Supplementary Materials: Hierarchical Data Fusion Method for Link Uncertainty in Multiplex Networked Industrial Chains

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A Related Work

A.1 Related Work on Swarm Intelligence Data Fusion

Swarm intelligence data fusion has emerged as a promising approach to enhance the accuracy and efficiency of data integration in complex systems. By leveraging the collective behavior and interactions of intelligent agents, swarm intelligence techniques aim to optimize the data fusion process and improve decision-making capabilities. Numerous studies have explored the application of swarm intelligence algorithms, such as particle swarm optimization (PSO) [16,20], ant colony optimization (ACO) [4,18], and bee colony optimization (BCO) [1,8], to address various challenges in data fusion, including data heterogeneity, scalability, and real-time processing.

However, existing swarm intelligence data fusion methods often assume reliable communication links between agents and overlook the impact of link uncertainty on the fusion process. In real-world scenarios, especially in adversarial environments, communication links are subject to external interference, malicious attacks, and dynamic changes, leading to incomplete or corrupted data transmission. The inability to effectively handle link uncertainty limits the applicability and robustness of these methods in practical settings. Moreover, most existing approaches focus solely on optimizing data integrity while neglecting other crucial factors, such as load balancing and response time, which are essential for efficient and reliable data fusion in large-scale systems.

To bridge this gap, our research focuses on addressing the link uncertainty problem in swarm intelligence data fusion by proposing a novel bi-level optimization approach. By incorporating link reliability assessment and adaptive optimization strategies, our method aims to enhance the resilience and efficiency of data fusion in the presence of uncertain communication links.

A.2 Related Work on Link Uncertainty

Link uncertainty has been recognized as a critical challenge in various domains, including wireless sensor networks (WSNs) [5,6], multi-agent systems [7,17], and IoT

Table 1: Inefficiency of Previous Algorithms

Existing algorithms	Concepts	Inefficiency
Methods for solving uncertainty problems by pre-storing sub-paths [3,13]	Sub-paths are pre-stored for nodes, and when a link fails, the pre-stored sub-paths are used as the new transmission links.	The approach fails to consider the load conditions between network layers, neglects the integrity of transmitted data, and struggles to cope with the complex and dynamic nature of industrial chains.
Adaptive allocation methods based on information theory [10,19]	Requests are adaptively allocated to agents with high-quality links, avoiding links that are prone to risk interference.	The approach overlooks the load conditions between network layers, which can easily lead to excessive waiting times for requests. Additionally, it struggles to handle the complex and dynamically changing nature of industrial chains.
Rescheduling methods based on a greedy approach [21,9]	For all requests affected by link issues, greedily select appropriate nodes for reallocation.	The approach fails to account for the load conditions between network layers, is prone to becoming trapped in local optima, and neglects the integrity of the transmitted data.

networks [14,12]. Researchers have proposed several techniques to mitigate the impact of link uncertainty on data transmission and system performance. These techniques include robust routing protocols [2], adaptive transmission power control [15,22], and error correction schemes [11].

Nevertheless, the majority of existing link uncertainty solutions focus on the physical and network layers, aiming to improve the reliability of individual communication links. They do not consider the higher-level data fusion process and the collaboration among intelligent agents. In the context of swarm intelligence data fusion, link uncertainty poses unique challenges due to the dynamic interactions and decentralized nature of the system. Traditional link uncertainty approaches fail to capture the complex dependencies and propagation of uncertainty in the fusion process, leading to suboptimal performance and reduced data quality.

Our research addresses this limitation by proposing a holistic approach that integrates link uncertainty modeling and collaborative optimization techniques. By considering the interplay between link reliability and the data fusion process, our method enables intelligent agents to adapt their collaboration strategies dynamically, ensuring reliable and efficient data fusion in the presence of uncertain communication links.

A.3 Inefficiency of Previous Algorithms

Due to the dynamic and complex nature of industrial chains, the transmission links between agents are susceptible to external disturbances, which can compromise the integrity of the transmitted data. As a result, previous algorithms fail to effectively mitigate the impact of uncertainties or are not applicable to this scenario. This subsection reviews the inefficiencies of several state-of-the-art and classic algorithms, with the details presented in Table 1.

B Detailed Procedure of the LUBDF Algorithm

Combining the GEP-based inter-layer coordination strategy optimization and intra-layer coordination strategy optimization, the link sequence improvement problem under link uncertainty scenarios can be represented by Algorithm 1.

Algorithm 1: Link Uncertainty Based Data Fusion Algorithm

Input: Set of tasks $\mathcal{T}$, network layer $\mathcal{N}$, agents $\mathcal{A}$
Output: Optimization Objective value $-\alpha \cdot \mathcal{C}(\pi) + \beta \cdot \mathcal{E}(\pi)$
`// perform GEP-based inter-layer data fusion optimization algorithm`
$\langle \pi, \mathcal{C}, \mathcal{E} \rangle \leftarrow$ GBDF($\mathcal{N}, \mathcal{T}$);
`// traverse each network layer`
for $\forall N^{[m]} \in \mathcal{N}$ **do**
  MaxHeap $H^{[m]} \leftarrow \emptyset$;
  for $\forall a_i \in N^{[m]}$ **do**
    Add tasks performed by a_i to $H^{[m]}$;
    `// perform Pareto-GEP-based intra-layer data fusion optimization algorithm`
    $\langle \pi, \mathcal{C}, \mathcal{E} \rangle \leftarrow$ PGBDF($N^{[m]}, H^{[m]}$);
return $-\alpha \cdot \mathcal{C}(\pi) + \beta \cdot \mathcal{E}(\pi)$

The LUBDF algorithm first performs GEP-based inter-layer coordination strategy optimization for different network layers, reallocating requests with significant link issues to suitable network layers. Then, it traverses the requests on the agents within each network layer. If the cumulative error of a request exceeds a certain threshold, it is added to the reallocation set of the corresponding network layer, and Pareto-GEP-based intra-layer coordination strategy optimization is performed for each network layer. Finally, the corresponding objective function values are calculated based on the actually selected coordination strategies.

The LUBDF algorithm mainly employs the gene expression programming algorithm, combined with actual scenario requirements and optimization objectives, to mitigate the impact of uncertainty factors on swarm intelligence data fusion. Moreover, considering the significant difference between the number of agents and the number of network layers, the algorithm is optimized within each network layer to make the final solution closer to the global optimum. The specific algorithm process is shown as follows.

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