Optimizing Relay Placement and Multi-Hop Routing for Smart Meter Networks

Jocelyne Elias*, Fabio Martignon†, Andrea Pimpinella†
* Department of Computer Science and Engineering, University of Bologna, Italy
† Department of Management, Information and Production Engineering, University of Bergamo, Italy

***Abstract*—Smart meter networks play a crucial role in modern utility management, supporting efficient and reliable data transmission for monitoring energy, water, and gas consumption across urban and rural areas. However, ensuring reliable communication poses challenges related to signal quality, coverage, and load balancing. This paper introduces QLiCk, a novel max-min optimization model that enhances network resilience and scalability by optimizing relay placement and supporting multi-hop routing. By maximizing minimum link quality and minimizing installation costs, the model provides reliable communication while ensuring fairness in load distribution, a key aspect for achieving energy consumption efficiency. Using real-world data from 35,000 meters and 100 concentrators, numerical results show QLiCk's ability to improve network performance, offering practical solutions for scalable, cost-effective and energy-efficient smart meter networks.**

***Index Terms*—Smart Meter Network Optimization, Relay Placement and Routing, Load balancing and Fairness, Link Quality Maximization.**

I. Introduction

The deployment of smart meters has revolutionized utilities management enabling real-time data transmission for efficient monitoring, dynamic billing and anomaly detection [1]. However, they require robust communication networks capable of operating reliably across varied terrains and environmental conditions. Challenges include ensuring signal quality and stability in both urban and rural areas [2], while overcoming obstacles like vegetation, buildings, and weather, particularly for meters deployed in underground or hard-to-reach locations [3]. These factors complicate the creation and maintenance of resilient and reliable smart meter networks.

A widely adopted solution for smart meter deployments is the wireless M-Bus (wM-Bus) protocol, which governs communication at the physical and data link layers. The latest version (EN 13757-4:2019) defines various modes of operation with differing carrier frequencies (434 MHz, 868 MHz, or 169 MHz), data rates, duty cycles, encryption options, and communication types. Many European countries, including Italy and France, favor the narrow-band mode N at 169 MHz, which offers reduced noise, extended range (up to 1 km in urban areas), and improved signal sensitivity (-115 dBm), albeit at lower data rates. In typical deployments, smart meters broadcast data that can be received by multiple concentrators, which forward the data to a central data management center via either wired (i.e., fiber optics) or wireless (e.g., LTE, 5G, LoraWAN) backhaul technologies [4].

While incremental deployment strategies dominate, they make it challenging to optimize meter and concentrator placements. To address connectivity gaps in a cost-effective and energy-efficient way, relay nodes are increasingly utilized to extend coverage to remote areas, enhance network reliability, and balance load among concentrators. Determining the optimal number and placement of these relays, however, involves trade-offs between cost and performance.

This paper makes the following contributions:

- We present QLiCk (Quality Links with Cost-efficient relays), a novel max-min optimization framework that explicitly integrates relay placement and routing into the network design process. The model identifies the optimal number and location of relays, performs traffic routing and smart meter assignment to concentrators, maximizing network coverage, reliability and minimum link quality.
- By introducing fairness concerns explicitly, the model ensures equitable load distribution among concentrators, improving resource utilization while mitigating bottlenecks and enhancing network stability.
- We integrate a pathloss-based model to estimate link quality based on physical distances and environmental conditions. This ensures that the optimization process reflects real-world propagation characteristics and accounts for the variability in signal strength.
- We provide a thorough performance evaluation on real network topologies, generated using a dataset measured at the access of a currently operative smart meters network, consisting of $35,000$ meters and 100 concentrators.

This paper is structured as follows: Section II reviews related work, focusing on approaches to planning and optimizing smart meter networks. Section III introduces the mathematical formulation of the optimization model that addresses both relay placement and traffic routing, ensuring high link quality, load balancing and fairness. Section IV describes the generation of realistic network topologies using real-world data, topology sampling and link quality estimation. Section V provides numerical results and analysis. Finally, Section VI concludes this work and outlines direction for future research.

II. Related Work

Wireless communication systems have been extensively studied to improve the efficiency and reliability of smart grid and smart meter networks. Research has addressed key challenges in deployment, data aggregation, and network optimization [5], [6], [7], often leveraging data-driven and machine learning techniques [8], [9], [10].

Wireless Sensor Networks offer a practical solution for smart grid communication, particularly in buildings. For example, [5] used integer programming to optimize relay placement for electricity metering and environmental monitoring, validating the method through simulations. Similarly, effective Neighborhood Area Network deployment is crucial for smart metering. Research in [7] introduced a network partitioning framework to minimize distances between Data

Aggregation Points (DAPs) and smart meters. Additionally, [9] demonstrated the effectiveness of machine learning-based clustering for optimal DAP placement in urban and rural environments.

Providing smart meters with multi-hop transmission capabilities is another key area of research. In [6], a heuristic optimization method integrates clustering and routing to minimize installation and delay costs, enabling meters to act as both data sources and relay nodes. An advanced approach is presented in [10], where a deep neural network selects relays based on real-time channel-state information, achieving higher throughput with reduced computational complexity.

Regarding wM-Bus protocol-based networks, challenges like backhauling congestion and computational overload at concentrators have been addressed. For instance, [8] introduces a data-driven framework to balance concentrator loads using forwarding whitelists, reducing backhauling traffic by 80% while maintaining high network quality. However, most works, including [11], focus on isolated aspects such as load balancing. In contrast, our research integrates relay placement and routing into a unified optimization model to enhance scalability, efficiency, and reliability, and is easily extendable to multi-access environments (e.g., where nodes utilize multiple transmission technologies with distinct pathloss curves and power levels).

III. Mathematical Model

In this section we present QLiCk, a mathematical model for planning a smart meter network to optimize relay node placement (considering installation costs) and determine routing paths between smart meters, relays, and concentrators. This model addresses both planning (relay installation) and operations (traffic routing).

Each smart meter generates packets that must reach a concentrator. A key feature of our model is that any concentrator can serve any smart meter, subject to load balancing constraints limiting the number of smart meters per concentrator. This flexibility distinguishes our approach from traditional multi-commodity flow models, which typically assume fixed source-destination pairs.

Routing can be either *single-hop*, a direct connection between the smart meter and a concentrator, or *multi-hop*, involving intermediate relays before reaching the concentrator.

Problem setup

Sets and parameters: Let M be the set of smart meters, C the set of concentrators, P the set of candidate sites for relay installation; $N = P \cup C$, a combined set of relay sites and concentrators (for model simplification). Each candidate relay site $p \in P$ has an installation cost c_p^I. To ensure load balancing, each concentrator can serve a maximum of N_{max} smart meters.

The following **decision variables** are defined:

- **Relay Installation**: z_p (binary) indicates whether a relay is installed at site $p \in P$.
- **Traffic Routing**:
  - y_{jn}^m (binary), indicates whether traffic from smart meter m is routed over the link between relay nodes or relay-concentrator $(j, n), j \in P, n \in N$. Traffic routing is contingent on the installation of relays, i.e. z_j, $z_l = 1$.
  - $x_{m,n}$ (binary) indicates whether smart meter m is connected to node $n \in N$.
  - $w_{m,c}$ (binary) indicates direct connectivity between smart meter m and concentrator $c \in C$. This variable, defined for ease of implementation, complements $x_{m,n}$, ensuring that traffic is either routed via a relay (multi-hop) or directly sent to a concentrator (single-hop). The two variables coincide when $n \in C$.
- **Link quality**: L_b (continuous in $[0, 1]$), represents the minimum link quality across the entire network.

The following **parameters** capture network constraints and link capabilities:

- $q_{i,j}$ (in $[0, 1]$) indicates the link quality between node i and j, where $(i, j) \in M \cup N$ (see Section IV for details on its setting).
- $a_{m,p}$ (binary) indicates whether relay p is within the coverage range of smart meter m.
- $b_{j,l}$ (binary) indicates whether relays j and l are within each other's coverage range.
- $e_{m,c}$ indicates whether smart meter m is within the coverage range of concentrator c.
- $h_{p,c}$ indicates whether relay p is within the coverage range of concentrator c.
- N_{max}: maximum number of smart meters a concentrator can serve, enabling load balancing and fair traffic distribution, as we will show in Section V.

A. Problem formulation

The optimization problem, hereafter referred to as QLiCk (Quality Links with Cost-efficient relays), aims to maximize the minimum quality experienced across all links while accounting for the installation costs of relays. The objective function is given by:

$$\max(L_b - \beta \sum_{p \in P} c_p^I \cdot z_p) \tag{1}$$

where L_b is the minimum link quality to be maximized, β is a weight balancing link quality and installation cost, and c_p^I is the installation cost of relay p.

The model is subject to the following **constraints**:

1. Connectivity constraint: each smart meter $m \in M$ must connect to exactly one node (a concentrator or a relay):

$$s.t. \sum_{n \in N} x_{m,n} = 1 \qquad \forall m \in M. \tag{2}$$

2. Flow balance for traffic originating from smart meters: at any relay j, the incoming and outgoing traffic balance is maintained:

$$x_{m,j} = \sum_{l \in P} y_{jl}^m - \sum_{l \in P} y_{lj}^m + \sum_{l \in P, c \in C} y_{lc}^m \qquad \forall j \in P, m \in M. \tag{3}$$

3. Flow balance for smart meters: when a smart meter m transmits directly to a concentrator c ($w_{m,c} = 1$), traffic bypasses relays:

$$\sum_{c \in C} w_{m,c} + \sum_{l \in P, c \in C} y_{lc}^m = 1 \qquad \forall m \in M. \tag{4}$$

When smart meter m transmits its measured data directly to concentrator c, $w_{m,c} = 1$, then in this case the traffic will not be forwarded through relays and hence variables y^m_{lc} are all null and $\sum_{l \in P, c \in C} y^m_{lc}$ is equal to zero.

4. Coverage constraints:

- Between smart meters and relays:

$$x_{m,p} \leq z_p \cdot a_{mp} \qquad \forall m \in M, p \in P \tag{5}$$

- Between any two relays:

$$y^m_{j,l} \leq b_{j,l} \cdot z_j \qquad \forall j, l \in P, m \in M \tag{6}$$

$$y^m_{j,l} \leq b_{j,l} \cdot z_l \qquad \forall j, l \in P, m \in M \tag{7}$$

- Between smart meters and concentrators:

$$w_{m,c} \leq e_{m,c} \qquad \forall m \in M, c \in C \tag{8}$$

- Between relays and concentrators:

$$y_{j,c} \leq h_{j,c} \cdot z_l \qquad \forall j \in P, c \in C. \tag{9}$$

5. Load balancing constraint: each concentrator can support a maximum of N_{max} smart meters (this helps introducing fairness concerns and load balancing among concentrators, which will be quantified in the numerical analysis)

$$\sum_{m \in M, l \in P} y^m_{lc} + \sum_{m \in M} w_{m,c} \leq N_{max} \qquad \forall c \in C. \tag{10}$$

6. Quality constraints: the quality $q_{m,n}$ of a chosen link (over all network links) must exceed the lower bound L_b:

$$q_{m,n} \geq x_{m,n} \cdot L_b, \qquad \forall m \in M, n \in N \tag{11}$$

$$q_{j,n} \geq y^m_{j,n} \cdot L_b, \qquad \forall m \in M, j \in P, n \in N. \tag{12}$$

When a link is chosen by the model to route traffic ($x_{m,n} = 1$ or $y^m_{j,n} = 1$), its quality ($q_{m,n}$ or $q_{j,n}$) should be greater or equal to the lower bound L_b since the model aims at maximizing the minimum quality experienced across all links. These coupled constraints can be linearized as follows:

$$q_{m,n} \geq L_b - (1 - x_{m,n}), \qquad \forall m \in M, n \in N \tag{13}$$

$$q_{j,n} \geq L_b - (1 - y^m_{j,n}), \qquad \forall m \in M, n \in N. \tag{14}$$

B. Example Network

We present in Figure 1 a toy example that illustrates the objectives and the operation of the optimization approach proposed in this paper. A Smart Meter needs (SM) to be connected to a Concentrator (C), and no direct connection is available. In this situation, when no relays are installed in the network (the solution currently adopted by many operators) no packet delivery is possible between SM and C. If on the other hand relays can be deployed in the network, let us consider two possible paths to connect a SM to C: (1) SM → R1 → R2 → C, and (2) SM → R3 → C. Link qualities, as defined hereafter, are reported above each link. If the cost for installing relays is sufficiently low, the optimal path will be the "longer one" (SM → R1 → R2 → C), with a minimum assured link quality of 0.8 and 2 installed relays. If installation cost is a concern, the shortest path would be chosen (SM → R3 → C) with only one relay installed in the network (R3) and a minimum quality over the pat of 0.6. Parameter β in the objective function (1) of our model permits to tune the trade off between minimum quality and relay installation cost. For example, if $\beta = 0.1$ and the installation cost of each relay is 1 monetary unit, the objective function value (1) would be $0.6 - 0.1 = 0.5$ for path SM → R3 → C and $0.8 - 0.1 \cdot 2 = 0.6$ for SM → R1 → R2 → C, which will hence be chosen. If, on the other hand, we give more weight to relay installation costs (e.g., $\beta = 0.5$), then the costs would be $0.6 - 0.5 = 0.1$ for SM → R3 → C and $0.8 - 0.5 \cdot 2 = -0.2$ for SM → R1 → R2 → C, hence only relay R3 would be installed and the shortest path will be chosen.

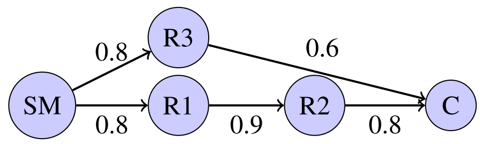

Fig. 1. Example network with two possible paths to connect a Smart Meter (SM) to a Concentrator (C) through Relays (R): (1) SM → R1 → R2 → C, and (2) SM → R3 → C. Link qualities are indicated on edges.

IV. Network Topologies and Instance Generation

We leveraged a real-world dataset collected from a smart meter network in a suburban area of northern Italy to design and evaluate our optimization framework. The dataset spans 14 days and includes approximately 35,000 smart gas meters transmitting data twice daily to 100 concentrators, all operating on the wireless M-Bus protocol in narrowband mode N at 169 MHz. The dataset provides critical metadata such as the geographic locations of meters and concentrators and the average Received Signal Strength (RSS) $r_{m,c}$ for meter-to-concentrator (m, c) links. However, it does not include data on meter-to-meter or relay-to-relay links.

Using this data-driven approach, we generated a diverse set of network topologies. Let $\mathcal{C}$ and $\mathcal{M}$ denote the sets of concentrators and smart meters, respectively. Each topology, referred to as a k-th instance, was generated through the following process:

1) **Select a Root Concentrator**: Randomly select one concentrator $c_k \in \mathcal{C}$.
2) **Spatial Sampling of Concentrators**: select C-1 additional concentrators within a maximum distance R from c_k, forming a set $\mathcal{C}_k$ of C concentrators. The parameter R controls the geographical extent of the instance.
3) **Select Smart Meters**: from $\mathcal{M}$ select M smart meters that successfully transmitted at least 10 frames to at least one concentrator among those selected at step 2.
4) **Assign Candidate Relays**: Randomly designate P of the selected smart meters as candidate relay nodes, forming the set of relays $\mathcal{P}$.
5) **Instance Definition**: Construct the instance with C concentrators, M-P smart meters, and P candidate relay sites.

To characterize the quality $q_{i,j}$ of the generic link (i, j), we utilized RSS measurements from the dataset. For links between meters and concentrators (m, c) or candidate relays and concentrators (p, c) the dataset provides direct RSS values. However, for meter-to-relay (m, p) and relay-to-relay (p_1, p_2) links, no measurements were available.

TABLE I
FAIR SHARE AND ADJUSTED N_{MAX} VALUES FOR DIFFERENT TOPOLOGIES

Topology	M	P	C	M/C	$N_{\max}$ 20%	50%	100%	∞
Small	50	5	5	10	12	15	20	∞
Medium	100	10	10	10	12	15	20	∞
Large-1	300	10	10	30	36	45	60	∞
Large-2	300	17	17	18	22	27	36	∞

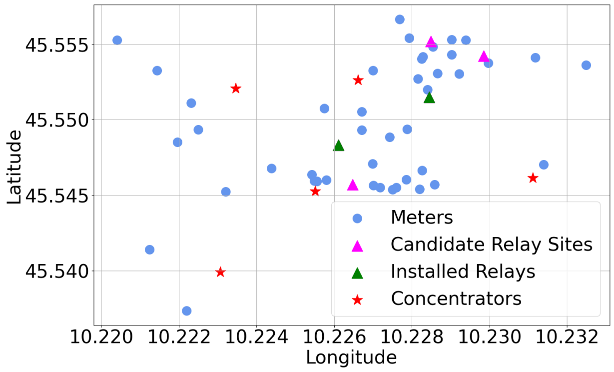

Fig. 2. Example topology in set **S**. Green triangles correspond to relay nodes installed by the optimization model.

We addressed this gap using a regression approach based on the log-distance pathloss model:

$$\hat{r}_{i,j} = q_0 + 10 \cdot \eta \log_{10}\left(\frac{d_{i,j}}{d_0}\right) \tag{15}$$

where $d_{i,j}$ is the distance between nodes i and j; q_0 is the RSS at a reference distance $d_0 = 1m$ and η the pathloss exponent. The parameters q_0 and η were estimated via least squares using RSS measurements for links with at least 10 successful transmissions (reliability $> 40\%$[1]). If fewer transmissions were observed for a link, we assumed the link was blocked and assigned the RSS a power floor value of -120 dBm. This threshold was also applied to predicted RSS values below -120 dBm for other link types. Finally, we set $q_{i,j} = \hat{r}_{i,j}$. We underline that a new model is estimated at each new run of the topology generation process, to better capture the characteristics of the sampled propagation environment.

Topology Configurations

We created 4 sets of 30 topology configurations — Small (**S**), Medium (**M**), Large-1 (**L1**), and Large-2 (**L2**) — designed to represent typical smart city scenarios of varying sizes and complexities. These configurations were defined by parameters such as the number of concentrators (ranging from 5 to 17), meters (from 50 to 300), and relays (from 5 to 17) within radii of 800 m to 1500 m. This diversity allowed for an in-depth assessment of the optimization framework across different deployment conditions. Table I summarizes the values of C, M, and P for the considered topologies, along with the fair share value for each concentrator (M/C) and the N_{max} settings that will be used in the numerical evaluation section.

Figure 2 illustrates an example of a Small (S) topology, while Figure 3 presents the relationship between RSS $r_{i,c}$

[1]Each meter transmits 2 frames per day, corresponding to a maximum of 24 transmissions in 2 weeks of operation.

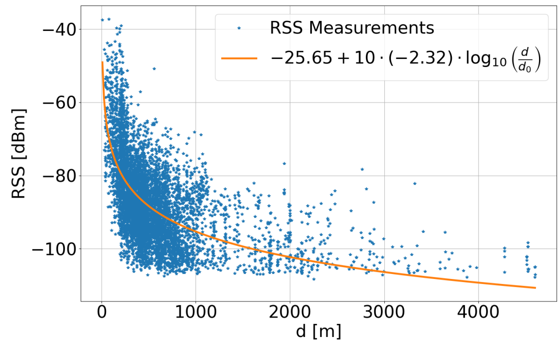

Fig. 3. Scatterplot of distance $d_{i,c}$ between meter or relay i and concentrator c versus true (blue) and estimated (orange) RSS.

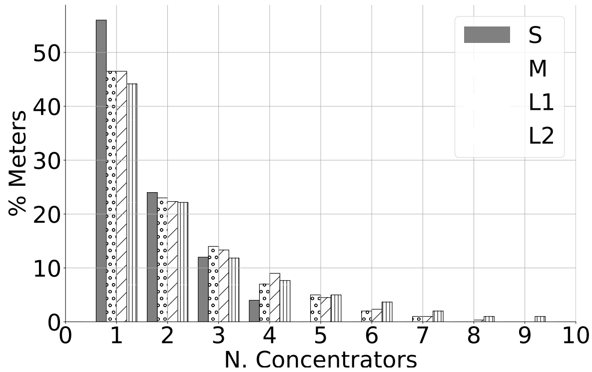

Fig. 4. Distribution of the number of concentrators within a meter's radio coverage area, in the case of No Relay installed.

and distance $d_{i,c}$ for all links involving meters or relays and concentrators. These measurements highlight significant RSS variance at fixed distances due to environmental factors like obstacles. To address this, all RSS values were regenerated using the path-loss model from equation (15), preserving the database's information about blocked meter-to-concentrator links. This approach ensures consistent link quality indicators across different link types.

Figure 4 further details the characteristics of the generated topologies, showing the average number of concentrators within each meter's radio coverage for the S, M, L1, and L2 scenarios. Notably, every smart meter connects to at least one concentrator, irrespective of the topology size. Over 40% of meters connect to a single concentrator, while another 40% establish connections with 2–4 concentrators. These insights provide a foundation for the subsequent analysis of the optimization model's performance.

V. NUMERICAL RESULTS

This section presents the results of the numerical analysis conducted using the proposed optimization model. The model was implemented in OPL and solved with IBM ILOG CPLEX v. 22. For each network topology, we tested the model under various parameter settings: N_{max} was varied as MAximum, while β (the weight balancing link quality and relay installation cost) was set to 1, 0.1, and 0.01. Each scenario consisted of 30 network instances randomly generated from the dataset described earlier.

As a baseline (referred to as *No Relay*), we analyzed scenarios without relay installations, a configuration commonly used by many operators. This approach involves solving model (1)-(14) with $z_p = 0, \forall p \in P$, effectively excluding relays. Comparing this baseline with the optimized model highlights the advantages of integrating relay placement with smart meter assignment and routing. Specifically, we assessed the improvements in terms of: 1) maximizing the percentage of smart meters reliably connected to a concentrator, 2) improving link quality, thereby reducing packet error rates and increasing the number of successfully delivered packets, ultimately enhancing measurement accuracy, and 3) improving fairness ensuring load balancing among concentrators.

A. Impact of Relays on Coverage and Fairness

We first evaluated the percentage of scenarios in which the optimization model achieved full coverage, possibly installing relays and using multi-hop routing. The results were compared to the baseline approach.

QLiCk consistently provided feasible solutions ensuring 100% coverage across all topologies and scenarios. This is noteworthy compared to the baseline approach, which frequently failed to achieve full coverage in demanding scenarios, especially under strict load-balancing constraints (i.e., for low N_{max} values), as reported in Table II. For example, the Table shows that the No Relay approach achieved 0% coverage in some cases (viz., the Large-2 topology with N_{max} = 20). Note that full coverage is mandatory in our considered scenario, since the operator needs to collect data gathered by all smart meters installed at customer's premises. While relaxing load-balancing constraints (i.e., higher N_{max} values) improved baseline performance, this often led to unfair traffic distribution. To quantify fairness, we used Jain's Fairness Index [12], defined as:

$$J(n) = \frac{(\sum_{c \in C} n_c)^2}{|C| \sum_{c \in C} n_c^2}$$

where n_c is the number of smart meters connected to concentrator c, and $|C|$ is the total number of concentrators. The index ranges from $\frac{1}{|C|}$ (least fair, where all smart meters are connected to one concentrator) to 1 (perfect fairness).

Table III summarizes the Jain's index achieved by the QLiCk model for different N_{max} values. All results were obtained setting $\beta = 0.01$, hence minimizing the impact of the installation cost and therefore allowing the model to install the maximum number of relays to increase load balancing.

Results indicate that as N_{max} increases, fewer relays are installed (see also Fig. 5 and the discussion below), leading to decline in fairness, with a smaller number of concentrators handling most connections.

As for the No Relay approach, it obtained lower fairness values, in some cases with a net decrease with respect to the optimal solution computed by QLiCk. For example, for the Large-2 and Medium topologies with $N_{max} = \infty$, No Relay obtained 0.4849 and 0.5651, that is, a significantly less fair solution, with reductions of around 39% and 25%, compared to the values achieved by QLiCk (0.7973 and 0.7577).

B. Number of Installed Relays

The number of relays installed by QLiCk was then analyzed. Figures 5 and 6 illustrate the distribution of installed relays for Medium and Large-2 topologies, respectively. For $\beta = 0.01$ (low installation cost), the model tends to install more relays (up to 4 for $N_{max} = 20\%$ and up to 3 for $N_{max} = 50\%$).

TABLE II
PERCENTAGE OF INSTANCES THAT HAVE A SOLUTION (I.E., FULL COVERAGE OF ALL SMS) FOR THE **NO RELAY** APPROACH, FOR DIFFERENT N_{max} VALUES AND ALL CONSIDERED TOPOLOGIES ($\beta = 0.01$)

N_{max}	**Small**	**Medium**	**Large-1**	**Large-2**
20%	46.67	13.33	16.67	**0**
50%	76.67	56.67	66.67	3.33
100%	96.67	73.33	66.67	80
∞	100	100	100	100

TABLE III
JAIN'S FAIRNESS INDEX OBTAINED BY QLICK FOR DIFFERENT N_{max} VALUES AND ALL CONSIDERED TOPOLOGIES ($\beta = 0.01$)

N_{max}	**Small**	**Medium**	**Large-1**	**Large-2**
20%	0.9871	0.9728	0.9706	0.9591
50%	0.9733	0.8970	0.8996	0.9152
100%	0.9578	0.8362	0.8196	0.8827
∞	0.9365	**0.7577**	0.7734	**0.7973**

Conversely, higher β values ($\beta = 1$) reduce relay installations to 2 and 1, respectively, due to increased cost sensitivity, as shown in the same figures.

Even under relaxed constraints (N_{max} = 100% and ∞), up to 5 relays were installed in challenging scenarios. Across all topologies and scenarios, installing ≤ 5 relays led to full coverage and improved fairness (as discussed before, see Tables II and III), demonstrating the model's efficiency.

C. Link quality (L_b)

Figure 7 presents the average L_b values, representing the minimum link quality across all selected paths. Compared to the baseline, the QLiCk model consistently achieved higher L_b values. For instance, in the Large-1 topology, the model improved L_b in average by 20%, with single-instance gains exceeding 45%. Notably, in scenarios like Large-2 with $N_{max} = 20\%$, the baseline approach failed to provide feasible solutions, while the proposed model ensured full coverage with improved link quality.

D. Computation Time

Table IV reports the average computation times for QLiCk and the baseline approach. The results were obtained on a server equipped with an Intel i9-12900KF and 128 Gbytes of memory. While No Relay required only fractions of a second, solving QLiCk took longer, ranging from under a second for Small topologies to more than 30 minutes for the largest ones.

To reduce computational overhead, a heuristic strategy could involve pre-installing a limited number of relays based on topological analysis or clustering methods, then solving the routing and assignment problems. Given that QLiCk rarely installs many relays (≤ 5 in our evaluation), this approach appears feasible and will be explored in future research.

VI. CONCLUSION

This paper presented QLiCk, a max-min optimization model addressing critical challenges in smart meter networks, including signal quality, coverage, and cost-efficiency. By integrating relay placement, multi-hop routing, and fairness

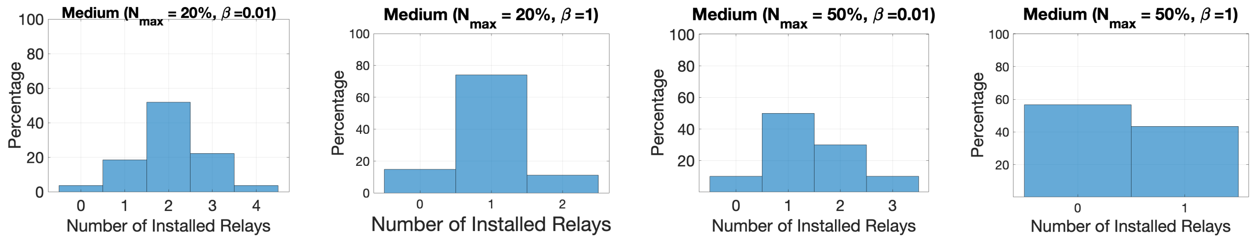

Fig. 5. Distribution of the number of installed relays for the Medium topology with different values of the parameters N_{max} and β.

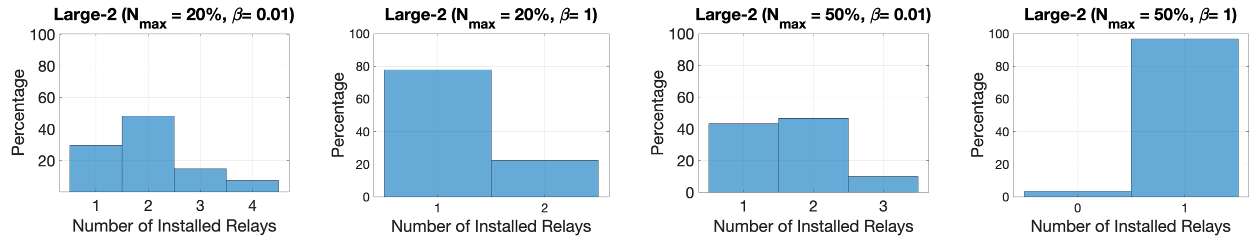

Fig. 6. Distribution of the number of installed relays for the Large-2 topology with different values of the parameters N_{max} and β.

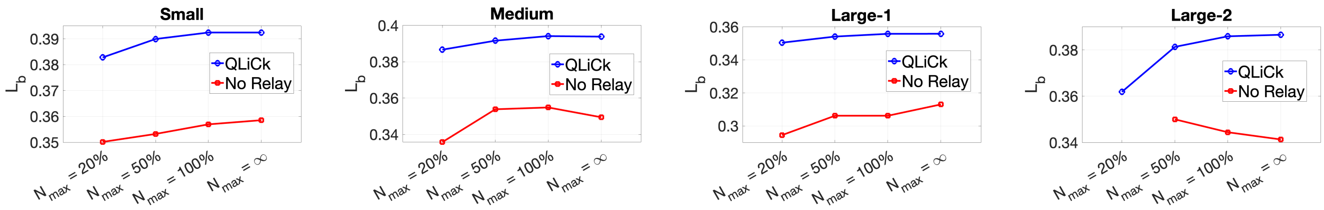

Fig. 7. L_b values for the 4 topologies as a function of N_{max}, for $\beta = 0.01$.

TABLE IV
AVERAGE COMPUTING TIME (SECONDS) FOR ALL CONSIDERED TOPOLOGIES ($\beta = 0.01$)

Model	**Small**	**Medium**	**Large-1**	**Large-2**
QLiCk	0.238	19.12	194.14	1889.97
No Relay	0.0063	0.0322	0.1018	0.2074

in load distribution, the model offers a scalable and practical solution for robust deployments.

Numerical evaluations on real-world data demonstrated QLiCk's ability to enhance network resilience and energy efficiency by maximizing minimum link quality. Even under stringent load-balancing conditions ($N_{max} = 20\%$), it consistently achieved 100% coverage, outperforming the baseline approach that failed in complex topologies like Large-2. The model improved average link quality (L_b) by up to 20%, with gains exceeding 45% in some cases, while maintaining high fairness metrics (Jain's Index > 0.95) and requiring at most 5 relays per instance.

These results highlight the model's potential to improve resource utilization and adapt to modern utility network requirements. Future work could optimize additional objectives, such as reducing latency or incorporating diverse transmission technologies, contributing to the advancement of robust, efficient, and sustainable utility networks.

ACKNOWLEDGMENT

This work is supported by Projects *SERICS* (PE00000014) under the NRRP MUR program, funded by the EU - NGEU, and PRIN *NEWTON* (2022ZA8T22).

REFERENCES

[1] M. Orlando et al., "A Smart Meter Infrastructure for Smart Grid IoT Applications," *IEEE Internet of Things Journal*, vol. 9, no. 14, pp. 12 529–12 541, 2022.

[2] M. Barbiroli, F. Fuschini, G. Tartarini, and G. E. Corazza, "Smart Metering Wireless Networks at 169 MHz," *IEEE Access*, vol. 5, pp. 8357–8368, 2017.

[3] O. BenRhouma, C. Rebai, M. Ben-Romdhane, D. Di Cara, G. Artale, and N. Panzavecchia, "The Environmental Impacts of Radio Frequency and Power Line Communication for Advanced Metering Infrastructures in Smart Grids," *Sensors*, vol. 23, no. 24, p. 9621, 2023.

[4] N. Suhaimy et al., "Current and future communication solutions for smart grids: A review," *IEEE Access*, vol. 10, pp. 43 639–43 668, 2022.

[5] Z. Zhou, X. Zhao, and P. H. J. Chong, "Optimal relay node placement in wireless sensor network for smart buildings metering and control," in *15th IEEE ICCT*, 2013, pp. 456–461.

[6] G. Wang, Y. Zhao, Y. Ying, J. Huang, and R. M. Winter, "Data aggregation point placement problem in neighborhood area networks of smart grid," *Mob. Net. and Applications*, vol. 23, pp. 696–708, 2018.

[7] A. Lang, Y. Wang, C. Feng, E. Stai, and G. Hug, "Data Aggregation Point Placement for Smart Meters in the Smart Grid," *IEEE Trans. on Smart Grid*, vol. 13, no. 1, pp. 541–554, 2022.

[8] A. Pimpinella, A. E. C. Redondi, and M. Cesana, "Load balancing and performance optimization in wM-Bus smart meter networks," in *17th MedHocNet Workshop*, 2018, pp. 1–8.

[9] J. L. Gallardo, M. A. Ahmed, and N. Jara, "Clustering Algorithm-Based Network Planning for Advanced Metering Infrastructure in Smart Grid," *IEEE Access*, vol. 9, pp. 48 992–49 006, 2021.

[10] T.-V. Nguyen et al., "A Deep-Neural-Network-Based Relay Selection Scheme in Wireless-Powered Cognitive IoT Networks," *IEEE Internet of Things Journal*, vol. 8, no. 9, pp. 7423–7436, 2021.

[11] S. Ebneyousef and A. Shirmarz, "A taxonomy of load balancing algorithms and approaches in fog computing: a survey," *Cluster Computing*, vol. 26, no. 5, pp. 3187–3208, 2023.

[12] R. Jain, D. Chiu, and W. Hawe, "A Quantitative Measure Of Fairness And Discrimination For Resource Allocation In Shared Computer Systems," *Digital Equipment Corporation, DEC-TR-301, Tech. Rep.*, 1984.