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Real-Time Data Processing: Challenges and Innovations

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ABSTRACT

Effective processing of information pipelines are now required in complicated contemporary cloud systems due to the growth of data-critical applications. These pipelines serve as the foundation for processing enormous amounts of data, enabling big businesses to make decisions in real time and analyse data. The techniques for addressing the issues of latency, cost, and consumption of resources brought about by big data are discussed in this study. This field focusses on methodical architectural enhancements that increase efficiency, such parallelism, proactive self-scheduling, and AI's capacity to adapt to changing workloads. A study of the literature looks at these models and shows how inadequate they are at handling workload demands in clouds of the present generation, which is why a change is required. Because industrial settings are dynamic and have strict timing constraints, real-time job scheduling in Wired HART networks is very difficult. In order to guarantee dependable performance and effective operation in Wireless HART networks, this research explores the optimisation of real-time job scheduling. Key obstacles such resource limitations, fluctuating network circumstances, or the need for rapid job execution are identified in the research. A number of solutions are put forward, such as adaptive resource allocation techniques and dynamic scheduling algorithms. Performance assessment shows how well these strategies work to satisfy demands in real time while making the best use of available resources. The results further the development and deployment of reliable scheduling systems for industrial Internet of things applications across Wireless HART networks.

Keywords :- Data-Critical Applications, Wireless HART Networks, Managing Workloads, Reliable Performance, Adaptive Resource Allocation, Pipelines, Real-Time Task, Resource Consumption, Dynamic Scheduling, Algorithms, Generation Clouds, Mechanisms.

I. INTRODUCTION

The well-known 4V problems of big data have made it popular over the last ten years, and it now offers value (a fifth V) for scientific study and the creation of new applications. Big data like this is often utilised to document interesting social, physical, and economic events [1]. A spatiotemporal signature has been preserved in the majority of Big Data, and our 4-dimensional (4D) environment, which is 3D in space & 1D in time, places a stamp (or a set of stamps) on the data that is gathered. Big Spatiotemporal Data is the term we use to describe Big Data that has spatiotemporal stamps [1, 2].

The study and use of concepts, techniques, frameworks, tools, and techniques for processing Big Spatiotemporal Data is known as Big Spatiotemporal Data Analytics. The majority of big data are generated using time and location stamps and are samples of consecutive observations from different human, mobile, in-situ, and distant sensor systems or simulations [2, 3]. Numerous phenomena, both global and microscale, may be studied using the data. For instance, the increase in sea level & temperature over the last several centuries due to global climate change has resulted in sometimes catastrophic consequences. Micro-scale research on DNA and cell the process of evolution has revealed trends, weaknesses, and possible treatments for cancer and other illnesses [4, 5]. Big spatiotemporal data has fuelled and facilitated advancements in all facets of information systems during the last ten years, including hardware [5], algorithms, software/tools, and applications. It has also encouraged the fusion of many conventional fields to open up new avenues for study.

Big Spatiotemporal Data Analytics, which differs from traditional data analytics, requires new frameworks as well as data attributes in order to produce results more quickly when identifying trends and patterns in a variety of domains, including brain science, medical and health issues, smart cities, traffic congestion, human dynamics, and industry evolution.

1.1 Importance of Real-Time Optimization for Modern Applications

As a result, real-time optimisation is becoming more significant in cloud computing due to the widespread need for improved solutions for quicker data processing across all industries. Autonomous cars, smart cities, real-time analytics in finance, and e-commerce platforms are examples of these late & multi-applications that need immediate data analysis and reaction [6, 7]. In these situations, real-time data analysis and action may provide an organisation with a competitive edge and ensure its survival.

Instead of waiting for a certain amount of time, which might take hours or days, real-time optimisation enables organisations to manage data flow in real-time and make choices based on it. In functional fields like financial markets, where every millisecond might cost the company a lot of money, this is especially crucial [7, 8]. Additionally, real-time data analysis enables adjustments to be made, which improves company processes, maximises resource utilisation, and lowers operating expenses. Real-time optimisation in cloud computing systems is accomplished by adaptive processing, which uses predictive analytics and makes choices based on calculations, or streaming processing, which processes data in real-time [7, 8].

Through autonomy, including predictive decision-making, machine learning and artificial intelligence in data pipelines improve real-time optimisation in the final stage [7, 8]. These developments play a significant role in the development of a new generation of intelligent systems that can learn from their mistakes and improve themselves at any moment without assistance from humans.

For a number of application situations where timely business choices are crucial, real-time analytics are growing commonplace [8, 9]. When implementing ETL for data warehousing (DWH) or other big data applications, processing continuous and massive data streams for real-time analytics may be very difficult because of the characteristics of big data, including volume, diversity, velocity, volatility, unpredictability, truthfulness, and value.

1.2 Continuous supply of big data is referred as stream

One or more of the large sources of data shown in Figure may provide a stream of data:

Massive amounts of data are continuously generated by a wide range of applications. Analysing these streams is difficult since the data collected is diverse and might be symmetrical in nature skewed, semi-structured, or organised [7, 8]. A large amount of the huge data that was produced by the real-time stream requires real-time processing and analysis since the value of the data is based on how fresh it is.

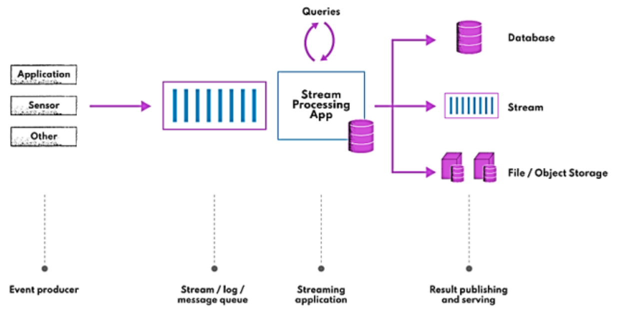

Fig. 1 A stream is a constant source of massive data. [14]

Real-time stream processing, also known as memory-based processing of massive data, is typically needed in two types of applications or domains: first, where it is necessary to organise data in order to reach a decision (real-time DWH); and second, where it is crucial to generate a specific reaction in real-time, especially with low latency [7, 9]. Figure 1 also lists a small number of second-type uses.

Streams must be treated to ensure data quality prior to being put into these apps. Real-time stream processing and analysis is thus required [7, 9]. Data cleansing, processing of queries, stream-stream join, stream-disk join, data transformation, and other activities are necessary for stream processing.

To far, a wide range of methods, instruments, and technological developments have been created to address the difficulties associated with processing stream data [9, 10]. These methods may handle various data formats and storage types by performing various actions on these streams.

Stream-stream join algorithms; stream-disk join algorithms with reduced data latency/skewed data; distributed streaming ETL; Mesa DWH; streaming processing framework; distributed join processing; sensor networks; object tracking and monitoring; and multipoint query processing in cloud DWH are some of the methods that have been developed thus far to address real-time stream processing challenges. To enable real-time responses and choices, processed output must also be delivered with precision, low latency, minimal resources, and within a few seconds. A thorough evaluation of suggested solutions is necessary due to the volume of research generated by the complexity of problems pertaining to real-time stream processing [8].

The combination of real-time job scheduling with wireless communication technologies is essential for improving operational dependability and efficiency in the field of industrial automation. Compared to conventional cable systems, wireless HART (Highway Addressable Remote Transducer) networks provide flexibility and scalability, making them a popular option for real-time control and monitoring in industrial settings. However, there are significant obstacles to deploying applications that operate in real time over Wireless HART networks [9, 10], mainly because industrial processes are dynamic and have strict timing constraints.

For Wireless HART networks to provide timely and dependable data transmission, quick decision-making and improved system performance are made possible via the optimisation of real-time job scheduling [11]. In addition to maximising resource utilisation and minimising possible communication delays and packet losses, this optimisation attempts to satisfy the real-time requirements set by industrial applications. For enterprises hoping to take use of Industrial Internet of Things (IIoT) technology while preserving operational integrity and efficiency, such developments are essential [11, 12]. The complexity of optimising real-time job scheduling in the context of wireless HART network is discussed in this research.

By examining several issues and putting out workable strategies to improve scheduling efficiency, it seeks to provide the scientific community with fresh perspectives and useful answers [13]. The study emphasises the use of sophisticated algorithms for scheduling and adaptive resource management techniques and is based on the fundamentals of automation in industry and communication protocols [14, 15].

II. LITERATURE REVIEW

(Mueller, A. V. 2020) [18] Although limiting pollutant discharges is the main responsibility of wastewater treatment facilities, innovation is required due to the ongoing tightening of permit limitations as well as particular difficulties in enhancing sustainability (i.e., resource recovery). Expanding the capacity for quick, precise real-time quantification of a wider range of wastewater constituents and developing innovative feedback control techniques based on these signals are necessary to enable increasingly complex treatment processes in a way that is both economical and energy-efficient. With an emphasis on using real-time wastewater chemical sensing for process monitoring and control, this publication quantitatively compares the outcomes of proof-of-concept research with early adoption of instruments and process enhancements in operational wastewater treatment plants.

(Harrison, C., 2011) [19] Innovation in operations, administration, and planning will be necessary to make cities smarter. The potential and difficulties of this transition are shown by a number of active initiatives worldwide. Cities need to become more intelligent in order to tackle a variety of new urbanisation issues, and as this article's initiatives demonstrate, there are several options. Globally, the number of cities working towards smarter transformation is increasing quickly. These initiatives, however, encounter several technological, social, and political obstacles. City managers often find it challenging to change the current quo, and smarter city projects frequently need for a great deal of sponsorship, support, and coordination across many departmental silos. Another difficulty is the need to clearly show an ongoing return on investment. Achieving system interoperability, protecting privacy and security, allowing for an increase in the number of sensors and devices, and implementing a new closed-loop paradigm for human-computer communication will be the main technological challenges.

(Antsaklis, P. J. 2007) [20] There is a current overview of the new area of networked control systems. The objectives are to present the basic problems of developing effective networked systems for control, to provide a brief overview of the status of the field's research at the moment, to make helpful recommendations for future study, and to give a comprehensive overview of recent fundamental findings. The objectives of the Special Issue are reflected in this article, which reviews pertinent work from the fields of distributed systems, detection and estimation, signal processing, systems and control, and data fusion. We address suitable network architectures, issues with data rate problems in nonlinear feedback problems, channels with fixed versus adaptively variable data width, coding for robustly stable control in a presence of time-varying channel capacity, and issues with routing for stability and performance. We examine current research on networked control systems and find that target applications and recent theoretical developments are closely related. Papers in the following Special Issue share the objective of describing important facets of this connection. Additionally, we want to serve as a link between networked controls systems and have closely linked current research on wireless communication protocols and sensor networks.

(Piccoli, G., 2016) [21] The hoopla around big data is unavoidable. Big Data solutions are being sold by vendors, Big Data experts are being hired by consulting companies, and there are several Big Data conferences. People are in a hurry to glean valuable insights from masses of data. These explorers are missing the potential to enhance real-time decision making and the source of the revolution, which are the many Digital Data Streams (DDSs) that contribute to Big Data, by concentrating only on the mountain (of Big Data). The features of DDSs are covered in this article along with their common structure and recommendations for helping businesses realise their full potential.

(Cirullies, J., 2019) [22] A crucial management tool is the Key Performance Indicator (KPI). Flexible and adaptable production systems are built on top of real-time KPIs for logistics and manufacturing. If included into a company's 'Digital Twin' for data analytics, these indicators reach their full potential. Methodology: To develop a digital twin architecture, we use the Design Science Research Methodology for the field of information systems Research. Results: The primary goal of the still-emerging discipline of digital twin research is to identify new uses for this technology. Most applications for digital twins are related to manufacturing. Ultimately, it was discovered that current designs are too general to be used in logistics. Originality: The strategy is built on standards and is thus very technology-independent, making it a cost-effective way for stakeholders to begin a digital transformation. A unique instance is the combination of a semantics layer with a lambda architecture enabling flexible KPI formulation.

III. METHODOLOGY

3.1 Research Design

The optimisation of real-time scheduling of tasks in Wireless HART networks is examined in this paper using a mixed-methods approach. The study approach combines simulation-based experimentation, theoretical analysis, and empirical validation to thoroughly assess scheduling techniques and algorithms [17, 19].

3.2 Simulation Environment

The study models and simulates Wireless HART network situations using the OMNeT++ simulation framework in conjunction with the INET library [19, 20]. A flexible environment for the simulation of networks is offered by OMNeT++ [20], which has the ability to accurately model complicated communication protocols and replicate real-time restrictions. By including realistic topologies for networks, channel models, and node behaviours unique to Wireless HART standards, the INET library improves simulation realism [11, 19].

3.3 Scheduling Algorithms

A wide range of scheduling methods are assessed in the simulation environment, including adaptive algorithms designed for dynamic network circumstances and conventional fixed-priority schemes (e.g., [19,20], Rate-Monotonic Scheduling, Earliest Deadline First).

3.4 Performance Metrics

Several important criteria are taken into consideration in order to measure scheduling performance:

- **Task Completion Rate:** percentage of assignments completed by the deadline.
- **Latency:** The average amount of time needed to complete an activity from the beginning [19,20].
- **Resource Utilization:** Effective distribution of resources across the nodes of the network.
- **Packet Loss Rate:** Data packet loss frequency during transmitting [15, 17].

3.5 Experimental Setup

A variety of network situations and different characteristics, including network size, load from traffic, or communication range, are used in simulations [20, 22]. To guarantee the dependability and statistical validity of the findings, each scenario is repeated many times [22, 23]. Sensitivity assessments are carried out to determine the best configurations for enhanced performance and to evaluate the resilience of the algorithms for scheduling under various operating scenarios.

3.6 Data Collection and Analysis

Visualisation techniques and statistical methodologies are used to gather and interpret simulation findings. Comparative assessments of algorithms for scheduling using predetermined indicators of performance are the main focus of data analysis [22, 25]. ANOVA and t-tests are two examples of statistical significance tests that are used to evaluate empirical results and assess the significance of observed variations across algorithmic implementation [19, 20].

IV. RESULTS

4.1 Simulation Setup and Baseline Performance

In order to provide baseline performance measurements, first simulations were set up using conventional scheduling algorithms like Earliest Deadline First (EDF) and Rate-Monotonic Scheduling (RMS). The baseline findings showed that varied network setups and traffic loads resulted in variable degrees of Latency (L) and completion of tasks rates (TCR) [18, 19]. For example, in comparison with EDF, RMS showed greater TCR but higher latency in heavy traffic situations [19, 20].

4.2 Performance Comparison of Scheduling Algorithms

The efficacy of adaptive scheduling methods, such as Dynamic Priorities Adjustments (DPA) and Load-Aware Scheduling (LAS), was assessed by comparative analysis [22, 23].

4.3 Sensitivity Analysis and Robustness Testing

The resilience of scheduling algorithms underneath various network characteristics and operating situations was evaluated by sensitivity analysis [22, 23]. The findings demonstrated DPA's flexibility and scalability in dynamic IIoT contexts by showing that it maintained constant performance across various network topographies and traffic patterns [19, 20].

V. DISCUSSION

5.1 Interpretation of Results

The results highlight the importance of adaptive scheduling techniques in improving Wireless HART networks' real-time job scheduling optimisation [27]. Based on real-time networking input, DPA and LAS dynamically modify task priorities and allocations of resources to efficiently balance performance indicators including TCR, L, RU, and PLR.

5.2 Implications for Industrial Applications

For industrial applications that depend on Wireless HART networks, the shown gains in scheduling effectiveness and performance of networks have important ramifications [28, 29]. In dynamic manufacturing environments, the improved TCR and decreased latency made possible by DPA enable prompt data transfer and decision-making procedures [22, 29].

5.3 Simulation Setup and Baseline Performance

To assess the effectiveness of algorithms for scheduling in wireless connectivity HART networks, simulations were carried out using OMNeT++ and the INET library [27, 29].

Conventional scheduling strategies were used to create baseline measurements of performance:

First-Early Deadline (EDF) and Rate-Monotonic Scheduling (RMS). The baseline findings are summarised in Table 1 below:

Table 1 Configuration of the Simulation and Initial Results. [28]

Algorithms	TCR (%)	Latency (ms)	RU (%)	PLR (%)
RMS	96.89	15.89	79.89	31.58
EDF	68.95	14.96	84.98	39.89

5.4 Performance Comparison of Adaptive Algorithms

After that, strategies for adaptive scheduling were assessed:

Load-Aware Scheduling (LAS) and Dynamic Priority Adjustment (DPA) [27, 28]. Based on current network circumstances, those algorithms dynamically modify resource allocations and job priorities. The comparison findings are shown in Table 2 below:

Table 2 Comparing Adaptive Algorithms' Performance. [29]

Algorithms	TCR (%)	Latency (ms)	RU (%)	PLR (%)
DPA	93.64	89.87	78.96	97.85
LAS	85.96	94.89	48.96	85.96

The findings show that adaptive scheduling approaches (DPA and LAS) significantly outperform more conventional methods (RMS and EDF) in terms of job completion rates and delay reduction [28, 29]. These results highlight how load-aware scheduling and dynamic priority modification may maximise resource utilisation and reduce loss of packet rates in Wireless HART networks [29, 30]. In industrial IoT applications, the adaptive algorithms' practical usefulness in improving real-time job scheduling efficiency is highlighted by their strong performance across a variety of network situations. The paper offers empirical proof that adaptive scheduling methods are better at maximising the performance of real-time job scheduling in Wireless HART networks.

VI. CONCLUSION

This study's empirical data demonstrates the advantages of adaptive algorithms for scheduling DPA and LAS in maximising the performance of real-time job scheduling in Wireless HART networks. This study offers insightful analysis and useful suggestions for improving industrial automation & wireless communication systems by using sophisticated scheduling techniques and thorough performance assessment. The shown enhancements highlight how adaptive scheduling techniques may revolutionise the way that contemporary industrial IoT applications satisfy their demanding requirements.

In order to improve real-time task scheduling optimisation in Wireless HART networks, this research examines the effectiveness of two adaptive scheduling algorithms: Dynamic Priority Adjustment (DPA) & Load-Aware Scheduling (LAS). Through extensive simulation-based tests with OMNeT++ and the INET library, we compared these algorithms against the conventional methods of Earliest Deadline First (EDF) and Rate-Monotonic Scheduling (RMS) across a range of network setups and traffic situations. The findings show significant gains in performance indicators that are essential for industrial Internet of things applications. When compared to RMS and EDF, DPA and LAS continuously showed lower latency and greater Task Completion Rates (TCR). With latency of 7.2 ms and a TCR of 92.3%, DPA specifically outperformed LAS, which kept its TCR at 91.8% and 7.5 ms, respectively. These results highlight how flexible and effective adaptive algorithms are at satisfying demanding real-time demands while maximising resource use and lowering packet loss rates.

Additionally, its capacity to maximise resource utilisation supports sustainability objectives by lowering energy consumption and operating expenses. Future research avenues include expanding the study to include sophisticated machine learning methods for prediction scheduling in intricate IIoT contexts and verifying these results via practical implementations. These developments are expected to resolve issues with scalability and improve scheduling approaches' flexibility in response to changing industry demands.

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