AMMOF: An Adaptive Multi-metric Objective Function for Enhanced RPL Routing in Industrial IoT Networks

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Abstract. The Routing Protocol for Low-Power and Lossy Networks (RPL) is the routing protocol of choice for Low-Power and Lossy Networks (LLNs) and constitutes the standard routing solution for 6TiSCH-based Industrial Internet of Things (IIoT) networks. RPL relies on a parent selection and switch mechanism, managed by Objective Functions (OFs) that critically impacts network performance in terms of latency, reliability, and energy consumption. However, default OFs such as OF0 and MRHOF are based on single metrics, hop count and expected transmission count, respectively. In this paper, we investigate the limitations of these two default solutions and propose AMMOF, an Adaptive Multi-Metric Objective Function that jointly considers link quality, residual energy, and queue occupancy to optimise parent selection decisions. We also design a distance-aware weight tuning mechanism to further enhance the parent selection process. Through extensive Cooja simulations, we demonstrate that AMMOF significantly improves network performance in terms of packet delivery ratio, end-to-end delay, energy efficiency, and topology stability compared to OF0 and MRHOF in 6TiSCH industrial scenarios.

Keywords: RPL · 6TiSCH · Parent Switch · Objective Function · IIoT · Multi-Factor Routing · TSCH

1 Introduction

The Industrial Internet of Things (IIoT) revolutionizes modern industrial environments by allowing dense and reliable interconnections between sensors, actuators, and controllers. Several industrial applications such as factory automation, robotic assembly lines, smart grid protection, and chemical plant safety monitoring, have been made possible thanks to this technology, however they require stringent conditions on the underlying communication infrastructure, notably in terms of high reliability, bounded end-to-end latency, and energy efficiency [1].

The 6TiSCH architecture [2] has emerged as an eminent and distinguished solution for IIoT networks. It combines the deterministic medium access control

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of IEEE 802.15.4e Time-Slotted Channel Hopping (TSCH) with the scalability of IPv6. Within 6TiSCH architecture, the IPv6 Routing Protocol for Low-Power and Lossy Networks (RPL) [3] is the standard routing protocol. RPL is responsible for building and maintaining a Destination Oriented Directed Acyclic Graph (DODAG) rooted at the edge router.

The *parent switch* is a central mechanism in RPL, whereby a node selects its preferred parent using an Objective Function (OF). The impact of this decision is critical in terms of the quality of the routing paths and, consequently, on the overall network performance. OF0 and MRHOF are the two default OFs standardized by the IETF. OF0 [4] minimizes hop count, while MRHOF [5] relies on the Expected Transmission Count (ETX). Despite these single-metric approaches are simple and effective under certain conditions, they suffer from significant limitations in complex industrial environment where multiple conflicting objectives must be considered and simultaneously optimized.

Contributions. This paper introduce the main contributions:

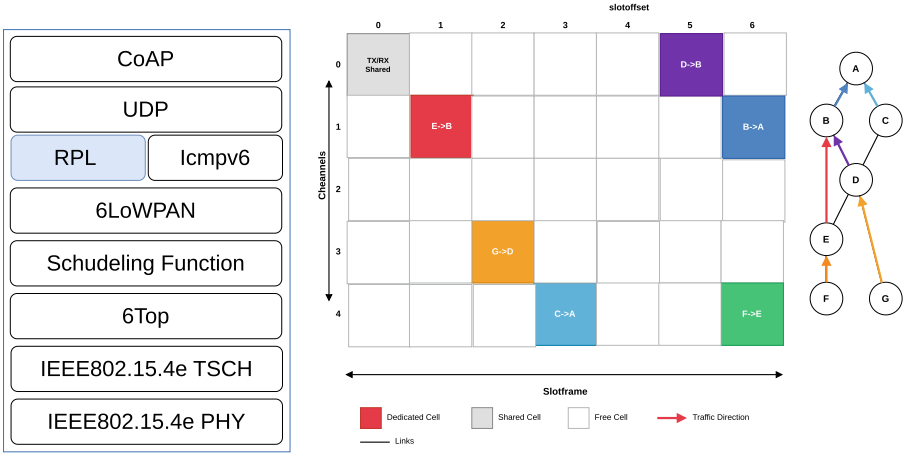
- An analysis of the default standardized OFs, OF0 and MRHOF limitations in 6TiSCH industrial environments.
- A novel multi-factor Objective Function that RSSI/LQI, residual energy, and queue occupancy are integrated into a unified weighted routing metric.
- A distance-aware weight tuning for parent selection, where the node distance to the root is used to adjust the OF weights.
- A hysteresis-based stabilization mechanism to reduce parent switch oscillations and ensuring more network stability.
- A comparative performance evaluation through simulation, demonstrating the performances of the proposed approach.

The remainder of the paper is organized as follows. Section 2 provides background on 6TiSCH and RPL. Section 3 reviews related work. Section 4 formulates the problem. Section 5 details the proposed multi-factor OF. Section 6 presents and discusses the evaluation results, and Sect. 7 concludes the paper.

2 Background

2.1 6TiSCH Architecture

6TiSCH [2] specifies a protocol stack (Fig. 1) to combine IPv6 connectivity with IEEE 802.15.4e TSCH networks. TSCH defines channel access into a cyclic *slotframe* divided into cells, each identified by a (timeslot, channel offset) pair (Fig. 1). This deterministic schedule aims to eliminate collisions and to enable energy-efficient communication through precise duty-cycling. The 6top sublayer manages cell negotiation between neighbors regarding a Scheduling Function (SF) policy, while the 6TiSCH minimal configuration provides a baseline shared schedule for bootstrapping and control traffic.



(a) The 6TiSCH network stack

(b) Example of a schedule in TSCH

Fig. 1. 6TiSCH architecture and TSCH scheduling overview

2.2 RPL Protocol

A DODAG is constructed by RPL [3], that is rooted at the border router (or LLN gateway), as shown in Fig. 2, providing upward (multipoint-to-point) and optionally downward routes. Nodes periodically exchange control packets as the DODAG Information Objects (DIOs) which is governed by the Trickle Timer algorithm, which adapts control message frequency to network stability. Each node maintains a *rank*, a scalar representing its score (for example, the distance to the root) as computed by the active OF. The preferred parent is the neighbor offering the best rank improvement.

Parent Switch Mechanism. The node occurs a parent switch when it identifies a neighbor offering a significantly better rank than its current parent. Despite this is necessary for topology adaptation, frequent switches introduce control overhead, routing instability, and transient packet losses. To limit unnecessary changes, a *hysteresis* parameter (MinHopRankIncrease) is defined by RPL, but default settings suffer in dynamic industrial environments (Fig. 3).

2.3 Default Objective Functions

OF0 [4] relies on hop count as the primary routing metric, to minimize path length to the root. This OF is designed to be metric-agnostic and acts as a fallback when no specific metrics are available. However, Of0 ignores link quality and energy considerations.

Moreover, **MRHOF** [5] aims to minimize the expected number of transmissions ETX along the path to the root. While ETX captures link reliability better

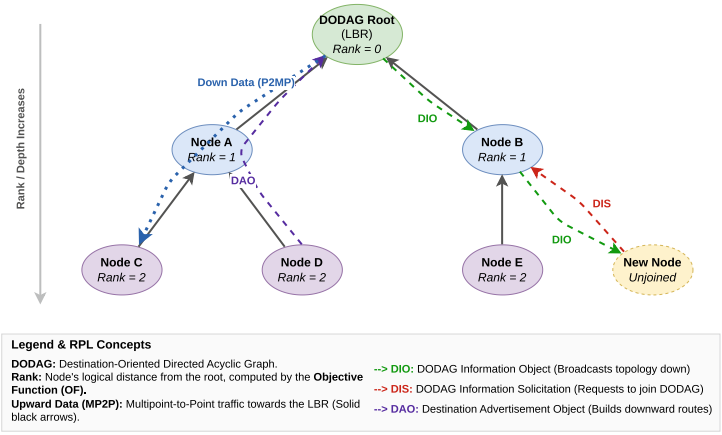


Fig. 2. DODAG Construction and Message Exchange in RPL protocol

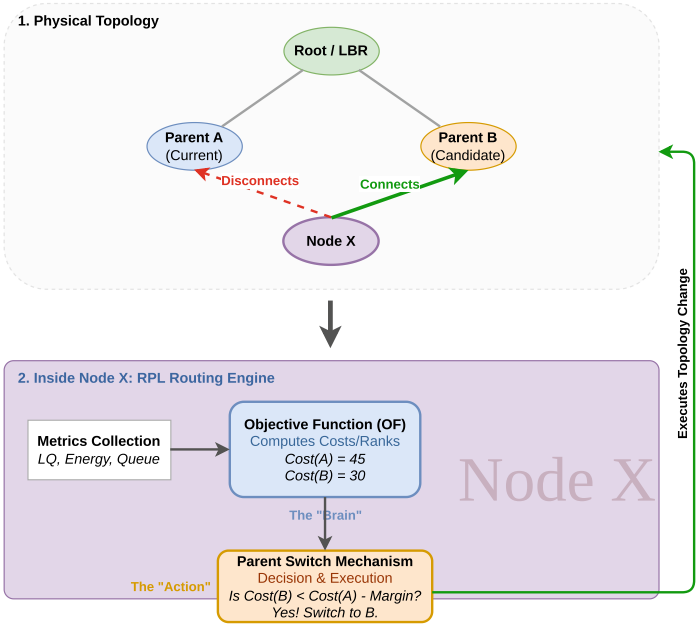


Fig. 3. Parent switch mechanism

than hop count, it remains a mono-metric approach that does not account for the parent state.

As illustrated in Fig. 4, Even if OF0 and MRHOF provide foundational routing mechanisms, their reliance on the only node parameters renders them ill-equipped to handle the multifaceted bottlenecks of dense IIoT environments. Specifically, optimizing custom made for path length or link reliability inevitably

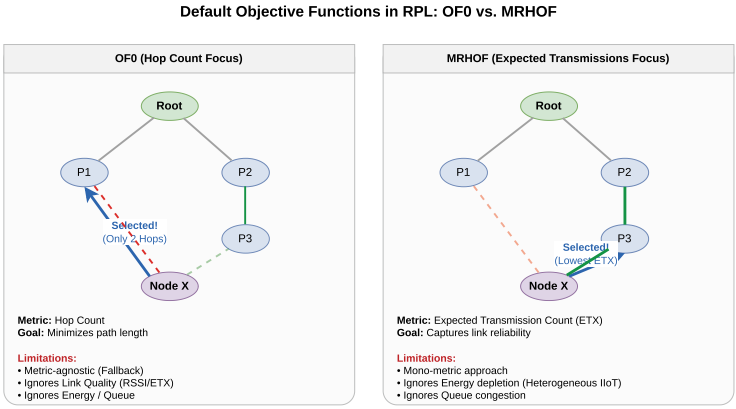


Fig. 4. Default Objective Functions in RPL: OF0 vs. MRHOF

ignores critical network conditions, leading to premature battery depletion and queue overflow, forcing nodes to frequently drop packets and trigger destabilizing parent switches.

3 Related Work

Many studies have examined RPL performance in IIoT and 6TiSCH environments. [6] evaluated RPL under various traffic loads and demonstrated that both OF0 and MRHOF suffer from instability under dense deployments. Multi-metric OF proposals have been explore in the literature: [7] proposed an energy-aware OF combining ETX and residual energy, while [8] employed fuzzy logic to combine multiple metrics into a composite routing cost.

More recently, machine learning approaches have been investigated for dynamic parent selection. [9] used reinforcement learning to adapt routing decisions to network conditions, and [10] proposed a DRL-based scheduler for 6TiSCH that jointly optimizes routing and scheduling. However, these approaches often require significant computational resources and are difficult to deploy on constrained IoT devices.

In contrast to existing work, this paper proposes a lightweight multi-factor OF that is directly compatible with standard RPL operation in 6TiSCH, without requiring modifications to the protocol stack or additional computational infrastructure.

4 Problem Formulation

To counteract the limitations observed in standard OFs, we propose, we propose **AMMOF**, a novel multi-factor objective function for RPL. AMMOF goes beyond traditional mono-metric evaluations by taking into account multi parameters like link quality (LQ), residual energy (E), and queue occupancy (Q) (see

Table 1). Furthermore, to address the heterogeneous traffic loads inherent at different DODAG depths, we introduce a distance-aware weight tuning mechanism that dynamically adjusts routing priorities based on each node's topological distance to the root. Our approach ensures a stable, energy-efficient, and resilient parent-selection process across the entire 6TiSCH network.

Table 1. Comparison of RPL Objective Functions: Default Approaches vs. Proposed AMMOF

Feature	OF0 (Default) [4]	MRHOF (Default) [5]	AMMOF (Proposed)
Primary Metric(s)	Hop Count	ETX (Expected Transmission Count)	Link Quality (LQ), Residual Energy (E), Queue (Q)
Primary Objective	Minimize path length to the root	Minimize expected transmissions	Balance reliability, energy consumption, and congestion
Link Quality Awareness	No (Metric-agnostic)	Yes	Yes (via RSSI/LQI)
Energy Awareness	No	No	Yes
Queue Awareness	No	No	Yes
Weight Tuning Policy	None (Single metric)	None (Single metric)	Dynamic (Distance-aware adaptation)
Parent Switch Stability	Low (Prone to routing loops)	Moderate (Prone to ping-pong effect)	High (Stabilized via adaptive hysteresis)
Target Environment	Basic, homogeneous deployments	Lossy networks with light traffic	Dense, heterogeneous, and heavy traffic IIoT

4.1 Network Model

We consider a 6TiSCH network composed of N nodes $\mathcal{V} = \{v_1, v_2, \ldots, v_N\}$ and a set of wireless links $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$. The network employs a DODAG rooted at a border router v_0. A set of candidate parents $\mathcal{P}_i \subseteq \mathcal{V}$ are mainted by each node v_i, discovered through DIO messages.

4.2 Parent Switch Decision

For each node v_i, the parent switch decision is autonomously made by the Objective Function, by assigning a *rank* R_i to each node based on the rank of its preferred parent p_i^* and the cost of the link (v_i, p_i^*):

$$R_i = R_{p_i^*} + \text{rank_increase}(v_i, p_i^*) \tag{1}$$

A parent switch is triggered when a candidate parent p' satisfies this condition:

$$R_{p'} + \text{rank_increase}(v_i, p') < R_{p_i^*} + \text{rank_increase}(v_i, p_i^*) - \delta \tag{2}$$

where δ is the hysteresis threshold. The main challenge consists of defining `rank_increase` to capture multiple performance objectives simultaneously.

4.3 Performance Metrics

The performance of the parent switch mechanism is evaluated along four dimensions: **Packet Delivery Ratio (PDR)** which represent the success rate of delivered packets. **End-to-End Latency**, that average delay of transmission from source to the border router. Moreover, **Energy Consumption**, to estimate average consumption of energy per node per unit time, and finally **Topology Stability**, or the parent switch number per node during the simulation duration (Fig. 5).

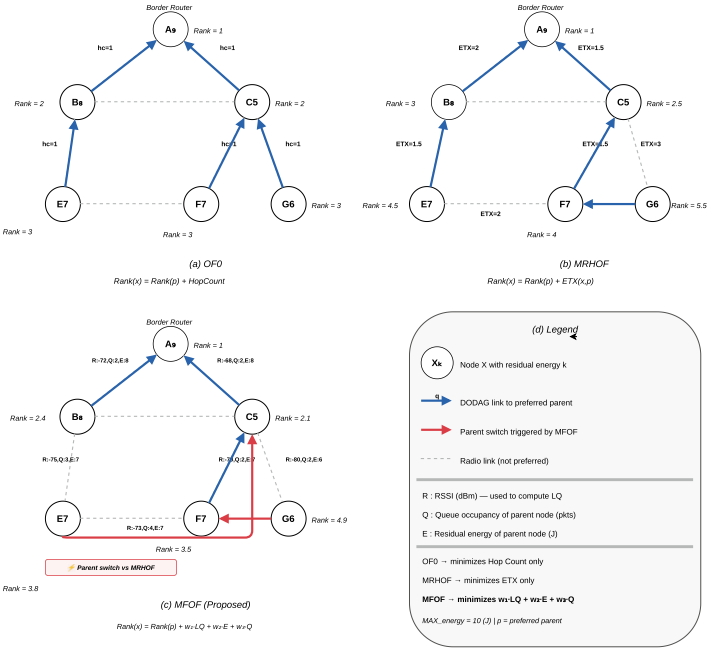


Fig. 5. Different Objective Function configurations

5 Proposed Multi-factor Objective Function

By designing the proposed OF, we took into account three principles: *comprehensiveness*, by including more metrics that reflect the diverse requirements in IIoT; *lightweight implementation*, to be deployable on constrained IoT devices; and *stability*, by integrating a lightweight hysteresis mechanism avoiding unnecessary expensive parent switches.

The complete execution flow of the proposed AMMOF is summarized in Algorithm 1. A node extracts the transmitted metrics in receiving DIO messages (Phase 1), and dynamically selects the weighting coefficients according to its topological position (Phase 2). Phase 3 consists to evaluate the composite cost for all candidate parents, and then the node applies the adaptive hysteresis threshold to make a final, stabilized routing decision (Phase 4), thereby mitigating unnecessary topology fluctuations.

5.1 Multi-factor Routing Metric

For a link (v_i, p_j), the composite link cost $C(v_i, p_j)$ is defined like a weighted combination of three normalized metrics as following:

$$C(v_i, p_j) = w_1 \cdot \hat{\text{LQ}}ij + w_2 \cdot \hat{E}j + w_3 \cdot \hat{Q}_j \tag{3}$$

where:

- $\hat{\text{LQ}}_{ij}$: normalized inverse link quality (derived from RSSI/LQI measurements).
- $\hat{E}_j$: normalized inverse residual energy of parent p_j (higher energy → lower cost).
- $\hat{Q}_j$: normalized queue occupancy of parent p_j(lower queue → lower cost).
- $w_1, w_2, w_3 \geq 0$, $\sum_{k=1}^{3} w_k = 1$: application-defined weight coefficients.

The rank increase function is then defined as follows:

$$\text{rank_increase}(v_i, p_j) = \text{MinHopRankIncrease} \times \lceil C(v_i, p_j) \times S \rceil \tag{4}$$

where S is a scaling factor that maps the composite cost to the RPL rank space.

5.2 Distance-Aware Weight Tuning for Parent Selection

In a 6TiSCH DODAG, nodes at different depths from the root are faced fundamentally to different network conditions. As nodes closer to the root as they operate under heavier traffic load due to data aggregation, making queue level and residual energy the dominant bottlenecks for parent selection. In Other hand, nodes far from the root suffer primarily from poor link quality, making RSSI the most critical metric. Thus, applying same and uniform weights w_k across all hops therefore sounds to lead to inconsistant parent selection: a fixed energy-aware policy may introduce unnecessary instability near the root, while a fixed RSSI-biased policy may drain distant nodes prematurely and reduce network lifetime.

Algorithm 1. AMMOF: Adaptive Multi-Metric Objective Function Parent Selection

Require: Set of candidate parents $\mathcal{P}$, Current parent p_{current}, Node topological distance to root d, Recent switch count $n_{\text{switch}}(t)$

Ensure: Selected preferred parent p_{best}

Phase 1: Metric Collection via DIO Messages

for each candidate parent $p \in \mathcal{P}$ **do**
  Receive DIO message from neighbor p
  Extract Link Quality LQ_p, Residual Energy E_p, and Queue Occupancy Q_p
end for

Phase 2: Distance-Aware Weight Tuning

▷ Adjust metric importance based on node depth

$(w_1, w_2, w_3) \leftarrow \text{ComputeWeights}(d)$

▷ Constraint: $w_1 + w_2 + w_3 = 1$

Phase 3: Composite Cost Calculation

for each candidate parent $p \in \mathcal{P}$ **do**
  $C(p) \leftarrow w_1 \cdot \text{LQ}_p + w_2 \cdot E_p + w_3 \cdot Q_p$
end for

$p_{\text{candidate}} \leftarrow \arg\min_{p \in \mathcal{P}} C(p)$ ▷ Find the neighbor with the lowest cost

Phase 4: Hysteresis-Based Stabilization

▷ Calculate adaptive threshold based on recent instability

$\delta(t) \leftarrow \delta_{\min} + (\delta_{\max} - \delta_{\min}) \cdot \frac{n_{\text{switch}}(t)}{n_{\text{switch,max}}}$

if $p_{\text{candidate}} \neq p_{\text{current}}$ **then**
  if $C(p_{\text{candidate}}) < C(p_{\text{current}}) - \delta(t)$ **then**
    $p_{\text{best}} \leftarrow p_{\text{candidate}}$ ▷ Trigger Parent Switch
  else
    $p_{\text{best}} \leftarrow p_{\text{current}}$ ▷ Maintain current parent to prevent oscillation
  end if
else
  $p_{\text{best}} \leftarrow p_{\text{current}}$
end if
return p_{best}

Depth-Dependent Weight Model. Let h_x represent the hop distance of node x from the root, extracted directly from its current RPL rank, and let $H_{\max}$ be the maximum network depth. The normalized depth factor could be given as (Fig. 6):

$$f(h_x) = \frac{h_x}{H_{\max}} \in [0,\, 1] \tag{5}$$

The weight of each metric $k \in \{1, 2, 3\}$ is then adapted as a linear function of $f(h_x)$:

$$w_k(h_x) = \bar{w}_k + \alpha_k \cdot f(h_x) \tag{6}$$

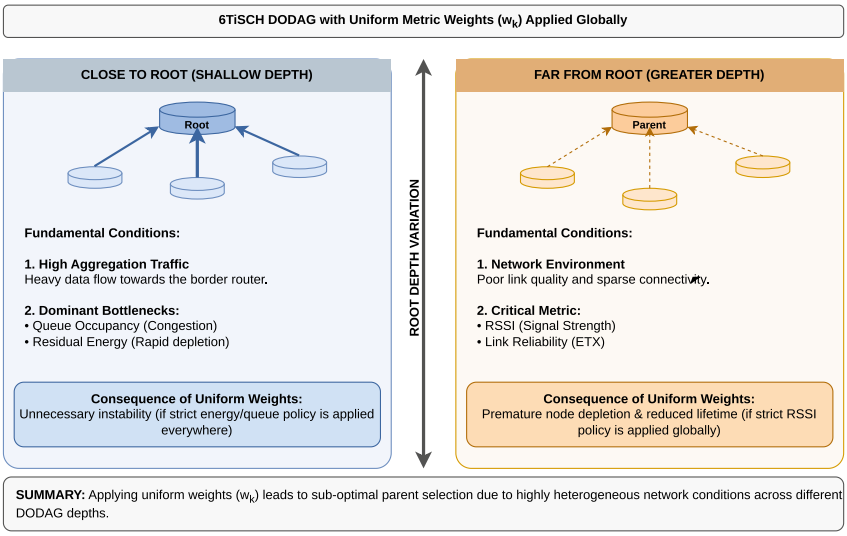


Fig. 6. Drawback of uniform weights

where $\bar{w}_k$ is the baseline weight at the root level and $\alpha_k \in \mathbb{R}$ is a signed adaptation coefficient controlling how the importance of metric k evolves with depth. The weights must satisfy the constraints:

$$\sum_{k=1}^{3} w_k(h_x) = 1, \quad w_k(h_x) \geq 0 \quad \forall\, h_x \in [0, H_{\max}] \tag{7}$$

which impose $\sum_k \bar{w}_k = 1$ and $\sum_k \alpha_k = 0$. The composite link cost is thus rewritten as:

$$C(v_i, p_j, h_{v_i}) = w_1(h_{v_i}) \cdot \widehat{\mathrm{RSSI}}_{ij}^{-1} + w_2(h_{v_i}) \cdot \hat{Q}_j + w_3(h_{v_i}) \cdot \hat{E}_j^{-1} \tag{8}$$

Adaptation Principles. The depth-dependent weight profiles are classified into three design level: **Near the root** ($f \to 0$): higher weights on queue occupancy w_2 and residual energy w_3, since these nodes relay aggregated traffic and their failure might impact the entire network and constitutes. Moreover, **Mid-depth nodes** ($f \approx 0.5$), where balanced weights across all three metrics, reflecting moderate traffic load and generally acceptable link conditions, and finally, **Leaf nodes** ($f \to 1$), where, higher weight on RSSI (w_1), since link reliability is paramount at the network periphery due to connectivity that is sparse and retransmissions are particularly energy-intensive and costly in terms latency.

Table 2 summarizes the recommended weight profiles for each depth zone.

Implementation Overhead. The hop distance h_x is directly available from the node's current rank field in DIO messages. Thanks of this approach, no

Table 2. Hop-Aware Weight Profiles per Depth Zone

Depth Zone		w_1 (RSSI)	w_2 (Queue)	w_3 (Energy)
Near root	$(h_x \leq H_{\max}/3)$	0.20	0.40	0.40
Mid-depth	$(H_{\max}/3 < h_x \leq 2H_{\max}/3)$	0.33	0.33	0.34
Leaf nodes	$(h_x > 2H_{\max}/3)$	0.60	0.20	0.20

additional control signaling is required. Weight adaptation is performed locally upon each rank update. We need only to define a Rank Max $R_{\max}$ to normalize the hop max. $R_{\max}$ is pre-configured at deployment time based on the known network topology, or estimated progressively as nodes observe the maximum rank announced in received DIO messages:

$$H_{\max} \approx \left\lfloor \frac{R_{\max}}{\texttt{MinHopRankIncrease}} \right\rfloor \tag{9}$$

where $R_{\max}$ is the highest rank value observed in the neighborhood. This estimation converges within a few Trickle Timer cycles and requires no modification to the standard RPL message format.

5.3 Hysteresis-Based Stabilization

In RPL based networks, parent switches are very expensive. To reduce parent unnecessarily switch oscillations, the hysteresis threshold δ in Eq. (2) is set adaptively based on recent switch frequency as described below:

$$\delta(t) = \delta_{\min} + (\delta_{\max} - \delta_{\min}) \cdot \frac{n_{\text{switch}}(t)}{n_{\text{switch,max}}} \tag{10}$$

where $n_{\text{switch}}(t)$ is the number of parent switches performed by the node in a recent observation window. This adaptive mechanism increases the switch threshold when frequent switches are detected, thereby penalizing oscillatory behavior and promoting topological stability.

The relevance of Eq. 10 resides in its bounded linear interpolation. Unlike a static threshold that rigidly locks a node to a degrading parent (leading to packet drops), or a zero-threshold which causes severe routing loops and control overhead, this adaptive formulation provides a proportional penalty.

6 Performance Evaluation

6.1 Simulation Setup

Simulation experiments are conducted under Cooja, the network simulator integrated with Contiki-NG [12]. We consider a 6TiSCH network with $N \in \{20, 60, 100\}$ nodes deployed in a maximum $100 \times 100\,\text{m}^2$ industrial environment. The TSCH slotframe consists of 101 timeslots, with a slot duration of 10 ms. Traffic rate used is $R = 2\,\text{pkt/s}$. Table 3 summarizes the simulation parameters.

Table 3. Simulation Parameters

Parameter	Value
Number of nodes	20, 60, 100
Area	$100 \times 100\,\mathrm{m}^2$
Slotframe size	101 slots
Slot duration	10 ms
Traffic model	Poisson
Packet size	127 bytes
Rate	2 pkt/sec
Simulation duration	3600 s
Number of runs	5
w_1, w_2, w_3	(0.2, 0.4, 0.4), (0.33, 0.33, 0.34), (0.6, 0.2, 0.2)
$\delta_{\min}$, $\delta_{\max}$	128, 512

6.2 Evaluation Metrics and Baselines

To evaluate our concepts and approach, the proposed multi-factor OF (AMMOF) is compared against:

- **OF0**: default hop-count-based objective function.
- **MRHOF**: default ETX-based objective function.

6.3 Results and Discussion

Packet Loss Ratio (Reliability). As shown in Fig. 7(a), AMMOF notably maintains the lowest Packet Loss Ratio (PLR) accross different network scenarios, reflecting a high reliability. For example, at 100 nodes, AMMOF achieves a PLR of approximately 1.8% (equivalent to a 98.2% PDR), outperforming the compared standard solutions, MRHOF (3.5%) and OF0 (4.8%). We obtained this result thanks to the consideration of link quality and queue occupancy, which helps the protocol to avoid routing data through congested or unreliable links.

End-To-End Latency. The AMMOF demontrates good performances in terms of latency. Figure 7(b) illustrates that AMMOF obtains lower average end-to-end latency with varying network topologies. For instance, at 60 nodes, the proposed AMMOF achieves a better score in terms of latency compared to standard solutions (approximately 42 ms, compared to 45 ms for MRHOF and 50 ms for OF0). At high density (100 nodes), AMMOF remains competitive when acheiving latency of roughly 66 ms. It incorporates queue occupancy into the composite metric, to make better choice in parent selection and successfully avoids forwarding packets through bottleneck nodes.

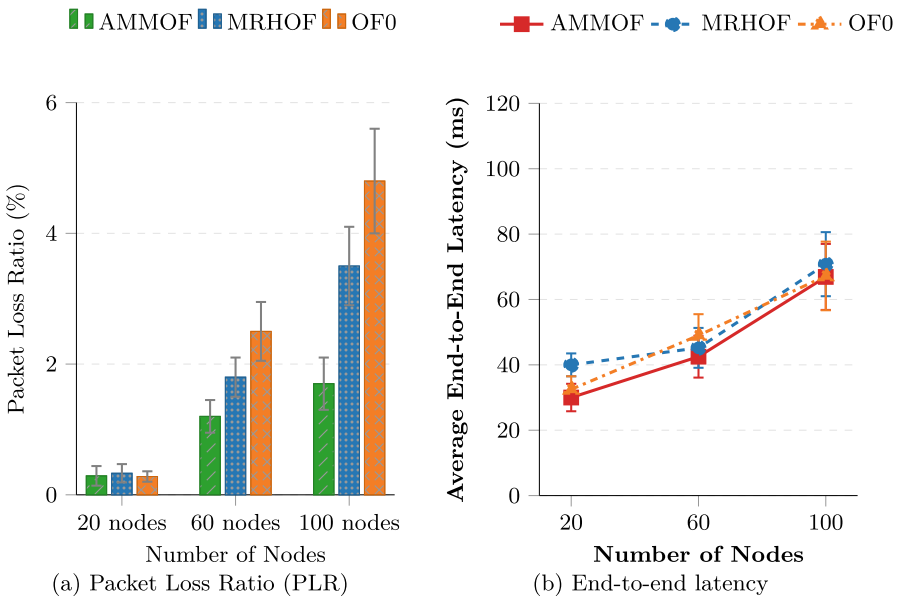
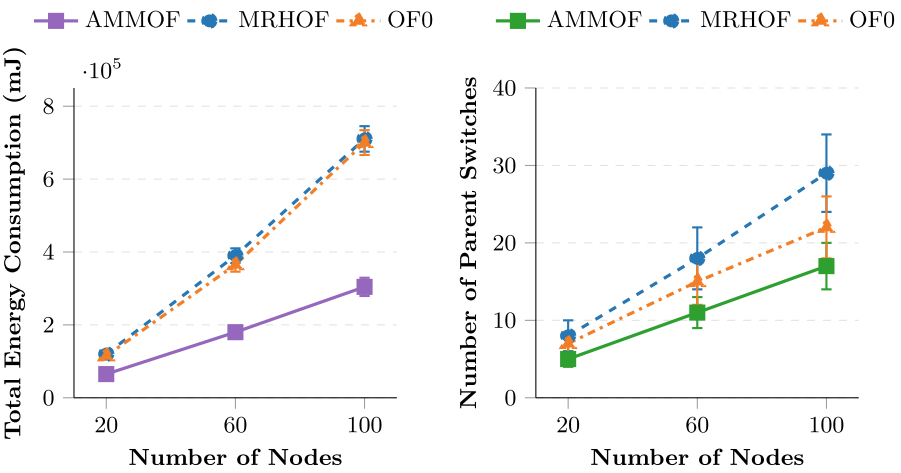


Fig. 7. Performance vs. network size (top row). Error bars represent standard deviation.

Energy Consumption. The adopted mechanisms in AMMOF of avoiding retransmissions and control overhead allow to minimize energy consumption, as shown in Fig. 8(a). At a network size of 100 nodes, AMMOF consumes roughly 3.0×10^5 mJ, whereas both MRHOF and OF0 exceed 7.1×10^5 mJ. This translates to a consistent energy savings than the default approaches. This performance is realized by prioritizing nodes holder of higher residual energy and reducing drastically control overhead. This approach allows thereby extending the overall network lifetime.

Topology Stability. The network is stable when the number of parent switches is reduced. Network stability degree is given by the number of parent switches, as depicted in Fig. 8(b). thanks to the adopted design,AMMOF consistently does not need a lot of parent switches unlike MRHOF and OF0. for instance, at 100 nodes, AMMOF incurs 5 and 12 fewer switches, compared respectively to OF0 and MRHOF. This enhanced stability is made possible with the hysteresis-based stabilization mechanism and the distance-aware weight tuning, which effectively decrease unnecessary topology fluctuation and avoid excessive ping-pong effect.

The results confirm that single-metric OFs are ill-suited for dense IIoT deployments where multiple objectives must be simultaneously satisfied. The proposed AMMOF provides a flexible and lightweight framework tuned to prioritize different application requirements.



(a) Total energy consumption (b) Parent-switch stability

Fig. 8. Performance vs. network size (bottom row). Error bars represent standard deviation.

7 Conclusion and Future Work

In this paper, we have presented a multi-factor Objective Function for RPL parent switch optimization in 6TiSCH IIoT networks. Our Approach consists of combining multiple network parameters as link quality, residual energy and queue occupancy into a unified routing metric, allowing to significantly improve network performances with the topology stability compared to the default standardized objective functions, OF0 and MRHOF.

Even if our proposed solution AMMOF could demonstrate significant enhancements in network performances such as stability, energy efficiency, and packet delivery ratio, the current formulation is based on statically defined or heuristically tuned weight coefficients (w_1, w_2, w_3). In highly dynamic 6TiSCH environments, network conditions such as traffic distribution, link interference, and node activity change continuously and unpredictably.

Determining the optimal weight configuration for all possible network states becomes fundamentally an NP-hard problem. The search space is virtually unlimited because of the continuous nature of the coefficients ($w_k \in [0, 1], \sum w_k = 1$) coupled with the combinatorial explosion of possible DODAG topologies and traffic loads. Thus, a uniform or manually configured weighting policy may be inefficient especially if network conditions are highly volatile or heterogeneous.

To address this computationally intractable problem, our future work will focus on integrating **Reinforcement Learning (RL)** into the AMMOF architecture to achieve dynamic, self-optimizing weight adaptation. We plan to for-

mulate the parent selection and metric weighting process as a Markov Decision Process (MDP).

By opting to an RL solution (such as Q-Learning for discrete weights or Deep Deterministic Policy Gradient (DDPG) for spaces of continuous action), as training progresses, nodes could learn autonomously the optimal routing policies. The RL approach consists of a cognitive and context-aware routing protocol capable of extending the lifetime of network under unpredictable IoT traffic conditions.

References

1. Wollschlaeger, M., Sauter, T., Jasperneite, J.: The future of industrial communication: Automation networks in the era of the internet of things and industry 4.0. IEEE Ind. Electron. Mag. **11**(1), 17–27 (2017)
2. Vilajosana, X., et al.: RFC 9030: An Architecture for IPv6 over the TSCH mode of IEEE 802.15.4 (6TiSCH). IETF (2021)
3. Winter, T., et al.: RFC 6550: RPL: IPv6 Routing Protocol for Low-Power and Lossy Networks. IETF (2012)
4. Thubert, P.: RFC 6552: Objective Function Zero for the Routing Protocol for Low-Power and Lossy Networks (RPL). IETF (2012)
5. Gnawali, O., Levis, P.: RFC 6719: The Minimum Rank with Hysteresis Objective Function (MRHOF). IETF (2012)
6. Gaddour, O., Koubaa, A.: RPL in a nutshell: a survey. Comput. Netw. **56**(14), 3163–3178 (2012)
7. Kamgueu, P.O., Nataf, E., Ndie, T.D., Festor, O.: Energy-based routing metric for RPL. In: Proc. IFIP/IEEE NOMS, pp. 1–4 (2013)
8. Lamaazi, H., Benamar, N.: A comprehensive survey on enhancements and limitations of the RPL protocol. J. Netw. Comput. Appl. **43**, 101–117 (2020)
9. Baddeley, M., et al.: DiSC: Reinforcement learning-based distributed scheduling for 6TiSCH. In: Proc. IEEE DCOSS, pp. 1–8 (2019)
10. Rodrigues, B., et al.: Deep reinforcement learning for scheduling in 6TiSCH networks. In: Proc. IEEE PIMRC, pp. 1–6 (2021)
11. Iova, O., Theoleyre, F., Noël, T.: Exploiting Multiple Parents in RPL to Improve both the Network Lifetime and its Stability. 610-616. https://doi.org/10.1109/ICC.2015.7248389
12. Oikonomou, G., et al.: Contiki-NG: The next generation of the Contiki OS (2022) . https://github.com/contiki-ng/contiki-ng
13. Aydin, B., Aydin, H., Gormus, S.: RL-OF: a reinforcement learning-inspired objective function for IETF 6TiSCH networks. In: IEEE Access **14**, 23598–23623 (2026). https://doi.org/10.1109/ACCESS.2026.3663078.
14. Ibersiene, L., Djamaa, B., Senouci , M.R., Tabouche, A.: Impact of manual parameter tuning on the performance of industrial 6TiSCH networks. In: 2025 7th International Conference on Pattern Analysis and Intelligent Systems (PAIS), Laghouat, Algeria, 2025, pp. 1–6. https://doi.org/10.1109/PAIS66004.2025.11126474(2025)
15. Zirak, M., Sedaghat, Y., Moghaddam, M.H.Y.: RPL-TSCH cross-layer design for improve quality of service in LLNs of IIoT, Ad Hoc Networks, vol. 174 (2025)