	Regional uncertainty budget
β_{kj}	Binary parameter indicating whether sensor k belongs to region R_j, where $j \in \mathscr{J}$
Variables	
f_{ij}^k	Proportion of s_k sensed by $k \in N$ transmitted on $(i,j) \in A$
e_i	Initial energy to be allocated to $i \in N$ (mJ)
$e_{\max}^{\text{rob}}$	Maximum energy assigned to a sensor in N under the robust model (mJ)
$e_{\max}^{\text{det}}$	Maximum energy assigned to a sensor in N under the deterministic model (mJ)
μ_{ik} , λ_{ik}	Deviation duals
θ_{ji}	Regional budget dual variable

Deterministic Network Model

Decision variables

f_{ij}^{k} : The transmission rate of the data sensed by sensor *k* from sensor *i* to sensor *j*

e_i : The initial energy allocated to sensor *i*

Parameters

T : Desired network lifetime *(s)*

e_{ji}^{RX} : Energy consumed by sensor *i* to receive a bit of data *(mJ)*

e_{ij}^{TX} : Energy consumed to transmit a bit of data from sensor *i* to sensor *j* (*mJ*)

s_k : Amount of data sensed by sensor k per unit time *(bits/s)*

$$\min \quad e_{max}^{det}$$

s.t.:

$$\sum_{(i,j)\in A} f_{ij}^{k} - \sum_{(j,i)\in A} f_{ji}^{k} = \begin{cases} 1, & i = k \\ -1, & i = BS; \\ 0, & otherwise \end{cases} \qquad \forall i \in N_G, \forall k \in N$$

$$\sum_{k\in N}\left[\sum_{(i,j)\in A} T e_{ij}^{TX} f_{ij}^{k} s_k + \sum_{(j,i)\in A} T e_{ji}^{RX} f_{ji}^{k} s_k\right] \le e_i \qquad \forall i \in N$$

$$e_{max}^{det} \ge e_i \qquad \forall i \in N$$

$$f_{ij}^{k} \ge 0 \qquad \forall (i,j) \in A, \forall k \in N$$

$$e_i \ge 0 \qquad \forall i \in N$$

Robust Network Model

Decision variables

f_{ij}^k : The transmission rate of the data sensed by sensor *k* from sensor *i* to sensor *j*

e_i : The initial energy allocated to sensor *i*

$\mu_{ik}, \lambda_{ik}, \theta_{ji}$: dual variables

$$\min \quad e_{max}^{rob}$$

s.t.:

$$\sum_{(i,j)\in A} f_{ij}^k - \sum_{(j,i)\in A} f_{ji}^k = \begin{cases} 1, & i = k \\ -1, & i = BS; \\ 0, & otherwise \end{cases} \qquad \forall i \in N_G, \forall k \in N$$

$$\sum_{k\in N}\left[\mu_{ik}\left(s_k^{nom} + s_k^{dev}\right) - \lambda_{ik} s_k^{nom} + \sum_{j\in \mathcal{J}} \theta_{ji}(1+\alpha)\beta_{kj} s_k^{nom}\right] \le e_i \qquad \forall i \in N$$

$$\mu_{ik} - \lambda_{ik} + \sum_{j\in\mathcal{J}} \theta_{ji}\beta_{kj} \ge \sum_{(i,j)\in A} T e_{ij}^{TX} f_{ij}^k + \sum_{(j,i)\in A} T e_{ji}^{RX} f_{ji}^k \qquad \forall k \in N$$

$$e_{max}^{rob} \ge e_i \qquad \forall i \in N$$

$$\mu_{ik}, \lambda_{ik}, \theta_{ji}, f_{ij}^k, e_i \ge 0 \qquad \forall (i,j) \in A, \forall i \in N, j \in \mathcal{J}, k \in N$$

Parameters

T : Desired network lifetime *(s)*

e_{ji}^{RX} : Energy consumed by sensor *i* to receive a bit of data *(mJ)*

e_{ij}^{TX} : Energy consumed to transmit a bit of data from sensor *i* to sensor *j* (*mJ*)

s_k^{nom} : Nominal sensing rate of sensor *k (bits/s)*

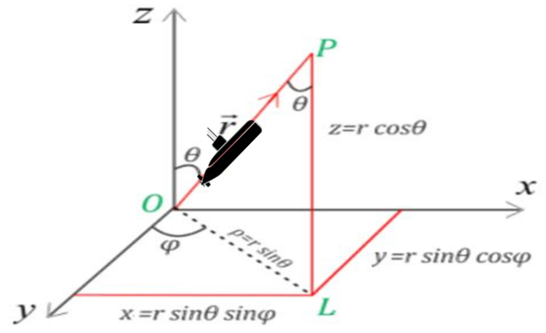
s_k^{dev} : Sensing rate deviation of sensor *k (bits/s)*

β_{kj} : Binary parameter indicating whether sensor *k* belongs to region R_j

- In our robust optimization model, Balanced K-Means partitions the network into equal-sized R_j subregions, ensuring uniform coverage and sufficient sensors to enable localized uncertainty analysis.
- This clustering supports a fair, symmetric robustness formulation by simplifying constraints and avoiding region-specific scaling.

Simulation Model

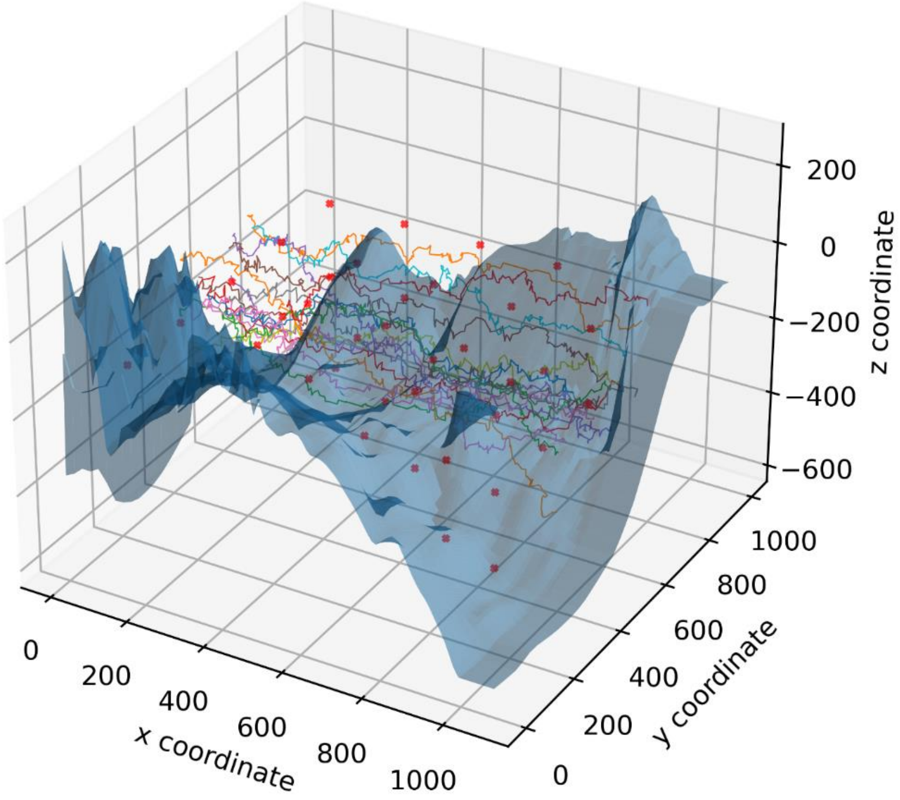
Network Dimension	1000m x 1000m x Bathymetric Depth	
Sensor Deployment	Uniform Grid	
BS Position	Center	
Number of Sensors	40	
Sensing Radius	100m	
Packet Size for Periodic Sensing	32 byte	
Packet Size for Event-driven Sensing	320byte	
Type of Underwater Vehicles	Submarine	AUV
Speed Range	10-20 m/s	4-10 m/s
Maximum Detection Horizon	60 m	30 m
Safety Margin in Seafloor Topography	20 m	10 m



$$x_{\mathrm{ship}[j],t} = x_{\mathrm{ship}[j],0} + \sum_{t_l}^{t} r_{\mathrm{ship}[j],t_l,i} \sin\left(\theta_{\mathrm{ship}[j],t_l}\right) \sin\left(\phi_{\mathrm{ship}[j],t_l}\right)$$

$$y_{\mathrm{ship}[j],t} = y_{\mathrm{ship}[j],0} + \sum_{t_l}^{t} r_{\mathrm{ship}[j],t_l,i} \sin\left(\theta_{\mathrm{ship}[j],t_l}\right) \cos\left(\phi_{\mathrm{ship}[j],t_l}\right)$$

$$z_{\mathrm{ship}[j],t} = z_{\mathrm{ship}[j],0} + \sum_{t_l}^{t} r_{\mathrm{ship}[j],t_l,i} \cos\left(\theta_{\mathrm{ship}[j],t_l}\right)$$



Simulation framework models underwater sensor–vehicle–seafloor interactions, producing *data generation rates of sensors* treated as uncertainty parameter for robust network model.

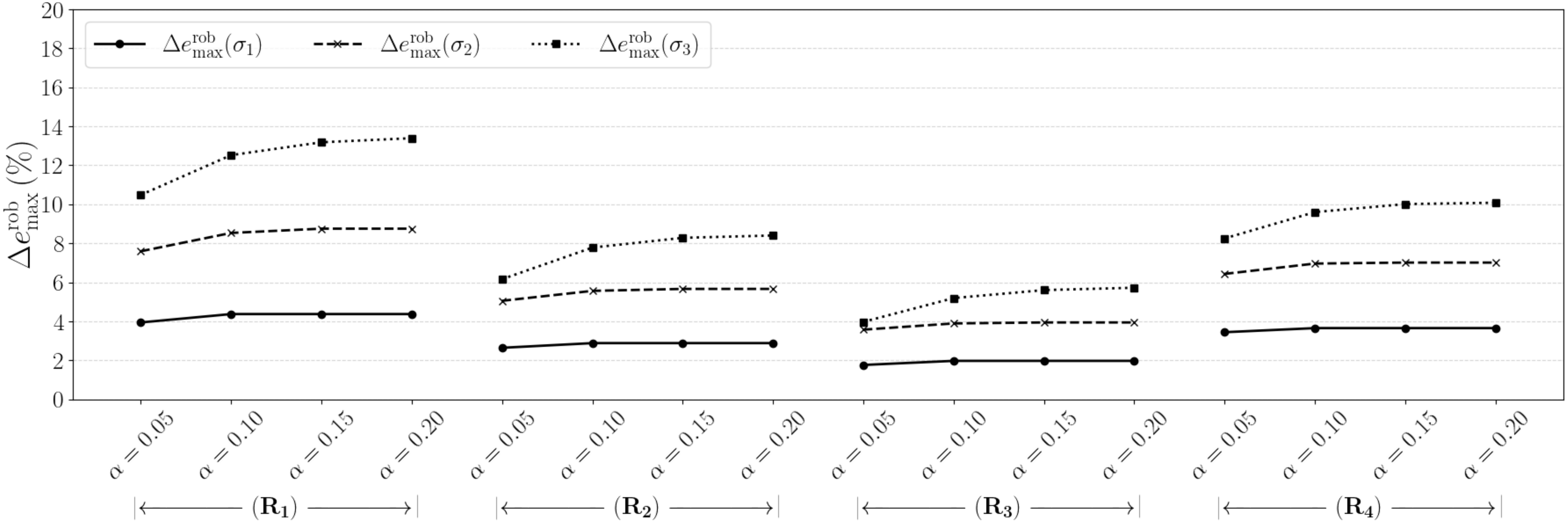
Algorithm for the Simulation and Modeling of Underwater Vehicle Motion

Algorithm 1 Underwater Vehicle Simulation in 3D Topological Space

Require: m: Number of ships to be deployed, n: Number of sensors to be deployed, r: Sensing radius, $total\_runs$: Number of simulation runs
Require: Bathymetric data: $x_{orig}, y_{orig}, z_{orig}, x_{safe}, y_{safe}, z_{safe}$
Require: Sensor coordinates: $x_{sensor[i]}, y_{sensor[i]}, z_{sensor[i]}$ $\forall i = 1, .., n$

```
Initialize: Load topography and sensor data. Initialize ship and sensor coordinate arrays.
Sensor Placement:
for each sensor i = 1, .., n do
    if z_sensor[i] is feasible then
        Set (x_sensor[i], y_sensor[i], z_sensor[i]) as the position of sensor i.
    else
        Exclude unfeasible sensor and proceed to the next.
    end if
end for
Ship Initialization:
for each ship j = 1, .., m do
    Generate initial y, z coordinates;
    if z is feasible then
        set (x_ship[j],0, y_ship[j],0, z_ship[j],0) as the initial location of ship j.
    else
        Exclude unfeasible ship and proceed to the next.
    end if
end for
Ship Movement:
for each time step t and ship j do
    Compute potential position (x_ship[j],t, y_ship[j],t, z_ship[j],t)
    if the position is feasible then
        Apply the standard movement for the ship
    else
        Search for possible traveling directions
        if any alternative route is feasible then
            Apply the alternative route
        else
            Apply emergency case procedure
        end if
    end if
    Sensor Detection:
    for each time step t, ship j and sensor i do
        Calculate distance to each sensor.
        Calculate detection status by considering conditions for probability of detection.
        Compute and update sensed_duration[i][j].
    end for
end for
Output:
Store and print ship and sensor coordinates.
Record total steps for each ship.
Record and print sensed duration results for each sensor.
```

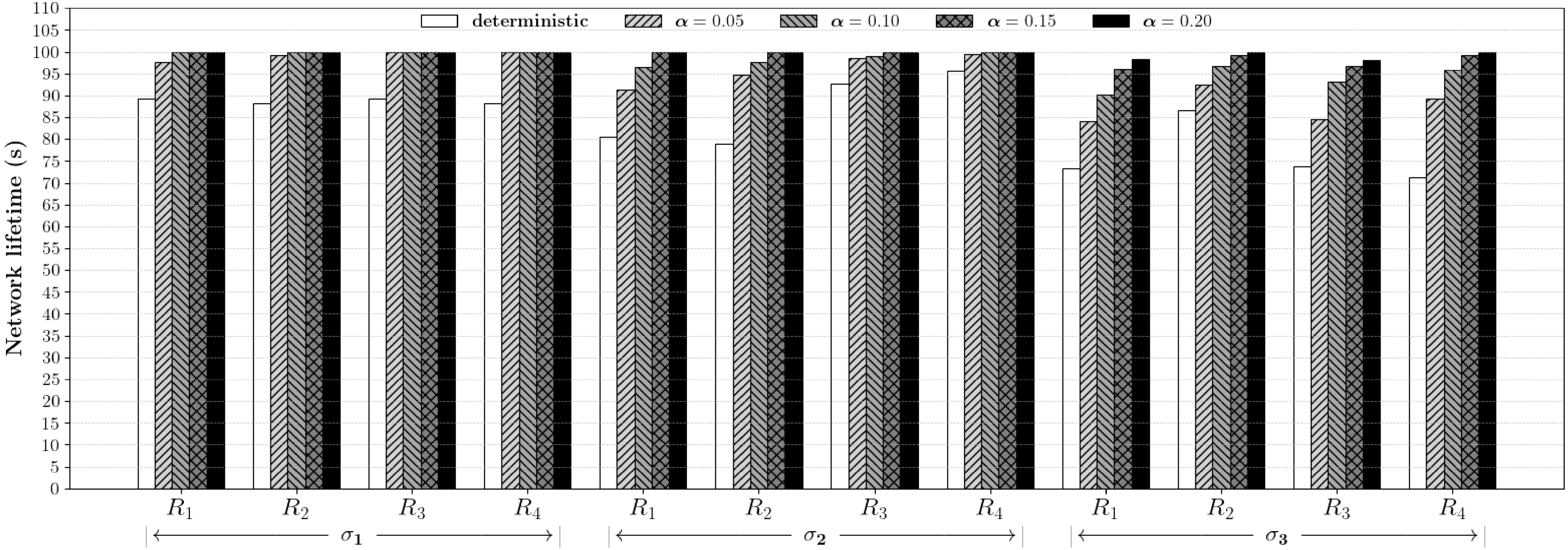
Computational Results



- In the configuration phase, the impact of the regional uncertainty budget (α) and node-specific deviations (σ) on maximum battery allocation requirements is evaluated.
- The robust model accounts for uncertainties that can increase battery allocations, whereas the deterministic model ignores them. Sublinear growth keeps allocations moderate even under high uncertainty.

Computational Results

Implementation Phase: Network Lifetime



- In the implementation phase, analysis based on α and σ shows that deterministic designs have network lifetimes approximately 9.44%, 11.15%, 11.94%, and 11.97% shorter across regions R_1–R_4 compared to the robust model under baseline conditions ($\alpha = 0.05$, $\sigma = 1$)
- As uncertainty increases, reductions reach 14.72%, 17.93%, 15.30%, and 21.75% in the most extreme cases.

Computational Results

- Compared with deterministic design, the robust design consistently sustains lifetimes close to the reference target, offering more efficient utilization of allocations for extended operation.

- Region-wise analysis confirms that lifetime variability grows with increasing α or σ, highlighting the trade-off between robustness and performance.

Conclusion and Future Work

Conclusion:

- This paper introduces a robust optimization framework for UWSNs that ensures reliable target detection while maintaining energy efficiency under uncertainty.
- By accounting for both regional and individual sensor deviations, the approach mitigates the vulnerabilities inherent in deterministic designs.
- Comprehensive tests demonstrate that the robust design consistently outperforms deterministic methods, sustaining network performance even under spatial and sensing-rate variations.

Future Work:

- Future research will explore more complex deviation models and alternative deployment strategies to further enhance the robustness and resilience of UWSNs under diverse and unstructured conditions.

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Thank you for your participation.