Computer Communications 234 (2025) 108082

Contents lists available at ScienceDirect

Computer Communications

journal homepage: www.elsevier.com/locate/comcom

Prioritization of smart meters based on data monitoring for enhanced grid resilience

Asma Farooq [a,*], Kamal Shahid [b], Rasmus Løvenstein Olsen [a]

[a] Department of Electronic Systems, Aalborg University, Aalborg, 9220, Denmark

[b] Institute of Electrical, Electronics and Computer Engineering, University of the Punjab, Lahore, 54590, Punjab, Pakistan

ARTICLE INFO

Keywords:
Smart meter
Smart grids
Communication network
Scheduling
Advanced metering infrastructure

ABSTRACT

Smart meters (SM) generate critical data that provides real-time insights into energy consumption, grid performance, and load management, which are essential for improving grid reliability, energy efficiency, and renewable energy integration. However, achieving effective communication between smart meters and the control center remains a challenge due to limitations in Advanced Metering Infrastructure (AMI), including communication delays, metering technology constraints, and restricted data storage and processing capabilities. These limitations hinder the precision and timeliness of real-time data delivery, negatively impacting the efficiency of energy management and grid operations. While existing research predominantly focuses on optimizing communication network algorithms, the critical issue of comprehensive SM data scheduling has received limited attention. Moreover, current methods often fail to account for the complexity of communication networks and the dynamic nature of information flow. To address this gap, this paper introduces a novel method for scheduling SM data access by leveraging real-time data assessment and analysis. A quality metric termed mismatch probability evaluates data quality, and the Hungarian algorithm is employed to optimize meter scheduling. The proposed method is validated using real-world data from a Danish grid, demonstrating significant improvements in information quality for real-time monitoring compared to heuristic-based scheduling approaches.

1. Introduction

Smart Meters (SMs) are digital energy meters that provide real-time data on power usage and improve customer service. They enable data communication between customers and providers, aiding in energy usage tracking and understanding power usage trends. SMs are also utilized in smart grids to help create a balance in power generation and distribution. However, there are several issues that need to be addressed before employing SMs with full strength in future grids. These issues are mostly related to measurements coming from SMs, controlling equipment based on the data or information received, communicating the data sent and received SMs, synchronization, etc. [1].

SMs provide a granular understanding of consumers' electricity consumption patterns by collecting detailed information on energy usage, allowing more accurate billing, and enabling demand-side management. Moreover, the utilization of SM data has initiated a new era of grid management and optimization. It empowers utilities with the potential to monitor the low-voltage grid extensively, detect power quality issues promptly, and respond swiftly to grid disturbances. Novel approaches to manage and improve energy infrastructure have fundamentally changed with the use of SM data to monitor the low-voltage grid.

Monitoring events such as voltage threshold crossings or abrupt load increases, such as the activation of large industrial motors, through SMs is imperative for a resilient grid infrastructure. These events often signify critical events that can have cascading effects on the stability and performance of the electrical grid. Voltage threshold crossings, for instance, might indicate fluctuations that could lead to equipment damage or even power outages if left unaddressed. Similarly, the sudden surge in load, as observed during the start-up of industrial motors, poses challenges to grid stability, potentially causing voltage drops and overloading certain network segments. For instance, studies [2,3] have shown that voltage non-sinusoidality has a negative impact on energy efficiency and equipment performance, highlighting the necessity of thorough monitoring and mitigating techniques.

SMs, with their real-time monitoring capabilities, offer an unparalleled opportunity to detect and proactively respond to these events, allowing for swift interventions and strategic grid management to

* Corresponding author.
E-mail address: asfa@es.aau.dk (A. Farooq).

https://doi.org/10.1016/j.comcom.2025.108082
Received 23 May 2024; Received in revised form 4 December 2024; Accepted 25 January 2025
Available online 4 February 2025

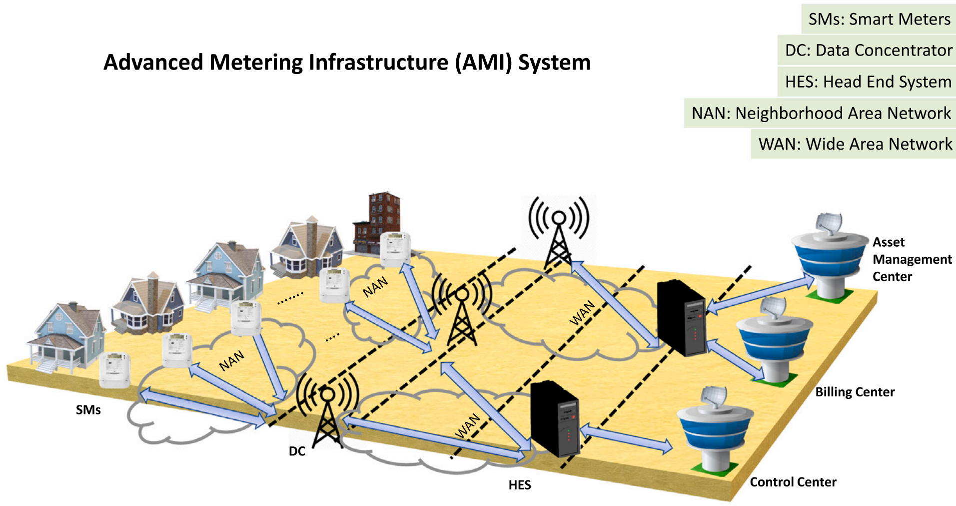

Fig. 1. Advanced metering infrastructure system [10].

enhance overall resilience. The advancement of innovative technology and data analytics has provided unprecedented access to real-time insights into the complex operation of the power grid. The massive amount of SM data offers a comprehensive view of voltage changes, load distribution, and power quality. Consequently, SMs and their meter data management system (MDMS) serve as powerful tools, enabling utilities and stakeholders to identify and address issues rapidly, thereby enhancing the grid's reliability and efficiency [4].

Fig. 1 represents a sophisticated framework of the AMI system, which consists of SM, data concentrators (DC), and head-end systems (HES). SM data is transmitted to DC through either power line communication (PLC) or wireless mesh network (WMN) [5–8]. The communication link between DC and HES depends on the type of DC and the operating mode of the communication system [9].

In AMI, the head-end system communicates with the DC to request data from SM. These DCs are precisely configured to monitor and control communication with a collection of SMs scattered around a specific geographic area. DCs are primarily responsible for the careful collection of data coming from these SMs and for ensuring their smooth transmission to the HES. Since there will be hundreds and thousands of SMs sending data to different DCs at the same time, the DCs must follow a systematic process to obtain SM measurements that are carried out continually within predefined cycles and strictly in line with a specified schedule to ensure that packets in transmission are not colliding with each other. This scheduling system manages the succession of data retrieval tasks according to a predetermined order. In this paper, this order is termed "schedule".

The low bandwidth of the AMI system causes challenges such as infrequent updates and high latency in data transmission from SM to HES and further to Distribution System Operators (DSO). Thus, it affects the quality of data in real-time applications [11]. During the early phases, when SM data was used only for invoicing, access sequence and time were deemed negligible. Nonetheless, temporal features of data access have taken on greater significance in the contemporary landscape due to the integration of time-sensitive applications. Scheduling SM data access can resolve the problems that occurred due to the low bandwidth of AMI [12].

Scheduling techniques maximize bandwidth usage by intelligently planning the transmission of data from SMs [13]. This technique guarantees the effective transmission or retrieval of crucial data while reducing network congestion. An example of a crucial real-time application can be the data based on energy use and grid performance measurements, which is vital for monitoring and responding to grid events and improving grid resilience [14]. Thus, scheduling SM data reduces bandwidth restrictions, ensures equal access to resources, and improves the overall performance and dependability of AMI systems, giving utilities and customers access to accurate data in a timely manner for effective grid operations and energy management.

Moreover, scheduled access is also essential in employing load management methods, as it allows utilities to prioritize data retrieval from SM that may exhibit anomalies or unusual situations, hence boosting the overall efficiency and efficacy of grid operations. To summarize, "orchestrating" access to SM data stands as a pivotal element in exploiting the full potential of smart grid technology and fostering a robust and intelligently structured data management system. Employing strategic and nuanced methods for accessing this data not only amplifies the benefits but also ensures sophisticated and astute management of the information.

Initial approaches to scheduling SM data access relied on brute force methods, which, while exhaustive, proved computationally intensive and impractical for large datasets. Recognizing the need for more efficient solutions, this research leverages the Hungarian algorithm, a well-established method for solving assignment problems optimally. Building upon the work of Farooq et al. [15], which demonstrated the Hungarian algorithm's superior execution speed and scalability compared to brute force and heuristic methods, this study advances the application of this algorithm to address critical challenges in SM data scheduling.

The primary contributions of this research are as follows:

1. A detailed evaluation of existing scheduling strategies for SM data access, highlighting their strengths and limitations.
2. Development of a new method for SM data scheduling based on real-time data assessment and analysis, ensuring timely and reliable data access.
3. Selection of the optimal monitoring time interval to balance the trade-offs between data granularity, network load, and system efficiency.
4. Rigorous evaluation of the proposed scheduling algorithm, demonstrating its effectiveness in handling large-scale datasets, scalability, and alignment with grid resilience objectives.

By addressing these aspects, this research provides a scalable, efficient, and robust solution for optimizing SM data scheduling, paving the way for improved grid operations and energy management in smart grid applications. The remainder of this paper is structured as follows:

The state of the art is given in Section 2. The description of the system used in this paper is presented in Section 3. The proposed SM data access schedule algorithm is presented in Section 4. Results and discussions are given in Sections 5 and 6. This paper is concluded in Section 7.

2. State-of-the-art

Scheduling of SMs has emerged as a significant emphasis area in the world of smart grid technologies and the effective management of low-voltage grids. By strategically planning the data gathering process from these meters, prioritizing SM data aims to maximize the allocation of resources and improve the overall performance of the grid. As a dynamic field, SM scheduling has seen a variety of techniques, each tackling particular aspects of the prioritization challenges.

Several directions for the scheduling of SMs research areas have emerged. Some studies have investigated scheduling methods based on the energy usage patterns of SMs and attempted to balance data collection needs with energy efficiency. Others have dug into the complex communication network channel allocation, coordinating and scheduling SM data transmission alongside other users of the network. With each methodology providing particular insights and solutions, these various strategies represent the complexity of the prioritization challenge. This state-of-the-art section briefly analyzes various scheduling schemes across diverse domains, such as smart grid traffic scheduling, data processing scheduling, energy consumption scheduling, and link scheduling and routing. The main emphasis, however, is on the thorough exploration of information-based data access scheduling approaches.

Z. Malekkhani et al. in [16] present an optimized solution for the scheduling of electric appliances in smart homes equipped with photovoltaic systems and storage batteries. They employ a two-stage stochastic programming model alongside a sample average approximation algorithm to address the unpredictability of power outages. Contrary to this work, which concentrates on appliance scheduling in smart homes, the proposed research targets the scheduling of SM data access to enhance grid resilience. By utilizing real-time data assessment and the Hungarian algorithm, the study addresses broader challenges in optimizing SM data scheduling for improved grid operations and energy management.

T. Pei et al. in [17] introduce a blockchain-based framework for anonymous identity authentication and data aggregation within AMI. The work employs elliptic curve cryptography for lightweight authentication and a reputation-based consensus protocol to secure and optimize communication between smart meters and the control center. While the blockchain-based solution emphasizes secure communication and data aggregation AMI, the proposed research focuses on optimizing SM data scheduling through real-time assessments and the Hungarian algorithm, aiming to improve grid resilience and operational efficiency.

Similarly, T. Fawcett et al. [18] analyze energy consumption patterns of prepayment meter users in Great Britain, exploring self-disconnection rates and the impact of high energy prices. Another work by K. Nweye et al. in [19] presents a method that integrates smart meter data and Wi-Fi-based occupancy profiles to optimize HVAC schedules in commercial buildings. By aligning HVAC operation with occupancy patterns, significant energy savings are achieved. Unlike [19], the proposed research focuses on improving data quality and grid resilience via SM data scheduling.

The study by E. A. Aghdam et al. [20] proposes a day-ahead scheduling model incorporating compressed air energy storage, dynamic line rating, and transformer rating. The approach minimizes load shedding, wind spillage, costs, and emissions using real-time capacity adjustments based on weather parameters. While, the proposed research advances SM data scheduling through real-time data evaluation and optimization, improving information quality and grid resilience.

Paper by A. Shaban et al. [21] develops a mixed-integer quadratic programming model to optimize household appliance schedules under an inclining block rate tariff and net-metering system in Egypt, reducing energy costs while accounting for local consumption patterns. Unlike this study, the proposed research enhances SM data scheduling to strengthen grid operations and improve real-time data management.

The work done by B. Alipour et al. in [22] introduces a model for Smart Energy Hub scheduling that integrates cyber security considerations in AMI. It incorporates renewable generation uncertainties, demand response programs, and Monte Carlo-based detection of false data injection attacks. Similarly, the paper presented by Iyengar et al. [23] introduces a system using smart meter data to infer occupancy patterns and generate optimized thermostat schedules for programmable thermostats. The method leverages time-series analysis and burstiness detection to align HVAC operations with occupancy patterns, improving energy efficiency. Unlike [23], the proposed research optimizes SM data scheduling using real-time evaluations, targeting enhanced grid resilience and operational efficiency.

A new Smart Utilities Traffic Scheduling Algorithm (SUTSA) has been introduced in [24] for smart utility companies in the electric, gas, and water sectors. The algorithm uses narrowband PLC, allowing wired hidden networks to send data across power lines. The model is claimed to be scalable and can achieve full network bandwidth utilization, minimize system complexity, and enable real-time monitoring and problem detection. While SUTSA offers scalability and cost-effectiveness through its narrowband PLC, its reliance on wired connections presents a significant downside. This wired infrastructure requirement limits its applicability, making it unsuitable for scenarios where deploying wires is impractical or cost-prohibitive. Additionally, unlike wireless options, troubleshooting and maintenance on the wired network can be more complex and expensive. For applications where flexibility and wider accessibility are priorities, SUTSA might not be the optimal solution.

Hajimirzaee et al. in [25] proposed a two-stage wireless smart grid traffic scheduling model considering quality of service (QoS) requirements for event-driven and fixed-scheduled traffic. The model maximizes utility for fixed traffic while meeting event-driven traffic delay requirements, effectively distributing bandwidth, and satisfying latency requirements.

Markkula et al. introduced a priority-based traffic scheduling approach for smart grid systems based on cognitive radio communication infrastructure in [26]. It includes various traffic types like control commands, multimedia sensing data, and meter readings. The paper highlights the benefits of wireless multimedia sensor networks and cognitive radio networks and discusses channel allocation and traffic scheduling schemes considering channel switch and spectrum sensing errors.

Khan et al. in [27] suggest a scheduling method that allocates resources to SMs while minimizing the impact on real-time traffic and takes channel quality, traffic prioritization, and the AMI packet delay budget into account. The proposed scheduler produces greater serviced user percentages, according to simulation trials, ensuring peaceful cohabitation between SMs and voice users.

Karupongsir et al. in [12] tackle the issue of ensuring QoS for smart grid data on long-term evolution (LTE) networks. They propose a new scheduling technique that prioritizes SM data by reserving two resource blocks and periodically polling each SM, thereby reducing latency. Carlesso et al. in [13] proposes a traffic scheduling mechanism for meter data collection in wireless smart grid communication networks, focusing on interference avoidance. However, the absence of real-world validation raises concerns about the practical applicability and performance of the proposed traffic scheduling mechanism in actual high-rise deployments. Moreover, the work leaves potential gaps in the scalability and overall applicability of the proposed solutions. This lack of detailed exploration limits its contribution toward addressing the full spectrum of challenges in the MDCBAN (Meter Data Collection Building Area Networks) setup. Authors in [28–33] contribute noteworthy insights to the domain of traffic scheduling in the context of smart grid challenges.

Huang et al. in [34] proposed a scheduling method based on consistent hash and greedy algorithms to optimize the storage, query, and analysis processes of SM data. The Unicage data processing system, based on Unix shell scripting, is proposed in [35] to process SM data in XML format. The authors present a case study where Unicage successfully processed 27 million XML files in under 10 min, exceeding the baseline performance. This demonstrates the potential of Unicage for efficiently handling real-world big data workloads involving SM data.

In order to address the problem of energy efficiency in the smart grid, authors in [36] suggest an energy scheduling method with priority within islanded microgrids (E2SP). The E2SP technique uses the Goal Programming Model with positive and negative deviation factors to determine how much electricity each energy supplier should supply to each consumer. The simulation results demonstrate that the E2SP technique can successfully guarantee that energy is supplied to consumers in the order of priority.

The clustering method has been used on SM data for identifying energy usage patterns in commercial and industrial customers over 24-h periods, showing accurate grouping of accounts with similar patterns in [37]. In the context of energy usage data, clustering is used to group accounts with similar energy usage patterns, allowing us to identify potential energy inefficiencies and work with the user to improve energy efficiency. There are limitations to this study, including data trimming to 1-h intervals for computational efficiency, using a specific normalization method, focusing on commercial and industrial customers, and not evaluating the effectiveness of the clustering method in improving energy efficiency. The results do not necessarily apply to other customer types.

Jain et al. in [38] presents transmission scheduling and energy-efficient data aggregation in wireless sensor networks. It suggests multi-channel time division multiple access (TDMA) scheduling algorithms to cut down on energy usage and prevent interference and overhearing. Additionally, the study offers a near-optimal heuristic technique based on backtracking and Langford subset creation as well as an integer linear programming (ILP) algorithm. Numerous simulations demonstrate that the heuristic algorithms outperform the ILP method in terms of computing time savings and optimal outcomes. This paper, however, exhibits certain limitations. For instance, while the proposed heuristic algorithms offer computational efficiency, their suboptimal nature compared to the ILP algorithm restricts their applicability in scenarios where precise optimality is crucial. Moreover, the evaluation scope primarily revolves around energy consumption, latency, and computational time, potentially overlooking aspects like scalability, adaptability to dynamic network conditions, or robustness across diverse network topologies. Additionally, the paper lacks explicit discussions about the generalizability of the proposed algorithms to diverse WSN applications or network architectures, potentially limiting their applicability in scenarios beyond the specific context addressed in the study.

Diwold et al. in [39] presented a method for assigning SMs in low-voltage grids to their respective grid affiliations using communication data and voltage measurements. It emphasizes the importance of precise placement for network operation and control, aiming for efficient and automated SM roll-outs. However, it does not give a comprehensive analysis of other elements that may impact grid performance, such as load changes, network restrictions, and variations in measurement intervals.

Link scheduling and routing algorithms in wireless networks are presented in [40–45]. Although the evaluated publications' principal objectives may not directly relate to the scheduling of SM data, they nonetheless provide insightful analysis and present expert scheduling techniques. Concerning the larger context of supporting effective data transfer for SMs from source to destination, this indirect relevance demonstrates substantial consequence. Through their examination of communication channel scheduling, these papers lay a foundation for the development of strategies for the efficient routing and transmission of SM data, thereby raising the overall effectiveness and dependability of low-voltage grid management systems.

Findrik et al. in [46] explore data collection scheduling in smart grid networks using sensor metadata and compare three data access mechanisms: push, pull, and event-based. It focuses on quantitative modeling of mismatch probability ($mmPr$) for periodic controllers, considering changing information dynamics and using this metric for smart grid data collection. Paper [47] presents an algorithm for optimizing SM data access scheduling for real-time voltage quality monitoring in active low-voltage distribution grids. The algorithm, evaluated on a real distribution grid in Denmark, shows improved information quality compared to heuristically chosen scheduling mechanisms. Furthermore, authors demonstrated minimal degradation compared to the best achievable schedule in all investigated scenarios in [11].

Olsen et al. in [48] paid significant attention to the critical role of information quality in stochastic networked control systems. This study underscores the primary objective of achieving the lowest mmPr within such systems. However, the intricate nature of order assignment presents challenges that necessitate the exploration of alternative strategies. Notably, the Hungarian algorithm has emerged as an efficient solution for navigating the challenges related to access order assignment, as evidenced by their demonstrated effectiveness in paper [15]. Farooq et al. in [15] tackle scheduling access to SMs using $mmPr$, a new quality metric. It proposes using the Hungarian algorithm to find the optimal access sequence for sending SM data, which is validated through experimental and theoretical analysis in Matlab.

The studies cited above provide a summary of the scheduling algorithms used in the field of SMs. These algorithms have mostly been focused on a variety of aspects, including energy consumption optimization, energy distribution management, traffic control tactics, channel allocation methodology, considerations of meter data size, data quality evaluations, and storage management. These studies have made a substantial contribution to the improvement of smart grid operations by highlighting the significance of effective scheduling procedures. Table 1 summarizes the work done in each cited research.

The literature review presented above reveals that most research efforts have concentrated on optimizing scheduling algorithms within a communication network framework. However, comprehensive approaches to scheduling SM data have received relatively limited attention, despite addressing critical challenges and parameters. Notably, the existing body of work lacks methods that consider both the complexity of communication networks and the dynamic nature of information flow. This gap highlights an opportunity for further investigation, as it necessitates the integration of network dynamics and information flow characteristics to develop more robust and holistic scheduling solutions.

The primary contribution of this paper is the development of a comprehensive methodology to enhance the effectiveness and efficiency of SM data access scheduling. This is achieved by introducing the concept of $mmPr$ as a key metric to evaluate and encapsulate the interplay between communication network characteristics and the dynamic nature of information flow [48]. The methodology emphasizes reliability in data acquisition, particularly during critical events such as voltage fluctuations or sudden load changes, to ensure that the scheduling framework is both resilient and responsive.

Key advancements presented in this work include:

1. A novel framework that combines network complexity and dynamic information flow to optimize SM data scheduling.
2. The proposed method prioritizes data acquisition reliability during critical events, enhancing the grid's ability to respond to rapid changes and maintain operational stability.

Table 1
Brief summary of state of the art.

Paper	Year	Problem domain	Techniques	Results (Evaluation metrics)
Z. Malekkhani et al. [16]	2024	Scheduling electric appliances in smart homes with photovoltaic arrays and storage batteries	Two-stage stochastic programming model and sample average approximation algorithm	Improved solution quality and reduced electricity costs
T. Pei et al. [17]	2024	Anonymous identity authentication and data aggregation in AMI	Blockchain, Elliptic Curve Cryptography (ECC), reputation-based consensus protocol	Ensures secure and efficient communication between smart meters and the control center
T. Fawcett et al. [18]	2024	Energy consumption patterns and policy targeting for vulnerable households	Analysis of smart meter data	Identifies self-disconnection rates, supports fuel-poor households, and proposes improved policies
K. Nweyw et al. [19]	2022	HVAC scheduling and energy savings in commercial buildings	Clustering of Wi-Fi-derived occupancy and smart meter energy profiles	Aligns HVAC operation with occupancy patterns, achieving significant energy savings
E. A. Aghdam et al. [20]	2024	Day-ahead scheduling of smart power systems	IGDT-based robust model, compressed air energy storage (CAES), dynamic line/transformer rating	Minimizes load shedding, wind spillage, costs, and emissions; validated on the IEEE 24-bus system
A. Shaban et al. [21]	2024	Household appliance scheduling under inclining block rate (IBR) tariff	Mixed-integer quadratic programming	Reduces energy costs by optimizing load schedules and energy exchange with the grid
B. Alipour et al. [22]	2023	Scheduling for Smart Energy Hub under uncertainties and cyber security threats	Possibilistic–Probabilistic MILP, Monte Carlo-based FDI detection and correction	Minimizes risks from renewable generation, demand response programs, and FDI attacks
S. Iyengar et al. [23]	2018	Smart thermostat scheduling based on occupancy patterns	Time-series analysis, burstiness detection	Improves HVAC efficiency without requiring additional sensors; reduces mismatch time between occupancy and HVAC operation
Sayed et al. [24]	2023	Smart utility data scheduling	Narrowband PLC	Scalability, Network-Bandwidth Utilization, Real-time Monitoring
Hajimirzaee et al. [25]	2017	Wireless smart grid traffic scheduling	QoS requirements, Bandwidth allocation	Utility maximization, Bandwidth distribution, Latency requirements
Huang et al. [26]	2013	Priority-based traffic scheduling for smart grids	Cognitive radio communication, Channel schemes	Traffic prioritization, Channel allocation, Spectrum sensing
Carlesso et al. [27]	2015	Scheduling for SMs in wireless smart grid	Resource allocation, Traffic prioritization	Serviced user percentages, Coexistence with voice users
Karupongsiri et al. [12]	2013	QoS for smart grid data on LTE networks	SM data prioritization, Resource reservation	Latency reduction, SM data prioritization
Shao et al. [13]	2015	Traffic scheduling in wireless smart grid networks	Interference avoidance	Efficient data transmission, Interference avoidance
Hematian et al. [28]	2019	SM data traffic scheduling in NAN	Transmission scheduling using Software Defined Radio (SDR) testbed	Performance assessment of SM data traffic over LTE network
Markkula et al. [29]	2020	Preservation of QoS for demand response data in highly loaded LTE network	Riverbed Modeler network simulations	Scheduling of channel resources
Khan et al. [30]	2021	Maintaining QoS in AMI applications	Machine learning based scheduling in CloudSim simulator	Priority based scheduling, improved efficiency in terms of CPU utilization
Hassebo et al. [31]	2018	Traffic scheduling	uplink LTE Cascaded Priority-based scheduling algorithm	Improved performance metrics compared to Proportional Fairness (PF) and Round Robin (RR) schedulers
Songxi et al. [32]	2016	Multi traffic scheduling	novel multi-QoS data traffic scheduling algorithm	Balanced resources, Congestion avoidance
Amarasekara et al. [33]	2017	Preserving QoS for dynamic data traffic	Dynamic bandwidth allocation algorithm	Satisfied QoS requirements for both users; Mobile and SM
Huang et al. [34]	2021	SM data optimization	Consistent hash, Greedy algorithms	Storage optimization, Query efficiency, Performance
Ferreira et al. [35]	2022	SM data processing	Unix shell scripting	Processing time for millions of XML files, Performance
Zhang et al. [36]	2019	Energy scheduling in microgrids	Goal Programming Model, Deviation factors	Energy prioritization, Consumer satisfaction, Simulation results
Lavin et al. [37]	2015	Energy usage pattern identification	Clustering	Grouping of accounts, Energy inefficiency identification
Kumar et al. [38]	2019	Energy-efficient data aggregation	Multi-channel TDMA scheduling algorithms	Energy savings, Interference prevention, Computing time savings

(continued on next page)

Table 1 (*continued*).

Diwold et al. [39]	2015	SM placement in low voltage grids	Communication data, Voltage measurements	Efficient meter placement, Automated roll-outs
Liao et al. [43]	2016	Resource Management in wireless networks	Resource allocation strategies	Network resource utilization, Efficiency
Pedersen et al. [44]	2016	System-Level Scheduling in wireless networks	Scheduling techniques	Network performance, Scheduling efficiency
Pocovi et al. [45]	2017	MAC Layer Scheduling in wireless networks	MAC layer scheduling algorithms	MAC layer efficiency, Data transmission efficiency
Findrik et al. [46]	2014	Smart grid data collection	Push, Pull, Event-based data access mechanisms	$mmPr$ modeling, Data collection efficiency
Olsen et al. [48]	2017	Information Quality	Markov Model	demonstrate mmPr optimization to improve control performance
Kemal et al. [47] [11]	2018	Real-time voltage quality monitoring	Algorithm for optimizing scheduling	Information quality improvement, Minimal degradation
Farooq et al. [15]	2022	SM data access scheduling	Hungarian algorithm, Theoretical analysis	$mmPr$ minimization, Experimental validation

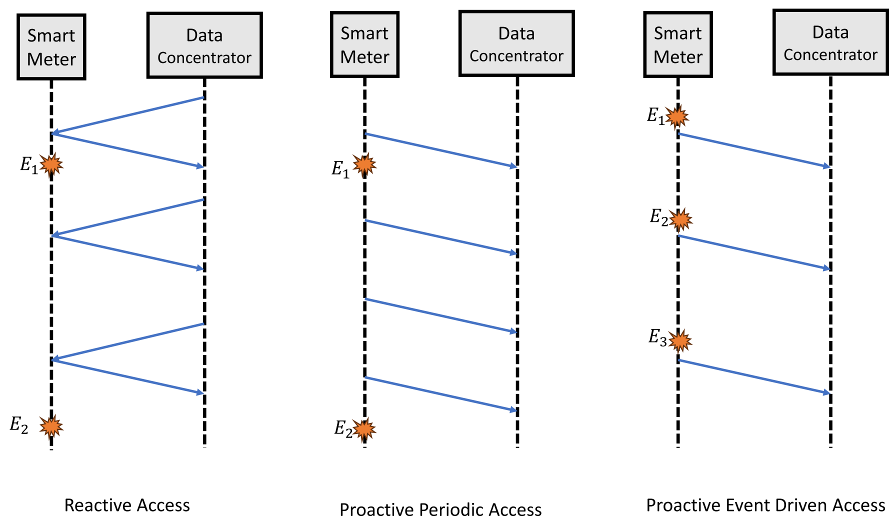

Fig. 2. SM data access approaches.

3. By addressing the identified limitations in the literature, this study provides a comprehensive, integrated perspective on SM data scheduling that bridges theoretical insights with practical applications.

Through these contributions, this research advances the field by offering a novel and robust approach to SM data scheduling, thereby strengthening grid resilience and improving the quality and timeliness of critical data acquisition.

3. System description

As shown in Fig. 2, communication between different entities within AMI takes place via two primary approaches:

1. Reactive Approach
2. Proactive Approach
    a. Periodical
    b. Event Driven

In reactive access, DC requests data from SMs. DC repeats this process with all SMs occasionally in a specific order [49]. On the contrary, within the Proactive Periodical Approach, SMs transmit data after predetermined intervals, and in Proactive Event-Driven Access, SMs dispatch information promptly upon detecting critical events. These events encompass a spectrum, including voltage fluctuations, dynamic load changes, and abrupt load variations resulting from the activation of heavy machinery, symbolized by $'E'$ in Fig. 2. In Periodical and Event-Driven proactive access, SMs proactively send data to the DC based on predefined schedules or triggered by these pivotal events, enhancing the timeliness and relevance of transmitted information. The details of each approach along with their sub-types are presented in [50].

For this work, the reactive access approach has been selected. The reactive access approach is also known as 'on-demand' access, in which an active request is made to the remote entity that possesses access to this information when a specific remote information item is required. This approach fundamentally implements the principles of a client–server architecture. Due to the legacy radio system in use, the reactive access network model assumes a multi-hop scenario with local domain access (Data concentrators). In this setup, smart meters are accessed individually to prevent interferences. Despite its legacy status, this approach remains highly prevalent and is expected to persist for the foreseeable future, primarily due to the significant cost associated with reinvesting in new metering infrastructure. Regardless of the access approach, there is a probability that information may change due to the underlying process before it reaches the HES.

For instance, it can be seen in Fig. 3 that meter data from all the SMs is gathered during a single collection cycle, and the next cycle begins once the previous data has been sent to the DC. The DC forwards this data to HES. DC collects this data in a certain order. *Cycle 1* represents an access order of $1, 2, 3, \ldots, N$ i.e. data from SM_1 is collected first and SM_N is collected at the last position. Similarly, *Cycle 3* represents an

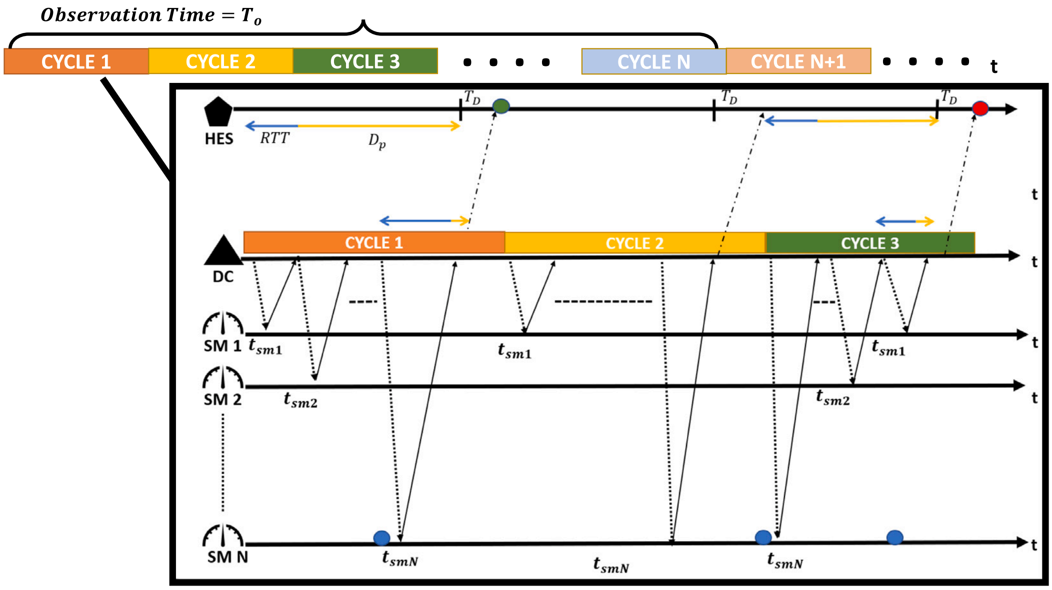

Fig. 3. SM data access approach and system description.

access order of $N, N-1, \ldots, 2, 1$.

In *cycle 1*, as shown in Fig. 3, HES receives correct data from SM_N. However, the data from SM_N received by HES after the completion of *cycle 3* is not new or accurate as there has occurred an event in SM_N. Blue circles represent events, i.e., changes in SM data that exceed certain limits. This configuration of the access network design is often employed to reduce meter interference, which is mainly caused by low data rates. This design choice is a result of strict requirements for accessibility, particularly in the context of billing purposes.

In this work, the data is monitored at HES for a certain observation time T_o and the average $mmPr$ (evaluation quality metric) is calculated for all SMs over this observation time interval. This observation time interval contains N number of cycles (C), as mentioned in (1). $mmPr$ is the probability of getting incorrect data at the HES [51]. $mmPr$ and selection criteria of observation time interval are explained in Sections 3.1 and 3.2, respectively.

$$T_o = \{C_1, C_2, C_3, \ldots, C_N\} \tag{1}$$

3.1. Evaluation metrics

This study focuses on the monitoring of data at the HES in order to propose an optimal schedule for data access to SMs, especially in the presence of an event such as over-voltage and under-voltage in the grid. Data at HES is observed for a specific period of time T_o and then the $mmPr$ is calculated for the observed data segment across all SMs. The SM exhibiting the highest $mmPr$ should be designated for prioritized access, while those with lower $mmPr$ values should be positioned at the end of the schedule. However, it is a daunting task given that hundreds of SMs are distributed throughout the LV grid. To address this complexity, the Hungarian algorithm is utilized to systematically assign SM according to access order, prioritizing those with higher related costs (i.e., $mmPr$), and presenting an optimal assignment for each SM.

As shown in Fig. 3, HES requests data from SM through reactive access strategy [51]. The $mmPr$ for reactive access strategy is given in (2) as:

$$mmPr = 1 - exp(\frac{-\lambda}{\upsilon}) \tag{2}$$

where υ is the downstream delay rate, i.e. $\upsilon = \frac{1}{D}$ and λ is event rate. It is assumed that the event process is a Poisson process in order to keep the model simple, with an unknown rate λ [50].

An unbiased and consistent estimate of the rate is given by (3) as:

$$\hat{\lambda} = \frac{E[T_o]}{T_o} \tag{3}$$

where T_o is observation time which refers to the duration of time in which the system collects data samples to estimate the average $mmPr$. This paper investigates the optimal observation time to be chosen for this study in Section 3.2. The estimated $mmPr$ based on this estimated rate is given in (4) as:

$$mm\hat{P}r = 1 - exp(-\hat{\lambda}D) \tag{4}$$

After computing the estimated value of the event rate, $\hat{\lambda}$, it has been found that the $mmPr$ is a biased function of the observation time [52] given in (5) as:

$$E[mm\hat{P}r] = 1 - E\left[exp(-\hat{\lambda}D)\right] = 1 - exp(\lambda T_o)(1 - exp(\frac{-D}{T_o})) \tag{5}$$

$$D = D_p + RTT \tag{6}$$

where λ is the event rate; hence, whenever an event occurs, λ values change accordingly. Eq. (6) shows D used in Eq. (5) as the sum of delays D_p and RTT, where D_p is the delay that SM experiences due to its position in the access order, and RTT round-trip time for accessing SM information. For instance, SM_1 in Fig. 3 has to wait for D_p seconds until its data is sent to HES because it is positioned at first place in access order of cycle 1 considering that there are N SMs and RTT is 1 s for each SM. Similarly, SM_N is in the last position and experiences the least delay before the data is sent to HES.

The time deadline, denoted by the variable T_D, is the amount of time within which all data must be accessed by the DC. In other words, T_D corresponds to the total time required to complete a cycle. When events or instances of voltage violations occur in SMs that were accessed earlier, say SM_1, their access order makes it more difficult to obtain their data immediately. As a result, prompt action cannot be taken in reaction to the events occurring in real-time within the SM. Due to this delay, out-of-date data is used, which emphasizes how important it is to prioritize SMs based on information dynamics to make more timely and effective decisions.

3.2. Temporal interval selection for data observation

In Eq. (5), it can be observed that $mmPr$ is a biased function of observation time. Delay bias refers to the variation or difference between

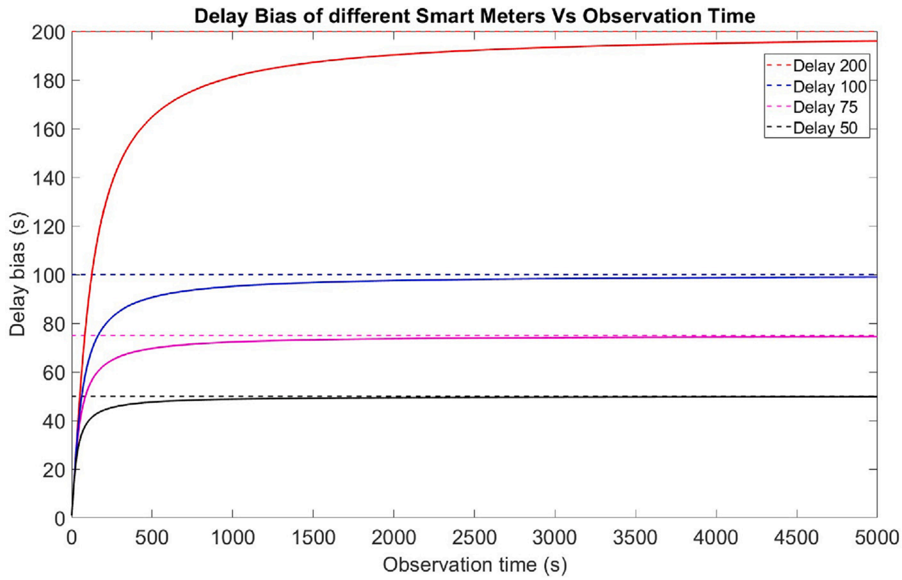

Fig. 4. Delay bias of different smart meters versus observation time.

Table 2
Delay vs. Delay bias and variance of mmPr at selected observation time interval.

Delay (s)	Delay bias at $T_o = 1000$ s	Percentage	Variance at $T_o = 1000$ s
200	181.2	90.6%	–
100	95.1	95.1	–
75	72.2	96.2	6.56×10^{-5}
50	48.7	97.4	0.0045

the true value of a delay experienced by SM and the observed value of the delay due to the communication network. It is the difference between the actual delay and the delay that is perceived or measured by HES. The time it takes for information to be sent and received might introduce bias and result in a discrepancy between the observed and real values of the delay. To ensure an accurate estimate of $mmPr$, it is necessary to analyze to ascertain the period needed for the bias to reach an acceptable value.

Fig. 4 shows the bias function of four different SMs plotted against observation time. These four SMs are experiencing different delay values depending on their position in the access order. This paper assumes that the maximum delay experienced by any SM is not more than 200 s. The delay values of 100 and 200 s are plotted for comparative purposes, aiming to illustrate how the delay bias evolves with increasing observation time intervals. It can be seen that biased function $T_o(1-exp(\frac{-D}{T_o}))$ $\rightarrow D$ as T_o increases.

Selecting a smaller observation value where bias exists in the function can lead the $mmPr$ estimator to overestimate or underestimate the $mmPr$, due to the bias arising from the fact that the $mmPr$ estimator is based on an exponential function, which has a non-linear relationship with the true parameter values. Increasing the observation time can reduce the bias in the estimation of the $mmPr$, which is desirable for accurate estimation. Around $T_o = 1000$ s, the delay bias of SMs having smaller delay values seems to be acceptably low. The delay bias of SMs with higher delays takes longer to settle down. Hence, observation time can be selected as low as $T_o = 1000$ s in order to get a correct estimate of the $mmPr$ value. Table 2 shows that delay bias achieves more than 90% of its corresponding delay value at $T_o = 1000$ s. Furthermore, the longer the observation time, the better the estimate of $mmPr$ is since one needs to ensure that the $mmPr$ estimate is reliable before using it to decide which SMs should be given priority.

The selection of the observation time interval is also affected by the variance of the estimator. At a certain observation time, even though a low delay bias is achieved, it is not useful if there is a high variance of $mmPr$ in the system [52]. Hence, variance is calculated for each SM to ensure the accurate selection of the observation time interval. Fig. 5 shows the standard error, i.e. $g(t, \lambda, D) = \sqrt{\mathbf{Var}[mm\hat{P}r]}$ versus the observation time interval for different SMs with different delay values. It can be seen that the variance decreased to an extremely low value as the observation time increased. The graphs in Fig. 5 show that the variance is not only dependent on the delay value; it is also affected by lambda. Hence, the variance of SMs can have different values with the same delays but different lambda values. The variance of the estimated $mmPr$ has the expression as shown in (7):

$$\mathbf{Var}[mm\hat{P}r] = E\left[exp(-2\hat{\lambda}D)\right] - E\left[exp(-\hat{\lambda}D)\right]^2 \tag{7}$$

Eq. (5) shows that the correct estimate of $mmPr$ and the selection of the observation time interval is also dependent on the value of event rate λ. To ensure a stable estimate of the $mmPr$ value, it is essential to have sufficient observation time during which events can occur. In this study, an event is defined as a voltage difference between certain samples k exceeding a certain value ϵ.

$$Events = Voltage(k) - Voltage(k-1) > \epsilon \tag{8}$$

If the observation time is too short and the number of events that occurred in that interval is zero, it leads to a lack of changes in the information, and therefore, the mismatch probability is not impacted by the event process. As a result, the mismatch probability would likely be low or zero, given that there are no instances where the received data differs from the actual data. With careful selection and consideration, this paper has developed an effective algorithm that prioritizes monitoring buses with higher mmPr values. This approach offers a promising solution to the scheduling problem by ensuring that critical events are more likely to be captured and accurately monitored.

Another critical factor in the selection of the observation time interval is the number of SMs under consideration. When employing the Hungarian algorithm for optimal schedule selection, the initial step involves populating a matrix with the cost associated with placing each SM at every position. In this paper, the cost is the sum of $mmPr$ and the standard error $g(t, \lambda, D)$. If, for instance, there are four SMs under observation, four schedules are required. Each schedule ensures that every SM is placed at each position, allowing the determination of the cost associated with placing a specific SM at a particular position.

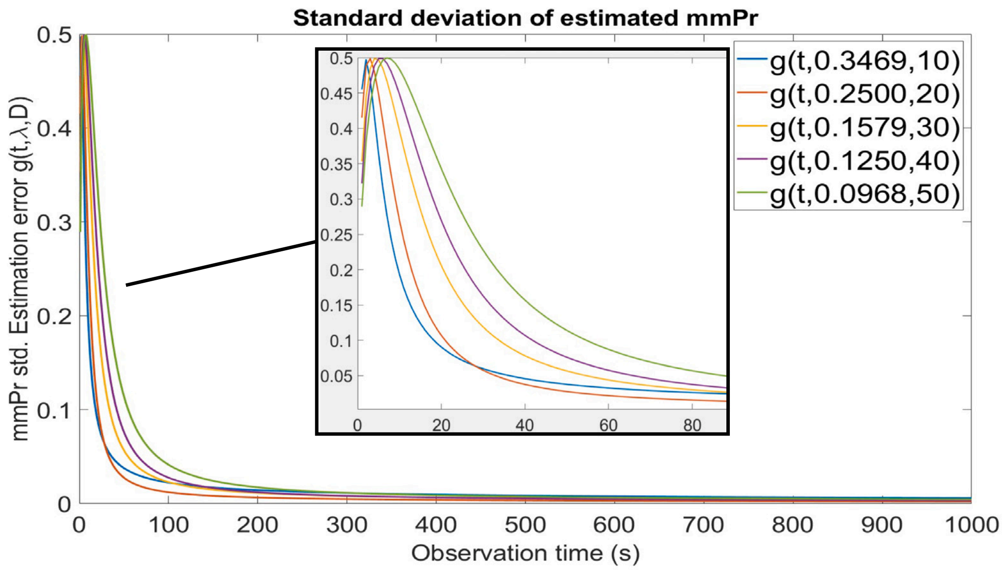

Fig. 5. Standard deviation of the estimated mmPr.

Subsequently, the Hungarian algorithm is applied to derive the optimal schedule based on these costs. As the quantity of SMs grows, the number of schedules needed to populate the cost matrix also increases. Given a finite amount of available data, it becomes imperative to decrease the observation time interval. This adjustment is essential to accommodate the generation of the requisite schedules for populating the cost matrix.

To calculate the information metric, $mmPr$, it is essential to provide a comprehensive description of the dataset used in this study. The dataset utilized in this study is sourced from a real Danish DSO. To safeguard privacy, the anonymity and confidentiality of the data have been ensured. It is pertinent to mention that each individual household SM data profile possesses a temporal resolution of 15 min and has undergone a meticulous validation process by the DSO to serve billing purposes, thereby ensuring data accuracy and reliability. While this study focused on this specific dataset, the methodologies and findings are designed to be applicable across various locations and datasets. The proposed technique has been applied to 21 days of data from 89 SMs, i.e., 1921 samples. The minimum observation time interval can be selected as $T_o = 1000$ s = 16.6 min ≈ 2 samples. However, 225 minutes = 15 samples have been selected.

3.3. Materials and methods

Given several methods, data, and software environments used in this work, Table 3 summarizes the involved suites, indicating their role in facilitating the understanding of interconnected functions, and providing the whole perspective about the presented approach.

4. Data access scheduling algorithm

The proposed scheduling strategy prioritizes SMs encountering heightened disruptions, offering them precedence in data access and reducing the overall cost of that particular access order. These disruptions, encapsulated by critical events such as voltage fluctuations or sudden load changes, define the urgency and relevance of data retrieval. By employing this responsive method, the system swiftly reacts to these abnormalities, ensuring efficient and timely retrieval of crucial data. This approach not only addresses but also leverages the occurrences of these critical events, thereby fortifying the overall efficacy of the smart grid infrastructure through proactive data management.

Fig. 6 represents the proposed algorithm. This work accesses data from 89 SMs and HES receives this data with a specific schedule, i.e., $SM_1, SM_2, SM_3, \dots, SM_{89}$. This means that the data from SM_{89} is accessed first, while the data from SM_1 is accessed at the last position. Similarly, if the schedule is $SM_{89}, SM_{88}, \dots, SM_3, SM_2, SM_1$, this means that SM_1 data is accessed first and vice versa.

When accessing SM_1 at position 1, it encounters a more prolonged delay compared to the SM whose data is accessed at the last position. Consequently, when receiving data at the HES, certainty about the freshness of the data from SM_1 is compromised. An evaluation metric, $mmPr$, is employed to assess data reliability. A higher $mmPr$ indicates an elevated level of mismatch between the received data at HES and the data at the respective SM. The Hungarian algorithm is applied to prioritize SMs based on their costs.

4.1. The use of the Hungarian algorithm

The Hungarian algorithm aims to determine the optimal assignment of SMs to positions by minimizing the total cost. This is achieved through analyzing a cost matrix, denoted in (9) as **M** having elements $cost_{m,n}$ that represent the cost of assigning an SM m to a position n, to find out the optimal assignment of the SMs that minimizes the total cost. For instance, if there are two smart meters under consideration, i.e. $m = n = 2$, then the cost matrix would be presented as follows:

$$M = \begin{bmatrix} & Position1 & Position2 \\ SM1 & cost_{1,1} & cost_{1,2} \\ SM2 & cost_{2,1} & cost_{2,2} \end{bmatrix} \tag{9}$$

where cost is defined in (10) as:

$$cost = mmPr_{m,n} + g(t, \lambda, D) \tag{10}$$

4.2. Pre-requisite for Hungarian algorithm

The following conditions should be met before populating the Hungarian matrix:

1. Each smart meter must be placed in only one position.
2. Each position must be occupied by only one smart meter.
3. To populate the cost matrix.

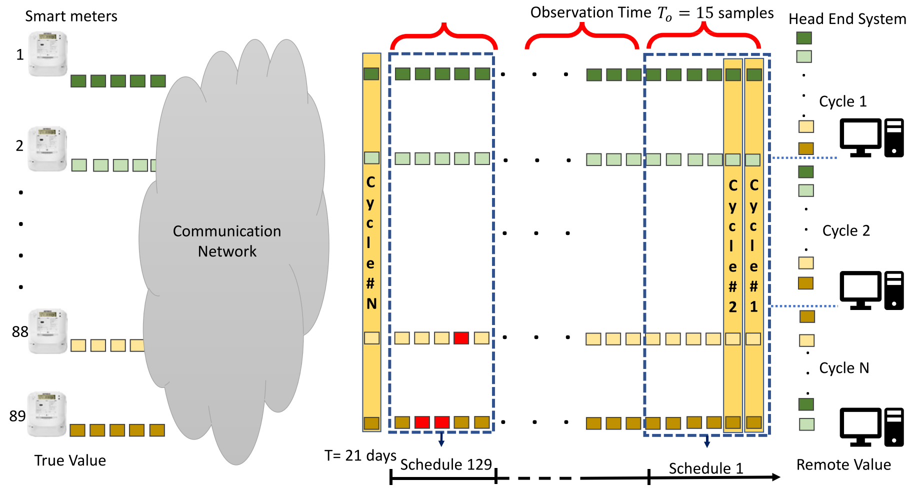

Fig. 6. Proposed data access scheduling algorithm.

Table 3
Summary of the involved suites and their role description.

Component	Description
Data source	Real smart meter data from a Danish grid
Software	MATLAB for simulating the proposed method and potentially analyzing benchmark methods
Hardware	No specific hardware requirements; work can be done on a standard computer
Evaluation metric	Mismatch Probability

The cost matrix, represented in Equation (9), for placing a specific SM at a particular position, needs to be populated. For instance, when working with ten SMs, ten predetermined schedules were presented to the system for the cost matrix population, after which the Hungarian algorithm commenced its optimization process.

Table 4 illustrates the access order for SMs during each cycle. The example of ten SMs is adopted for clarity and ease of presentation. Each row of this table signifies a distinct access order. It is noteworthy that the initial ten rows are arranged in a Predetermined Access Order (PAO), facilitating the placement of each SM at various positions. For instance, first row represents that $SM2$ is at position 1 ($P1$), $SM3$ is at position 2 ($P2$) in access order and so on. This systematic arrangement enables the population of the cost matrix for the Hungarian algorithm. Subsequently, the last three rows depict the access order derived through the implementation of the Hungarian algorithm and are represented as the Hungarian Access Order (HAO).

Thus, in the case of 89 SMs, the cost matrix of length 89×89 needs to be filled with the corresponding costs. This paper develops a code that yields 89 pre-defined access orders/schedules, each representing a unique placement of every SM at each position in the matrix.

Given that, a dataset of 1921 samples was obtained and the minimum observation time interval was set at 15 samples, resulting in a total of 129 possible observation time intervals and, hence, 129 schedules. Among these schedules, 89 are predetermined access orders for populating the Hungarian cost matrix. Following the generation of the required cost matrix, the Hungarian algorithm is initiated, providing an optimal schedule based on the $cost$ values for the rest of the samples and keeping it updated after every 15 samples.

SMs that are experiencing significant disruptions may experience lengthy queue waits without any scheduling algorithm, especially in real grids with thousands of SMs. Implementation of the proposed method ensures the grid's capability for real-time monitoring and its ability to respond to disruptions. A block diagram of the proposed algorithm is presented in Fig. 7. The dotted lines in the data access schedule algorithm in Fig. 7 show that to utilize the Hungarian algorithm for generating schedules, it is necessary to first populate the cost matrix as explained earlier in this section.

Table 4
Smart meter access orders in all cycles for 10 SMs.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
PAO# 1	2	3	4	5	6	7	8	9	10	1
PAO# 2	3	4	5	6	7	8	9	10	1	2
PAO# 3	4	5	6	7	8	9	10	1	2	3
PAO# 4	5	6	7	8	9	10	1	2	3	4
PAO# 5	6	7	8	9	10	1	2	3	4	5
PAO# 6	7	8	9	10	1	2	3	4	5	6
PAO# 7	8	9	10	1	2	3	4	5	6	7
PAO# 8	9	10	1	2	3	4	5	6	7	8
PAO# 9	10	1	2	3	4	5	6	7	8	9
PAO# 10	1	2	3	4	5	6	7	8	9	10
HAO# 11	7	3	10	5	6	2	4	8	9	1
HAO# 12	7	2	10	4	6	1	5	9	3	8
HAO# 13	7	6	3	4	2	1	8	5	10	9

Once the cost matrix is populated, the Hungarian algorithm starts generating the optimal schedule for data access. Before this step, the data collection mechanism acquires schedules according to a predefined access order. The predefined access orders are designed to ensure that each smart meter occupies every position within the access order. This arrangement facilitates the determination of the cost associated with placing a specific smart meter at a particular position. Following the acquisition of a new schedule from the data access scheduling algorithm, the data collection mechanism initiates a request to the AMI to retrieve data from smart meters in accordance with the updated schedule.

Although the code comprises various steps, the core method revolves around the computation of the $mmPr$ and total cost for each SM at predetermined intervals of time, i.e., T_o. The algorithm has been implemented using Matlab, with the code structured according to the guidelines outlined in Algorithm 1.

Algorithm 1 Smart Meter Scheduling Algorithm

Initialize Parameters
$NoSM \leftarrow 89$ ▷ Number of smart meters
$count \leftarrow 1$

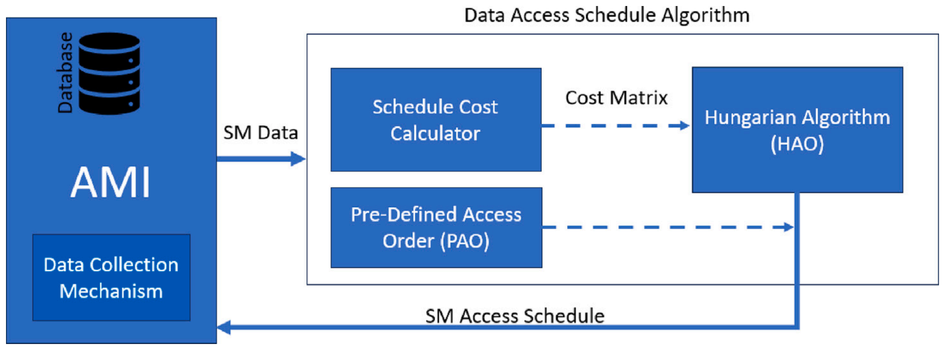

Fig. 7. Block diagram of the proposed data access scheduling algorithm.

```
matrix ← zeros(NoSM)
Dimensions of the Matrix
matrixSize ← NoSM
CostMatrix ← zeros(matrixSize)    ▷ Initialize cost matrix with all zeros
Load Grid Data
All_Voltages
Selection of # of SMs to be Used
dataMatrix ← All_Voltages(:, 1 : NoSM)    ▷ Example: 1921x89 matrix
NuS ← size(dataMatrix, 1)    ▷ Number of samples for each SM
Parameters
OTI ← NuS/NoSM    ▷ Observation time interval
Initialize empty vectors
differences ← []
Pre-defined schedules according to the NoSM
for i = 1 to NoSM do
    matrix(i, :) ← mod((1 : NoSM) + i − 1, NoSM) + 1
end for
Schedules ← matrix
for ik = 1 to size(Schedules, 1) do
    DD(ik, :) ← flip(Schedules(ik, :))
end for
ADelay ← DD(count, :)    ▷ Delay due to their access order
Divide Data into OTI and Calculate mmPr
chunkSize ← OTI    ▷ Number of rows in each chunk
[numRows, numCols] ← size(dataMatrix)
for startIndex = 1 to chunkSize to numRows do
    if count ≥ NoSM then
        [assignment, cost] ← munkres(CostMatrix)    ▷ Use HA
        [assignedrows, _] ← find(assignment)
        SCH ← assignedrows′    ▷ HA's optimal schedule based on cost
        assignmnetss(count, :) ← SCH    ▷ Saving schedules
    else
        SCH ← Schedules(count, :)    ▷ Use pre-defined schedule to populate the cost matrix
        assignmnetss(count, :) ← SCH    ▷ Saving schedules
    end if
    endIndex ← min(startIndex + chunkSize − 1, numRows)
    currentChunk ← dataMatrix(startIndex : endIndex, :)
    for k = 1 to size(currentChunk, 2) do
        Check number of events occurring in each chunk
    end for
    for l = 1 to matrixSize do
        Calculate Lambda
    end for
    for kl = 1 to matrixSize do
        Calculate mmPr
        Calculate SD
    end for
    Replace mmPr value in the cost matrix
    for i = 1 to length(Schedules) do
        CostMatrix(i, columnIndex) ← mmPr(count, i) + SD
    end for
    count ← count + 1
end for
```

5. Results

SMs in distribution grids play a crucial role in monitoring voltage quality, but challenges remain in ensuring real-time data access. This study addresses these challenges by introducing an innovative scheduling approach based on the quality of data received at the HES. Data quality is assessed using the mmP r metric, and the Hungarian algorithm is employed to optimize SM scheduling. This approach has been validated using real data from a Danish grid, offering significant advantages over previously proposed heuristic algorithms.

5.1. Comparison with existing methods

The Hungarian algorithm's effectiveness was previously demonstrated in our work [15] through comparative analysis involving 10 SMs. Table 5 presents the smart meters' arrangement across different access orders used in various methods. In the round-robin (RR) access order, smart meters are arranged sequentially in ascending order, with smart meter 1 placed in position 1, smart meter 2 in position 2, and so on, up to smart meter 10 in position 10. The total mmPr calculated for this access order is shown in the last column. Similarly, randomly generated access orders were simulated for comparison, with their total mmPr values also evaluated. One example of a randomly selected access order, labeled as "R AO", is provided in the second row of the table. The last row displays the access order generated by the Hungarian algorithm, which produces the lowest overall total mmPr among all methods. This study advances beyond earlier assumptions of direct SM data access by focusing exclusively on data available at the HES, reflecting real-world conditions. A refined *mmPr* formulation was adopted to accurately assess data reliability under these conditions, considering the duration of data observation, frequency of process repetition, and variance analysis.

Table 6 offers a detailed breakdown of the mmPr values for each smart meter when placed in different positions across various access orders. For instance, placing smart meter 1 in position 1 results in an mmPr of 0.7447, whereas placing smart meter 9 in position 1 yields a lower mmPr of 0.3750. The Hungarian algorithm consistently delivers the lowest overall total cost of using that access order, confirming its superiority in optimizing access orders.

Table 5
Comparison of different access orders with Hungarian Algorithm generated access order in terms of lower mmPr.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	Total mmPr
RR AO	SM1	SM2	SM3	SM4	SM5	SM6	SM7	SM8	SM9	SM10	4.6383
R AO	SM4	SM3	SM2	SM1	SM8	SM7	SM6	SM5	SM10	SM9	4.7659
HA AO	SM9	SM8	SM3	SM5	SM10	SM7	SM1	SM6	SM4	SM2	3.3396

Table 6
MmPr for placing a specific SM at a specific position in an access order.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	Total mmPr
RR mmPr	0.7447	0.8936	0.8085	0.8085	0.0426	0.5319	0.1064	0.5106	0.0426	0.0638	4.6383
R mmPr	0.8723	0.9326	0.8723	0.5957	0.8298	0.1702	0.3617	0	0.1064	0.0213	4.7659
HA mmPr	0.3750	0.8750	0.8936	0.0625	0.3750	0.1702	0.1064	0.1875	0.0652	0.2292	3.3396

Table 7
Comparison of Algorithms for the scheduling of SM data.

Criteria	Heuristic algorithm [11]	Hungarian algorithm [15]	Proposed Hungarian algorithm
Certainty	Low	Medium	High
Complexity	$O(n!)$	$O(n^3)$	$O(n^3)$
Optimality	Exhaustive search ensures all possibilities are considered	Guarantees an optimal solution	Guarantees an optimal solution
Use cases	Small-scale problems (Educational or analytical exploration)	Small and Medium-scale assignment problems	Small and Large-scale assignment problems
Computational efficiency	Suitable for small-scale problems	Complexity increases with increased number of SMs	Suitable for both small and large-scale problems

5.2. Implications for smart grid applications

The refined approach using the Hungarian algorithm offers a robust solution for scheduling SM data access, ensuring reliable monitoring and management in smart grid applications. With its cubic complexity, the algorithm is scalable for large datasets, making it suitable for extensive real-world deployments. A comparison of different scheduling algorithms (Table 7) demonstrates that while heuristic methods are effective for small-scale problems, the Hungarian algorithm provides superior scalability and versatility for larger applications.

6. Discussion

6.1. Assessment of data reliability received at the HES

As mentioned in Section 3, the proposed algorithm is applied to 15-minute interval SM data collected over 21 consecutive days, totaling 1921 data samples for 89 SMs. The reliability of this data is evaluated using the $mmPr$ metric, accounting for communication delays and the SM's position in the access order. To derive accurate $mmPr$ estimates before scheduling SMs, the study evaluates $mmPr$ over specific observation time intervals, aiming to minimize bias due to inherent delays.

6.2. Assessment of optimal observation time interval for scheduling

Our method updates the smart meter (SM) data access schedule based on observation time intervals. Analysis reveals that if SMs experience delays of 200 s or less, selecting an observation interval longer than 1000 s minimizes bias, closely reflecting the original delay. This stabilization of delay bias beyond 1000 s ensures more accurate scheduling, as confirmed in earlier simulations. Additionally, the event rate significantly impacts the selection of the observation time interval. A longer interval is generally preferred to capture a sufficient number of events. When the event rate is low, selecting too short an observation interval can lead to data sparsity, causing instability in the cost matrix and impacting the Hungarian algorithm's performance. For instance, when working with 1921 samples from 4 SMs, an interval of fewer than 80 samples results in an unstable cost matrix due to insufficient data points. This issue leads to mismatches in data and potential empty rows or columns in the cost matrix, which can render the Hungarian algorithm unstable. For larger numbers of SMs, such as 89, a shorter observation interval, like 15 samples, maintains matrix stability. In this case, the schedule is updated 129 times across the total 1921 samples, with 89 predefined schedules and the remaining generated by the Hungarian algorithm. However, very short intervals may still result in insufficient event data per interval, causing some cost matrix elements to become zero or undefined (NAN). This highlights the need for further investigation into optimal scheduling under conditions of sparse data.

6.3. Limitations and future directions

While this study confirms the effectiveness of the Hungarian algorithm for scheduling SM data access, challenges remain in scenarios where the observation interval is too short, resulting in insufficient events and destabilizing the cost matrix. Addressing these issues through further algorithm refinements, such as improving the algorithm's handling of sparse data, is a priority for future work. Additionally, exploring the algorithm's application across different grid environments, especially those with varying SM densities and event rates, will provide deeper insights into its scalability and robustness. By advancing our understanding of SM scheduling under real-world constraints, this research contributes to the development of more efficient and reliable smart grid systems.

7. Conclusions

This research explored the critical impact of access and communication delays on the reliability of SM data in modern power grids. The findings reveal that access delays are influenced by the SM's position in the access queue and the event rate, which highlights vulnerabilities in the communication network. A higher mismatch probability indicates unreliable data, while a lower mismatch probability reflects more trustworthy information, underscoring the importance of prioritizing data from reliable sources to ensure effective grid operations.

The proposed Hungarian algorithm was rigorously evaluated and compared to a heuristic approach. While the heuristic algorithm is effective for small-scale scenarios, its factorial complexity limits its applicability as the number of SMs increases. In contrast, the Hungarian algorithm, with its cubic complexity, demonstrates superior scalability and is well-suited for larger, real-world deployments. This scalability, coupled with its ability to handle substantial data volumes, establishes the Hungarian algorithm as a robust solution for optimizing SM data access scheduling.

The study also emphasizes the computational challenges associated with processing data from SMs at the HES, which depend on factors such as the number of SMs, transmission frequency, data payload size, and HES processing power. The proposed algorithm efficiently manages these challenges, particularly under high data loads and with a growing number of SMs, ensuring optimal solutions that align with predefined scheduling objectives.

Key contributions of this work include a novel approach to prioritizing and scheduling SM data access, which enhances grid resilience and operational efficiency. The extensive evaluation confirms the algorithm's versatility and effectiveness across both small-scale and large-scale applications.

Future research will leverage the extensive dataset collected in this study to explore advanced analytical techniques. Correlation and regression analyses will be conducted to develop mathematical models that reveal deeper insights into the relationships between various factors and electricity consumption. Furthermore, the integration of artificial intelligence techniques, such as neural networks, will be explored to enhance forecasting accuracy for both short- and long-term consumption patterns. These advancements will aid stakeholders in grid planning and resource allocation, paving the way for a more resilient, efficient, and sustainable power grid.

CRediT authorship contribution statement

Asma Farooq: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kamal Shahid:** Writing – review & editing, Supervision, Resources, Investigation. **Rasmus Løvenstein Olsen:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Asma Farooq reports was provided by Aalborg University. Asma Farooq reports a relationship with Aalborg University that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

References

[1] S.H. Alsaiari, S. Alsulami, Y. Asiri, N. Kannan, Smart meters based household electricity consumption, in: 2022 International Conference on Futuristic Technologies, INCOFT, IEEE, 2022, pp. 1–8.

[2] P. Zhang, L. Li, Vibration and noise characteristics of high-frequency amorphous transformer under sinusoidal and non-sinusoidal voltage excitation, Int. J. Electr. Power Energy Syst. 123 (2020) 106298.

[3] R. Klyuev, I. Bosikov, A. Alborov, Research of non-sinusoidal voltage in power supply system of metallurgical enterprises, in: Advances in Automation: Proceedings of the International Russian Automation Conference, RusAutoCon 2019, September 8-14, 2019, Sochi, Russia, Springer, 2020, pp. 393–400.

[4] C. Huang, C.-C. Sun, N. Duan, Y. Jiang, C. Applegate, P.D. Barnes, E. Stewart, Smart meter pinging and reading through AMI two-way communication networks to monitor grid edge devices and DERs, IEEE Trans. Smart Grid 13 (5) (2021) 4144–4153.

[5] Recent advances in communication technologies for smart grid application: A review, 2014, http://dx.doi.org/10.1109/IEECON.2014.6925952.

[6] Communication device, smart meter, and wireless mesh network, 2015.

[7] Gateway Placement for Wirless Mesh Networks in Smart Grid Network Planning, IEEE, 2016, pp. 144–147, http://dx.doi.org/10.1109/CPE.2016.7544174.

[8] BeagleBone black powered data concentrator for connected devices, 2017,

[9] Data communication system with multiple data links and operating modes, 2020.

[10] A. Farooq, K. Shahid, R.L. Olsen, Prioritization of smart meters based on data monitoring for enhanced grid resilience, 2024, Available At SSRN 4724676.

[11] M.S. Kemal, R.L. Olsen, H.-P. Schwefel, Optimized scheduling of smart meter data access: A parametric study, in: 2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids, SmartGridComm, IEEE, 2018, pp. 1–6, http://dx.doi.org/10.1109/smartgridcomm.2018.8587478.

[12] C. Karupongsiri, M.F. Hossain, K.S. Munasinghe, A. Jamalipour, A novel scheduling technique for smart grid data on LTE networks, in: 2013, 7th International Conference on Signal Processing and Communication Systems, ICSPCS, IEEE, 2013, pp. 1–5.

[13] S. Shao, S. Guo, X. Qiu, L. Meng, M. Lei, Traffic scheduling mechanism based on interference avoidance for meter data collection in wireless smart grid communication networks, China Commun. 12 (7) (2015) 142–153.

[14] S. Zhang, J. Rong, B. Wang, An optimal scheduling scheme for smart home electricity considering demand response and privacy protection, Int. J. Electr. Power Energy Syst. 132 (2021) 107159.

[15] A. Farooq, K. Shahid, R.L. Olsen, Scheduling of smart meter data access using hungarian algorithm, in: 2022 25th International Symposium on Wireless Personal Multimedia Communications, WPMC, IEEE, 2022, pp. 351–356.

[16] Z. Malekkhani, M. Ranjbar, Optimal scheduling of smart home appliances with a stochastic power outage: A two-stage stochastic programming approach, Sustain. Energy Grids Netw. 40 (2024) 101564, http://dx.doi.org/10.1016/j.segan.2024.101564, URL https://www.sciencedirect.com/science/article/pii/S2352467724002947.

[17] T. Pei, Z. Hou, J. Zhou, C. Xiao, J. Zou, Blockchain-based anonymous authentication and data aggregation for advanced metering infrastructure in smart grid, Int. J. Crit. Infrastruct. Prot. 46 (2024) 100702, http://dx.doi.org/10.1016/j.ijcip.2024.100702, URL https://www.sciencedirect.com/science/article/pii/S187454822400043X.

[18] T. Fawcett, J. Palmer, N. Terry, B. Boardman, U. Narayan, Using smart energy meter data to design better policy: Prepayment meter customers, fuel poverty and policy targeting in Great Britain, Energy Res. Soc. Sci. 116 (2024) 103666, http://dx.doi.org/10.1016/j.erss.2024.103666, URL https://www.sciencedirect.com/science/article/pii/S2214629624002573.

[19] K. Nweye, Z. Nagy, MARTINI: Smart meter driven estimation of HVAC schedules and energy savings based on wi-fi sensing and clustering, Appl. Energy 316 (2022) 118980, http://dx.doi.org/10.1016/j.apenergy.2022.118980, URL https://www.sciencedirect.com/science/article/pii/S0306261922003890.

[20] E.A. Aghdam, S. Moslemi, M.S. Nakisaee, M. Fakhrooeian, A.J.K. Al-Hassanawy, M.H. Masali, A.Z.G. Seyyedi, A new IGDT-based robust model for day-ahead scheduling of smart power system integrated with compressed air energy storage and dynamic rating of transformers and lines, J. Energy Storage 105 (2025) 114695, http://dx.doi.org/10.1016/j.est.2024.114695, URL https://www.sciencedirect.com/science/article/pii/S2352152X24042816.

[21] A. Shaban, M. Salhen, M.A. Shalaby, T.F. Abdelmaguid, Optimal household appliances scheduling for smart energy management considering inclining block rate tariff and net-metering system, Comput. Ind. Eng. 190 (2024) 110073, http://dx.doi.org/10.1016/j.cie.2024.110073, URL https://www.sciencedirect.com/science/article/pii/S0360835224001943.

[22] B. Alipour, A. Abdollahi, M. Rashidinejad, A.Y. Kermani, M. Jadidoleslam, Possibilistic–probabilistic risk-based smart energy hub scheduling considering cyber security in advanced metering infrastructures, Sustain. Energy Grids Netw. 36 (2023) 101159, http://dx.doi.org/10.1016/j.segan.2023.101159, URL https://www.sciencedirect.com/science/article/pii/S2352467723001674.

[23] S. Iyengar, S. Kalra, A. Ghosh, D. Irwin, P. Shenoy, B. Marlin, Inferring smart schedules for dumb thermostats, ACM Trans. Cybern.-Phys. Syst. 3 (2) (2018) http://dx.doi.org/10.1145/3226031.

[24] H.A. Sayed, A.M. Said, A.W. Ibrahim, Smart utilities IoT-based data collection scheduling, Arab. J. Sci. Eng. (2023) 1–15, http://dx.doi.org/10.1007/s13369-023-07835-4.

[25] P. Hajimirzaee, M. Fathi, N.N. Qader, Quality of service aware traffic scheduling in wireless smart grid communication, Telecommun. Syst. 66 (2017) 233–242, http://dx.doi.org/10.1007/s11235-017-0285-4.

[26] J. Huang, H. Wang, Y. Qian, C. Wang, Priority-based traffic scheduling and utility optimization for cognitive radio communication infrastructure-based smart grid, IEEE Trans. Smart Grid 4 (1) (2013) 78–86.

[27] M. Carlesso, A. Antonopoulos, F. Granelli, C. Verikoukis, Uplink scheduling for smart metering and real-time traffic coexistence in LTE networks, in: 2015 IEEE International Conference on Communications, ICC, IEEE, 2015, pp. 820–825.

[28] A. Hematian, W. Yu, D. Griffith, N. Golmie, Performance assessment of smart meter traffic over LTE network using SDR testbed, in: 2019 International Conference on Computing, Networking and Communications, ICNC, IEEE, 2019, pp. 408–412.

[29] J. Markkula, J. Haapola, Shared lte network performance on smart grid and typical traffic schemes, IEEE Access 8 (2020) 39793–39808.

[30] A. Khan, A.I. Umar, A. Munir, S.H. Shirazi, M.A. Khan, M. Adnan, A qos-aware machine learning-based framework for ami applications in smart grids, Energies 14 (23) (2021) 8171.

[31] A. Hassebo, M. Marciniak, M. Ali, Uplink LTE cascaded priority-based scheduler in IoT and smart grid applications: performance and comparison, in: Metro and Data Center Optical Networks and Short-Reach Links, vol. 10560, SPIE, 2018, pp. 206–215.

[32] L. Songxi, W. Qinghua, W. Han, F. Yuanliang, P. Hui, Z. Gonglin, P. Haibo, Traffic scheduling with sustainable cyber physical systems applying in smart grid, in: 2016 Seventh International Green and Sustainable Computing Conference, IGSC, IEEE, 2016, pp. 1–6.

[33] B. Amarasekara, C. Ranaweera, R. Evans, A. Nirmalathas, Dynamic scheduling algorithm for LTE uplink with smart-metering traffic, Trans. Emerg. Telecommun. Technol. 28 (10) (2017) e3163.

[34] F. Huang, M. Sun, J. Zhong, N. Liu, P. Yuan, Energy data collection and scheduling of AMI based on consistent hash and greedy optimization, in: 2021 11th International Conference on Power and Energy Systems, ICPES, 2021, pp. 456–461, URL https://api.semanticscholar.org/CorpusID:246288736.

[35] M. Ferreira, A. Neves, R. Gorjao, C. Cruz, M.L. Pardal, Smart meter data processing: a showcase for simple and efficient textual processing, 2022, arXiv preprint arXiv:2212.13656.

[36] X. Zhang, L. Guo, H. Zhang, L. Guo, K. Feng, J. Lin, An energy scheduling strategy with priority within islanded microgrids, IEEE Access 7 (2019) 135896–135908.

[37] A. Lavin, D. Klabjan, Clustering time-series energy data from smart meters, Energy Effic. 8 (2015) 681–689.

[38] S. Kumar, H. Kim, Energy efficient scheduling in wireless sensor networks for periodic data gathering, IEEE Access 7 (2019) 11410–11426.

[39] K. Diwold, M. Stifter, P. Zehetbauer, Network and feeder assignment of smart meters based on communication and measurement data, in: 2015 International Symposium on Smart Electric Distribution Systems and Technologies, EDST, IEEE, 2015, pp. 541–546, http://dx.doi.org/10.1109/sedst.2015.7315267.

[40] J. Zhang, H. Wu, Q. Zhang, B. Li, Joint routing and scheduling in multi-radio multi-channel multi-hop wireless networks, in: 2nd International Conference on Broadband Networks, 2005, IEEE, 2005, pp. 631–640.

[41] K. Jain, J. Padhye, V.N. Padmanabhan, L. Qiu, Impact of interference on multi-hop wireless network performance, in: Proceedings of the 9th Annual International Conference on Mobile Computing and Networking, 2003, pp. 66–80.

[42] R.L. Cruz, A.V. Santhanam, Optimal routing, link scheduling and power control in multihop wireless networks, in: IEEE INFOCOM 2003. Twenty-Second Annual Joint Conference of the IEEE Computer and Communications Societies (IEEE Cat. No. 03CH37428), vol. 1, IEEE, 2003, pp. 702–711.

[43] Q. Liao, P. Baracca, D. Lopez-Perez, L.G. Giordano, Resource scheduling for mixed traffic types with scalable TTI in dynamic TDD systems, in: 2016 IEEE Globecom Workshops, GC Wkshps, IEEE, 2016, pp. 1–7.

[44] K.I. Pedersen, M. Niparko, J. Steiner, J. Oszmianski, L. Mudolo, S.R. Khosravirad, System level analysis of dynamic user-centric scheduling for a flexible 5G design, in: 2016 IEEE Global Communications Conference, GLOBECOM, IEEE, 2016, pp. 1–6.

[45] G. Pocovi, B. Soret, K.I. Pedersen, P. Mogensen, MAC layer enhancements for ultra-reliable low-latency communications in cellular networks, in: 2017 IEEE International Conference on Communications Workshops, ICC Workshops, IEEE, 2017, pp. 1005–1010.

[46] M. Findrik, J. Groenbaek, R.L. Olsen, Scheduling data access in smart grid networks utilizing context information, in: 2014 IEEE International Conference on Smart Grid Communications, SmartGridComm, IEEE, 2014, pp. 302–307, http://dx.doi.org/10.1109/smartgridcomm.2014.7007663.

[47] M.S. Kemal, R.L. Olsen, H.-P. Schwefel, Optimized scheduling of smart meter data access for real-time voltage quality monitoring, in: 2018 IEEE International Conference on Communications Workshops, ICC Workshops, 2018, pp. 1–6.

[48] R.L. Olsen, J.T. Madsen, J.G. Rasmussen, H.-P. Schwefel, On the use of information quality in stochastic networked control systems, Comput. Netw. 124 (2017) 157–169.

[49] M. Findrik, T. le Fevre Kristensen, T. Hinterhofer, R.L. Olsen, H.-P. Schwefel, Information-quality based lv-grid-monitoring framework and its application to power-quality control, in: Ad-Hoc, Mobile, and Wireless Networks: 14th International Conference, ADHOC-now 2015, Athens, Greece, June 29–July 1, 2015, Proceedings 14, Springer, 2015, pp. 317–329.

[50] R.L. Olsen, H.-P. Schwefel, M.B. Hansen, Quantitative Analysis of Access Strategies to Remote Information in Network Services, IEEE Globecom 2006, 2006, pp. 1–6.

[51] R.L. Olsen, H.-P. Schwefel, M.B. Hansen, Qrp01-5: Quantitative analysis of access strategies to remote information in network services, in: IEEE Globecom 2006, IEEE, 2006, pp. 1–6.

[52] M.L. Jakobsen, J.G. Rasmussen, R.L. Olsen, Online estimation of context dynamics and its impact on context sensitive applications, in: 2009 1st International Conference on Wireless Communication, Vehicular Technology, Information Theory and Aerospace & Electronic Systems Technology, IEEE, 2009, pp. 921–925.