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Coupled Q-Learning-Based Routing Reconstruction Method for Collaborative Operation of Transmission Network and Data Network

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ABSTRACT

As power systems evolve, diverse power services increase bandwidth demands, posing challenges like variable transmission loads and slow data transfer. Routing reconstruction dynamically adjusts paths, balances loads, and reduces delays, ensuring reliable power service data. However, current technologies lack global state awareness, integrated risk-delay optimization, and efficient algorithms. This paper introduces a unified model and risk evaluation framework for both data and power transmission networks. Considering the enduring operational demands of the transmission network, a joint minimization strategy is devised which focuses on minimizing both transmission delays and risks. Furthermore, a coupled Q-learning methodology for collaborative network operation is introduced, which sets routing priorities and resolves differences via cost to enhance routing results. Simulations validate that the proposed methodology drastically decreases transmission risks and delays.

KEYWORDS

Auction-Based Matching, Dual Network Coupling, Routing Decision, Transmission Risk

INTRODUCTION

Rapid advancement in energy systems demands seamless synchronization of providers, networks, demands, storage solutions, and auxiliary resources, which is essential to boost sustainable energy adoption (Li & Wang, 2021). In this scenario, numerous emerging electrical services rely heavily on the transmission network for data transactions. Service demands heighten balancing challenges, raising network vulnerability (Atat et al., 2023; X. Liu et al., 2017). Moreover, data networks depend on transmission systems, risking data disruptions and grid failures (Chen et al., 2023). Hence, ensuring

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resilient synchronization and minimizing risks in data exchanges is crucial for power grid reliability (Zhang et al., 2023).

To accommodate data and service demands, network routing adaptability techniques dynamically streamline pathways, ensuring balanced loads, efficient resource allocation, and reliable power service data transmission (Lohani et al., 2022; Samreen, 2018; Vivarekar et al., 2021). By simplifying routing searches in power-reliant networks, Kong (2020) lowered operational hazards. J. Liu et al. (2022) introduced an ACO-based self-healing strategy, using node delay and packet delivery rates to model routing capability and identify high-performance paths. Tomovic & Radusinovic (2019) aimed at minimizing routing costs and reconstruction overhead with a multi-objective model. Destounis et al. (2018) proposed a software-defined networking-based method for adaptive routing. However, modeling dual-network cooperation is challenging due to network integration and unpredictable fiber outages, often leading to poor convergence and local minima in data-driven optimization.

Reinforcement learning improves decision-making in uncertain environments by balancing exploration and exploitation (Dong et al., 2022; Han et al., 2023; Sun et al., 2022). Utilizing a model-free methodology, Q-learning extracts historical insights and anticipates future returns through a “state-action” valuation function. This capability facilitates adaptive strategy shifts in intricate power communication infrastructures, guiding toward optimal routing and restoration selections (Shuai et al., 2023; Zhou et al., 2023). Ravipudi and Brandt-Pearce (2023) implemented Q-learning to identify link disruptions, boosting service dependability. Su et al. (2023) presented a Q-learning-driven routing technique that selects adjacent sensors by evaluating their state and behavioral data, fostering energy-saving, decentralized data transmission. Additionally, Fu et al. (2020) introduced a deep reinforcement learning method for autonomously generating optimal path plans in software-defined networking-enabled data centers. Nevertheless, despite progress in routing restoration, several obstacles persist:

The synchronization between transmission and data networks is overlooked. Transmission network failures can disrupt data services, but current restoration techniques do not address swift path alternation or recovery (Yuan et al., 2022). Risk modeling for dual networks lacks precision, neglecting synchronized operation and multi-dimensional risks (X. Liu et al., 2019). Additionally, Q-learning algorithms ignore coupled risks during routing conflicts, lacking a penalty function to quantify these conflicts, thus hindering optimal routing strategy reconstruction.

Addressing the aforementioned challenges, this research introduces a coupled Q-learning-based routing reconstruction algorithm (CQ-R^2). We first create a coupled model that integrates both networks and their risk frameworks. Prioritizing long-term transmission network functionality, we set an optimization goal to minimize transmission delays and risks in electric power data. Furthermore, we propose an enhanced coupled Q-learning algorithm with reinforcement learning and auction-based matching. This not only resolves resource allocation conflicts but also dynamically refines routing plans. Key advancements include the following.

A coordinated framework for transmission and data network operations: An integrated approach is proposed, recognizing the interconnected nature of data and transmission networks. This approach leverages their common traits to apply service risk modeling, thereby improving the efficiency and speed of routing recovery strategies.

Integrated minimization of service transmission risk and delay: Acknowledging the interconnectedness of transmission and data networks, comprehensive risk modeling is conducted across service, transmission, and physical layers. Operational data dynamically adjusts risk weights. The aim is to optimize and minimize transmission delays and risks in electric power service data.

A routing reconstruction technique leveraging coupled Q-learning for integrated transmission and data network operations: Considering router node selection conflicts in interconnected transmission and data networks, this paper frames routing reconstruction as an Markov decision process (MDP) using Q-learning. A penalty function assesses routing conflict severity, iteratively refining Q-values