International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2025: 7.089

# RPL Objective Functions and Cross-Layer Energy-Efficient Design for the Internet of Things

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**Abstract:** ***The Routing Protocol for Low-Power and Lossy Networks (RPL) is the de-facto standard for constructing routing topologies in resource-constrained Internet of Things (IoT) and wireless sensor network (WSN) deployments. Because RPL's behaviour is largely determined by its Objective Function (OF), a substantial body of research has examined how different metrics- hop count, expected transmission count (ETX), residual energy, bandwidth, congestion and quality-of-service (QoS) indicators- shape path selection, energy consumption and network lifetime. A parallel line of work has argued that single-layer optimisation is insufficient for severely constrained devices and has proposed cross-layer designs that jointly consider the physical, medium access control (MAC), network and application layers. This paper reviews and synthesises eighteen recent studies spanning three related themes: (i) the design and comparative evaluation of RPL objective functions, (ii) cross-layer architectures for energy-efficient routing in IoT and WSNs, and (iii) metaheuristic and machine-learning-based optimisation of energy usage and routing decisions. The review identifies recurring trade-offs between energy efficiency, latency, control overhead and QoS, highlights the growing role of cross-layer and learning-based methods in addressing these trade-offs, and outlines open research directions, including standardised benchmarking, security-aware objective functions and lightweight machine-learning integration for constrained devices.***

**Keywords:** RPL routing, Low power IoT networks, Cross layer routing, Energy efficient routing, Wireless sensor networks

## 1. Introduction

The proliferation of low-power, battery-operated devices in the Internet of Things (IoT) has made energy-efficient and reliable routing a central design concern. In Low-power and Lossy Networks (LLNs)- characterised by unreliable links, limited memory, and constrained processing and energy budgets- the IETF-standardised RPL protocol has become the dominant routing solution, building a Destination-Oriented Directed Acyclic Graph (DODAG) rooted at a sink or border router. A node's position within this topology, and consequently its energy expenditure and the quality of the paths it offers, is governed by the protocol's Objective Function, which ranks candidate parents according to one or more routing metrics.

Because the default objective functions specified for RPL (OF0 and the Minimum Rank with Hysteresis Objective Function, MRHOF) rely on comparatively simple metrics such as hop count and ETX, they do not always yield energy-balanced or QoS-satisfying topologies, particularly for heterogeneous and traffic-diverse IoT applications such as multimedia streaming, industrial monitoring or underwater sensing. This limitation has motivated two complementary research directions. The first proposes new or extended objective functions that incorporate additional metrics- residual energy, bandwidth, congestion level, or link quality- to better match application requirements. The second recognises that routing decisions taken purely at the network layer cannot fully exploit the energy-saving opportunities available at the physical and MAC layers (e.g., duty cycling, transmission power control, or scheduling), and therefore advocates cross-layer designs that share state information across the protocol stack. More recently, metaheuristic optimisation and machine learning have been introduced as tools for tuning these routing and cross-layer decisions adaptively.

This paper reviews eighteen studies that collectively address these three directions. Section 2 introduces RPL and its objective-function mechanism. Section 3 reviews studies that design or evaluate RPL objective functions. Section 4 reviews cross-layer approaches for energy-efficient routing in IoT and WSNs. Section 5 discusses metaheuristic and machine-learning-based optimisation techniques. Section 6 presents a comparative synthesis and discussion, and Section 7 concludes with open issues and future directions.

## 2. Background: RPL and the Role of the Objective Function

RPL organises nodes into one or more DODAGs using control messages- DODAG Information Object (DIO), Destination Advertisement Object (DAO) and DODAG Information Solicitation (DIS)- exchanged according to the Trickle timer algorithm, which adapts control-traffic frequency to network stability so as to conserve energy while retaining responsiveness to topology change. Trickle behaviour itself has been shown to materially affect convergence time and overhead, motivating study of Trickle variants alongside objective-function design (Kumar and Suresh, 2020).

The objective function determines a node's Rank, a scalar approximation of its distance from the DODAG root, and is used to select and maintain preferred parents. Because Rank computation can be based on virtually any combination of link- or node-level metrics, the choice of objective function is the primary lever through which RPL's energy, latency, reliability and QoS behaviour can be tuned, which explains the sustained research interest in this component.

## 3. RPL Objective Functions: Design and Evaluation

A first group of studies focuses on characterising and improving RPL objective functions. Yassien et al. (2019) performed a comparative performance analysis of established RPL objective functions, evaluating their effect on network behaviour under varying topologies and traffic patterns and providing baseline evidence of the trade-offs between hop-count-based and ETX-based path selection. Building on this, Solapure and Kenchannavar (2020) designed and analysed RPL objective functions using a range of routing metrics tailored to IoT applications, demonstrating that metric selection should be application-aware rather than fixed, since no single metric performs best across heterogeneous deployment scenarios. Complementing these network-layer studies, Kumar and Suresh (2020) assessed how variants of the Trickle algorithm influence overall RPL performance, underscoring that control-plane timer behaviour and objective-function design are interdependent contributors to network efficiency.

Several works propose objective functions targeted at specific QoS requirements. Aissa et al. (2019) introduced QCOF, an RPL extension that incorporates congestion awareness alongside QoS metrics, aiming to reduce packet loss and delay in congested LLNs. Bouzebiba and Lehsaini (2020) proposed FreeBW-RPL, an objective function designed for the Internet of Multimedia Things, which selects parents on the basis of available bandwidth to better support bandwidth-sensitive traffic such as audio or video streams.

Arat and Demirci (2021) conducted an experimental analysis comparing energy-efficient and QoS-aware objective functions, concluding that a trade-off generally exists between minimising energy consumption and maximising QoS, and that the relative importance of each depends on the target application domain.

A further set of studies extends the objective-function concept toward cross-layer and intelligent designs. Safaei, Monazzah and Ejlali (2020) proposed ELITE, an elaborated cross-layer RPL objective function that combines residual energy and link-quality information drawn from lower layers to achieve more energy-efficient parent selection than purely network-layer metrics allow. Santos et al. (2023) presented ML-RPL, a machine-learning-based routing protocol built on RPL foundations, illustrating a shift toward learning-based path selection rather than static metric formulas.

Related to network robustness, Al-Amiedy et al. (2022) conducted a systematic literature review of machine- and deep-learning approaches for detecting attacks in RPL-based 6LoWPAN networks, indicating that objective-function and topology-related vulnerabilities remain an active security concern alongside performance optimisation.

## 4. Cross-Layer Design for Energy-Efficient Routing

A second body of work argues that energy efficiency in constrained networks cannot be achieved by network-layer optimisation alone and instead proposes architectures that share information across the physical, MAC, network and, in some cases, application layers. Zhou et al. (2020) developed a cross-layer scheme for underwater wireless sensor networks that jointly considers physical-layer transmission characteristics and network-layer routing to maximise overall network lifetime, addressing the particularly severe energy and propagation constraints of the underwater domain. Callebaut, Ottoy and van der Perre (2019) proposed a cross-layer framework and optimisation methodology for making efficient use of the limited energy budget available to IoT nodes, coordinating decisions across layers rather than optimising each in isolation.

Focused specifically on industrial wireless sensor network (IWSN)-based IoT applications, Singh, Joshi and Raghuvanshi (2022) proposed a duty-cycle-based cross-layer routing model that couples MAC-layer duty cycling with network-layer route selection to reduce energy consumption while preserving acceptable latency. Earlier, Abdessalem and Tabbane (2014) proposed RPL-SCSP, a network–MAC cross-layer design for wireless sensor networks that integrates scheduling considerations from the MAC layer into RPL's routing decisions, illustrating that cross-layer coupling with RPL has been explored since relatively early in the protocol's adoption. Parween, Hussain and Hussain (2021) provided a broader survey of the issues and possible solutions associated with cross-layer design in the Internet of Things, cataloguing the architectural challenges- such as increased design complexity, reduced modularity and interoperability concerns — that accompany the energy and performance benefits of cross-layer approaches.

Connectivity-oriented cross-layer considerations also appear in Laguidi, Tamtam and Mejdoub (2023), who examined a technique for improving IoT connectivity based on Narrowband-IoT (NB-IoT) and device-to-device (D2D) communication, reflecting how choices at the radio-access and communication-technology level interact with the routing and energy-management strategies discussed elsewhere in this review.

## 5. Metaheuristic and Optimisation-Based Energy Management

A third strand of the literature applies metaheuristic optimisation to energy management in IoT and WSN deployments, often independent of, but complementary to, RPL-specific mechanisms. Rekha and Garg (2023) proposed a metaheuristic approach for improving energy efficiency in energy-harvesting-enabled IoT networks, targeting scenarios where nodes can replenish energy from ambient sources and therefore require optimisation strategies that account for both harvesting and consumption dynamics. Sathish Kumar et al. (2022) presented a modern energy-optimisation approach aimed at efficient data communication in IoT-based wireless sensor networks, addressing energy balancing across the


Paper ID: SR26806123655 DOI: https://dx.doi.org/10.21275/SR26806123655

network to extend operational lifetime. Iwendi et al. (2020) proposed a metaheuristic optimisation approach for improving energy efficiency across IoT networks more generally, contributing to a growing consensus that heuristic and bio-inspired optimisation methods can complement protocol-level mechanisms such as RPL objective functions when the underlying optimisation problem is non-convex or the search space is large.

Taken together, these optimisation-oriented studies suggest that energy-efficiency gains can be pursued at multiple levels: through protocol-native mechanisms (objective functions and cross-layer coupling), and through higher-level algorithmic optimisation layered on top of, or alongside, the routing protocol itself.

## 6. Comparative Synthesis and Discussion

Table 1 summarises the reviewed studies according to the network layer(s) they address, the metric(s) they primarily optimise, and their principal contribution. Several patterns emerge from this synthesis.

First, there is a clear progression from single-metric objective functions (hop count, ETX) toward multi-metric and application-aware designs that incorporate energy, bandwidth, congestion or QoS indicators, reflecting the diversification of IoT application requirements from simple monitoring to multimedia and industrial use cases. Second, cross-layer designs consistently report energy or lifetime improvements over purely network-layer approaches, but this comes at the cost of increased architectural complexity, tighter coupling between layers, and, in several studies, greater implementation and standardisation difficulty- a tension explicitly discussed by Parween, Hussain and Hussain (2021). Third, the emergence of machine-learning-based approaches such as ML-RPL (Santos et al., 2023) and metaheuristic optimisation techniques (Rekha and Garg, 2023; Sathish Kumar et al., 2022; Iwendi et al., 2020) signals a shift away from static, hand-tuned metric formulas toward adaptive schemes capable of responding to dynamic network conditions, albeit typically at higher computational cost, which is a concern for the most resource-constrained devices.

A recurring trade-off across nearly all reviewed studies is between energy efficiency and other performance dimensions- latency, control overhead, reliability, and QoS. No single objective function or cross-layer scheme dominates across all these dimensions simultaneously; instead, the appropriate design choice depends on application priorities, for example bandwidth-sensitive multimedia traffic favouring FreeBW-RPL-style bandwidth awareness (Bouzebiba and Lehsaini, 2020), congestion-prone deployments favouring QCOF-style congestion awareness (Aissa et al., 2019), and severely energy-constrained deployments favouring cross-layer, energy-aware designs such as ELITE (Safaei et al., 2020) or duty-cycle-integrated routing (Singh et al., 2022).

## 7. Open Issues and Future Directions

Several open issues emerge from this review. Standardised, reproducible benchmarking remains limited: reviewed studies employ different simulators, topologies and traffic models, which complicates direct comparison of reported energy and QoS gains. Security-aware objective-function design is comparatively underexplored relative to performance-oriented design, despite Al-Amiedy et al. (2022) documenting a substantial and growing body of attacks targeting RPL topologies. The integration of lightweight machine learning directly into resource-constrained nodes, rather than at a more capable border router or edge gateway, remains an open engineering challenge given the memory and energy budgets typical of LLN devices. Finally, closer integration between emerging connectivity technologies such as NB-IoT and D2D communication (Laguidi et al., 2023) and RPL-based routing and cross-layer energy management represents a promising but still nascent research direction.

## 8. Conclusion

This review has synthesised eighteen studies addressing RPL objective-function design, cross-layer energy-efficient architectures, and metaheuristic or learning-based optimisation for IoT and WSN routing. The literature demonstrates steady progress from simple, single-metric objective functions toward multi-metric, application-aware, and increasingly cross-layer or learning-based designs that better balance energy efficiency against latency, reliability and QoS. At the same time, the field lacks standardised evaluation methodology, and security and lightweight machine-learning integration remain comparatively underdeveloped. Addressing these gaps offers a clear path for future research aimed at making RPL-based routing both more energy-efficient and more robust for real-world, resource-constrained IoT deployments.

**Table 1:** Comparative summary of reviewed studies.

| Study / Approach | Layer(s) Addressed | Primary Metric(s) Optimised | Key Contribution |
|---|---|---|---|
| Yassien et al. (2019) | Network (RPL) | Hop count, ETX | Comparative performance analysis of standard RPL objective functions |
| Solapure & Kenchannavar (2020) | Network (RPL) | Multiple routing metrics | Design and evaluation of RPL OFs using varied routing metrics for IoT scenarios |
| Kumar & Suresh (2020) | Network (RPL/Trickle) | Control-message overhead, latency | Assessment of Trickle algorithm variants on RPL performance |
| Aissa et al. (2019) – QCOF | Network (RPL) | QoS, congestion | Congestion- and QoS-aware RPL extension |
| Bouzebiba & Lehsaini (2020) – FreeBW-RPL | Network (RPL) | Available bandwidth | Bandwidth-aware objective function for multimedia IoT traffic |
| Arat & Demirci (2021) | Network (RPL) | Energy, QoS | Experimental comparison of energy-efficient and QoS-aware OFs |


Paper ID: SR26806123655 DOI: https://dx.doi.org/10.21275/SR26806123655

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|---|---|---|---|
| Safaei et al. (2020) – ELITE | PHY/MAC + Network | Residual energy, link quality | Cross-layer RPL objective function for energy efficiency |
| Zhou et al. (2020) | PHY/MAC + Network (UWSN) | Network lifetime | Cross-layer scheme maximising lifetime in underwater sensor networks |
| Callebaut et al. (2019) | PHY/MAC + Application | Energy budget | Cross-layer optimisation framework for constrained IoT nodes |
| Singh et al. (2022) | MAC (duty cycle) + Network | Energy consumption | Duty-cycle-based cross-layer routing model for IWSN-based IoT |
| Abdessalem & Tabbane (2014) – RPL-SCSP | MAC + Network | Scheduling, delay | Network–MAC cross-layer design for WSNs |
| Rekha & Garg (2023) | Network/Application | Harvested energy utilisation | Meta-heuristic optimisation for energy-harvesting IoT nodes |
| Sathish Kumar et al. (2022) | Network | Energy consumption, throughput | Optimisation approach for efficient data communication in WSN-IoT |
| Iwendi et al. (2020) | Network | Energy efficiency | Metaheuristic optimisation approach for IoT network energy savings |
| Santos et al. (2023) – ML-RPL | Network (RPL) | Path selection accuracy | Machine-learning-based routing protocol built on RPL |

## References

[1] Abdessalem, R. B., & Tabbane, N. (2014). RPL-SCSP: a Network-MAC Cross-Layer design for wireless sensor networks. In Lecture Notes in Electrical Engineering (pp. 27–35). https://doi.org/10.1007/978-81-322-1823-4_3

[2] Aissa, Y.B., Grichi, H., Khalgui, M., Koubâa, A. and Bachir, A. (2019). QCOF: New RPL Extension for QoS and Congestion-Aware in Low Power and Lossy Network. [online] www.cister.isep.ipp.pt.

[3] Al-Amiedy, T. A., Anbar, M., Belaton, B., Kabla, A. H. H., Hasbullah, I. H., & Alashhab, Z. R. (2022). A Systematic Literature Review on Machine and Deep Learning Approaches for Detecting Attacks in RPL-Based 6LOWPAN of Internet of Things. Sensors, 22(9), 3400. https://doi.org/10.3390/s22093400

[4] Arat, F. and Demirci, S. (2021). Experimental Analysis of Energy Efficient and QoS Aware Objective Functions for RPL Algorithm in IoT Networks. Sakarya University Journal of Computer and Information Sciences, 4(2), pp.192–203.

[5] Bouzebiba, H., Lehsaini, M. (2020). FreeBW-RPL: A New RPL Protocol Objective Function for Internet of Multimedia Things. Wireless Personal Communications, 112, 1003–1023. https://doi.org/10.1007/s11277-020-07088-6

[6] Callebaut, G., Ottoy, G. and van der Perre, L. (2019). Cross-Layer Framework and Optimization for Efficient Use of the Energy Budget of IoT Nodes. 2019 IEEE Wireless Communications and Networking Conference (WCNC), Marrakesh, Morocco, pp. 1–6. doi: 10.1109/WCNC.2019.8885739

[7] Iwendi, C., Maddikunta, P.K.R., Gadekallu, T.R., Lakshmanna, K., Bashir, A.K. and Piran, M.J. (2020). A metaheuristic optimization approach for energy efficiency in the IoT networks. Software: Practice and Experience.

[8] Kumar, J.N.V.R.S. and Suresh, D.D. (2020). Assessment of RPL Performance with Trickle Algorithm Variants. International Journal of Advanced Science and Technology, 29(3), pp.5785–5790. Available at: http://sersc.org/journals/index.php/IJAST/article/view/6462

[9] Laguidi, A., Tamtam, S., & Mejdoub, Y. (2023). A technique to improve IoT connectivity based on NB-IoT and D2D communications. ITM Web of Conferences, 52, 01010. https://doi.org/10.1051/itmconf/20235201010

[10] Parween, S., Hussain, S.Z., & Hussain, M.A. (2021). A Survey on Issues and Possible Solutions of Cross-Layer Design in Internet of Things. International Journal of Computer Networks and Applications (IJCNA).

[11] Rekha and Garg, R. (2023). Improved energy efficiency using meta-heuristic approach for energy harvesting enabled IoT network. Kuwait Journal of Science, 50(2A), pp.1–18.

[12] Safaei, B., Monazzah, A.M.H., and Ejlali, A. (2020). ELITE: An Elaborated Cross-Layer RPL Objective Function to Achieve Energy Efficiency in Internet of Things Devices. IEEE.

[13] Santos, C. L. D., Mezher, A. M., León, J. P. A., Cárdenas-Barrera, J., Guerra, E. C., & Meng, J. (2023). ML-RPL: Machine Learning-Based Routing Protocol for Wireless Networks.

[14] Sathish Kumar, L., Ahmad, S., Routray, S., Prabu, A. V., Alharbi, A., Alouffi, B., and Rajasoundaran, S. (2022). Modern Energy Optimization Approach for Efficient Data Communication in IoT-Based Wireless Sensor Networks. Wireless Communications and Mobile Computing, 2022.

[15] Singh, G., Joshi, P., Raghuvanshi, A. S. (2022). A Novel Duty Cycle Based Cross Layer Model for Energy Efficient Routing in IWSN Based IoT Application. KSII Transactions on Internet and Information Systems, 16(6), pp. 1849–1876. DOI: 10.3837/tiis.2022.06.005

[16] Solapure, S.S. and Kenchannavar, H.H. (2020). Design and analysis of RPL objective functions using variant routing metrics for IoT applications. Wireless Networks, 26(6), pp.4637–4656.

[17] Yassien, M.B., Alzoubi, O., Shatnawi, M. and Rawashdeh, A.A. (2019). Performance analysis of RPL objective functions. Proceedings of the Second International Conference on Data Science, E-Learning and Information Systems (DATA '19).

[18] Zhou, Y., Yang, H., Hu, Y.-H. and Kung, S.-Y. (2020). Cross-Layer Network Lifetime Maximization in Underwater Wireless Sensor Networks. IEEE Systems Journal, 14(1), pp. 220–231. doi: 10.1109/JSYST.2019.2920681