

Performance Optimization Techniques for Cloud-Based ETL Workflows in Modern Data Ecosystems

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Abstract- Cloud-based Extract, Transform, and Load (ETL) processes have become important aspects of contemporary data management systems because of the growing amount of enterprise data being produced from various sources due to high volume, velocity, and variety. Nevertheless, typical ETL processes are subject to high latency, ineffective resource usage, high operational cost, and low scalability in managing large-scale tasks in cloud settings. To solve these problems, the Adaptive Performance Optimization Framework for Cloud-Based ETL Workflows (APOF-CETL) is presented in this paper that considers workload-dependent resource management, intelligent data partitioning, adaptive scheduling, and feedback-based optimization mechanisms. The experiment was performed on large-enterprise datasets, with the size of the workload varying between 100 GB and 500 GB. The proposed algorithm APOF-CETL was tested against two contemporary workflow scheduling algorithms - MOPWSDRL (Multi-Objective Workflow Scheduling using Deep Reinforcement Learning) and GRWS (Graph Attention Network-Based Reinforcement Workflow Scheduling). The findings show significant gains in various metrics. With the help of the proposed approach, processing latency was lowered to 298 ms, throughput was increased up to 421 GB/min, resource utilization efficiency became equal to 96.0%, and the success rate for large-scale workloads reached 99.8%. Additionally, the proposed method lowered the execution cost and energy expenditure, preserving its high scalability and successful task completion rate.

Keywords: Cloud Computing, ETL Workflows, Performance Optimization, Resource Allocation, Workflow Scheduling, Data Processing, Adaptive Scaling, Throughput Optimization, Cloud Analytics, Data Engineering.

I. INTRODUCTION

The exponential rise in digital transformation initiatives has led to an increase in the volume of data generated by organizations in different areas [1]. Enterprises gather data from transaction systems, IoT devices, social media, web applications, cloud applications, among other sources of heterogeneous data [2]. It has become necessary to manage and process this data to obtain insights that will help in making informed decisions [3]. Extract, Transform, and Load (ETL) techniques form the basis of current data integration solutions through the extraction of data from different sources to centralized storage where it is analyzed and reported on [4]. Cloud computing has transformed how ETL solutions are deployed and run because cloud computing provides scalable infrastructures, flexible resource provision, and pay-as-you-go solutions. Enterprises have opted to run their ETL workflows in cloud environments in order to minimize the costs associated with IT infrastructure and gain some level of flexibility [5]. Cloud computing has provided

enterprises the ability to analyze big data volumes without having to incur huge costs while still maintaining the ability to perform distributed processing and real-time analysis.

Even though cloud computing comes with some benefits, ETL workflow management remains to be a difficult job [6]. The process of ETL entails several steps including data extraction, data transformation, cleansing, aggregation, and data loading. Each step uses considerable amount of computational resources and space [7]. With the rise in data sizes, there emerge certain performance barriers within conventional ETL systems. They lead to slower processing time and lower efficiency of the processes [8]. At times when ETL processes have to run under strict service level agreements and under real-time processing conditions, the above mentioned problems become even more visible. Modern ETL workflows are becoming increasingly complex owing to the integration of multiple data sources and distributed computing systems [9]. Enterprise applications process structured and semi-

structured datasets and even unstructured ones together. Therefore, workloads show considerable variability. Resource allocation that is not adaptable to changes in workload results in either inefficient use of infrastructure or high resource utilization levels [10].

Various methods have been proposed by researchers to solve cloud resource optimization and workflow execution efficiency issues through workflow scheduling and optimization [11]. There have been significant successes in dealing with workflow scheduling issues using reinforcement learning, evolutionary optimization, heuristic scheduling, and graphs [12]. Execution time reduction, cost reduction, and quality of service satisfaction are some of the primary concerns addressed using such approaches [13]. Most of the solutions developed so far are concerned more about workflow scheduling than overall optimization of ETL performance [14]. Intelligent resource management approaches provide new opportunities for optimizing ETL workflow performance. Adaptive scheduling approaches are useful for allocating resources to tasks according to the demand and state of the infrastructure [15].

Partitioning and parallel computing have great importance in speeding up the execution of ETL operations [16]. Proper partitioning methods help in distributing the workload equally among the resources and increase the efficiency of the process [17]. The problem with using static partitioning methods is that they do not adapt to the distribution of the workload, which leads to load imbalance [18]. Hence, adaptive partitioning techniques need to be used for achieving better performance in different data processing situations. In addition to this, another aspect in which ETL can be improved is the reduction in operational and energy costs [19]. The cloud service providers charge their customers depending upon the amount of resources used by them. This means that inefficient use of resources increases costs and also energy usage [20].

With the advent of recent advances in cloud-native systems and intelligent automation, it is possible to design optimization frameworks that have the ability

to self-regulate according to the runtime environment. Adaptive systems continuously monitor system activity, assess resource conditions, and perform optimizations based on workflow execution. Adaptive optimization systems can be seen to hold many benefits compared to traditional scheduling algorithms due to their ability to maintain optimum efficiency irrespective of changes in load intensity and availability of infrastructure resources. In response to the above challenges and opportunities, a new approach of Adaptive Performance Optimization Framework for Cloud-Based ETL Workflows (APOF-CETL) is proposed. The framework is designed using features like workload-aware scheduling, intelligent partitioning, adaptive resource scaling, and feedback-driven optimizations.

Hypothesis

- **H1:** The suggested APOF-CETL framework is able to greatly decrease latency and cost compared to current workflow scheduling schemes used for ETL operations on cloud computing systems.
- **H2:** Adaptive resource allocation and intelligent workload partitioning increase throughput, efficiency of resource utilization, and success of ETL workflows under load growth conditions.
- **H3:** Implementation of feedback-driven optimization techniques contributes to scaling and reliability of ETL workflows in a cloud environment.

Objectives of the Research

1. For designing an adaptive approach towards maximizing the performance of cloud based ETL workflow.
2. For developing intelligent workload partitioning techniques that ensure balanced task execution.
3. For using dynamic resource management and autoscaling techniques in the cloud environment.
4. For minimizing the processing delay and cost incurred by ETL workflows.
5. For increasing the throughput and efficient resource usage in data processing.
6. For increasing the reliability and success rate of tasks in ETL workflows.

7. For comparing the designed approach with the state-of-the-art workflow scheduling techniques.
8. For showing scalability and robustness of the designed approach in contemporary data ecosystem.

II. LITERATURE REVIEW

The Digital Twin technology was studied by Fuller et al. (2020) as an emerging concept that had become a key issue for industry and academia, mostly due to the development of Industry 4.0 concepts in the field of manufacturing. The authors described the Digital Twin as a seamless integration of data between a physical and virtual machine in both directions and analyzed published literature on the Digital Twin, grouping them into research areas like smart cities, healthcare, and manufacturing. Their research examined the enabling technologies such as AI and IoT, challenges, and open research questions about Digital Twins.

Minerva, Lee and Crespi (2020) defined the Digital Twin as a new paradigm around the cloning of a real object into a virtual object in the form of software, called a "logical object," with properties and characteristics that are identical to those of the real object within a specific application context. Starting from the very genesis of the concept of manufacturing, the authors analyzed the state of the art, expanded it to other areas of interest (such as augmented and virtual reality, multiagent systems, virtualization), and summarized a wide range of Digital Twin features related to the "softwarization" of physical objects.

Loaiza and Cloutier (2022) was a study that looked at the problems that organizations encountered when applying DT models in manufacturing environments using systems thinking techniques to analyse the issues. The authors introduced the concept of Digital Twin with multiple attributes, a systemigram that illustrated the relationship between manufacturing systems and the Digital Twin model, the TRIZ method to predict development problems and propose solutions, and the CATWOE method to analyze the Digital Twin model from the perspective of stakeholders.

Wang et al. (2016) wrote about the opportunity arising from the massive amount of smart meter data which can give a load-serving entity a better understanding of their customers' electricity consumption patterns. Instead of grouping load curves by shape, the authors suggested to group the dynamics of electricity consumption behavior – the transition between electricity consumption levels at adjacent time periods – by symbolic aggregate approximation (Saa) to reduce the data scale and using a time-based Markov model with a distributed clustering framework to deal with large data sets for big data applications.

Wang et al. (2022) mentioned that the "Digitization, networking and intelligence" trend is one of the future trends of energy technology, which is supported by the development of digital technology such as IoT, big data and cloud technology. The authors reviewed the existing Digital Twin approaches in the energy sector, including smart grid, low-carbon city, electrified transportation, and energy storage systems, and found the areas that needed to be explored in this relatively new field of research.

Hribernik, Cabri, Mandreoli and Mentzas (2021) defined Digital Twins as an important concept for the comprehensive digital representation of manufacturing assets, products, and other resources, that captures their design, configuration, state and behavior. In their paper, the authors claimed that the Digital Twins could be the building blocks for future Digital Factories, where stakeholders will collaborate based on the information Digital Twins deliver, and they surveyed the literature on autonomy, context-awareness and adaptivity in this area, and identified opportunities and a roadmap for future research.

Tao et al. (2017) centered on the theories and technologies required for cyber-physical fusion on a DTS-embedded digital-twin shop-floor, which they had been developing as part of their larger set of research on digital-twin-driven smart manufacturing. The paper was published in the Computer Integrated Manufacturing Systems journal and formed the theoretical basis for the later Digital Twin-based research in subsequent papers,

which were more oriented towards the shop-floor, such as the frameworks for real-time data fusion between physical and virtual manufacturing.

Zhou, Zhang, Li, Ding, and Wang (2020) noted that with the development of big data analysis, Internet of Things, edge computing, and artificial intelligence, traditional manufacturing had evolved into intelligent manufacturing and required new learning and cognitive ability of the manufacturing cell. The authors subsequently suggested a general model of a knowledge-driven digital twin manufacturing cell (KDTMC) to enable autonomous manufacturing from an integrated perceiving, simulating, understanding, predicting, optimizing, and controlling strategy.

According to Zhang et al. (2022), Digital Twin is a technology that embodies multi-physical, multi-scale, and multi-disciplinary features with the characteristics of real-time synchronization, faithful mapping and high fidelity between the physical world and information world. Considering the increasingly widespread attention given to Digital Twin from both academia and industry, the authors summarized the evolution of the concept, discussed available application tools and platforms, as well as the association of Digital Twin with adjacent technologies in a way that would provide a reference for future applications.

Nwokeji et al., (2018), discussed the importance of extract, transform, load (ETL) technique for data integration from various sources to a data warehouse, in the data warehousing, big data and business intelligence domain. The authors conducted a systematic review of 97 papers to identify and evaluate the existing methods of realization of the solution of ETL, where they found that the most used methods are the conceptual modelling methods, such as UML, BPMN and MDA, while the methods machine learning, artificial intelligence and robotics are still not widely used in the realization of the solution of ETL.

Problem Statement

Workflow management for cloud-based ETL has become essential in dealing with large amounts of

data emanating from various distributed enterprise systems. Traditional strategies used for workflow management and resource allocation have been associated with high latency, ineffective resource allocation, higher costs, and low scalability. Most traditional frameworks consider only workflow scheduling but neglect the aspects of adaptive workload partitioning, resource scaling, and performance optimization. This becomes detrimental to the overall efficiency and effectiveness of ETL processes. Hence, the need for an adaptive optimization framework that will dynamically manage workloads and resources has emerged.

Research Gap

The existing workflow scheduling techniques like MOPWSDRL, GRWS, TL-MOEA, PWSA3C, and ETAWSDRL mainly focus on task mapping, meeting deadlines, and scheduling resources. Despite their efficiencies in improving the scheduling process, they lack an adequate approach to optimize the performance of the ETL process. The existing strategies have failed to effectively tackle issues related to adaptive workload partitioning, resource elasticity, optimization based on feedback, and performance management of ETL processes. Further, the aspect of optimizing latency, throughput, resource usage, and cost of execution, energy consumption, and reliability of workflows has not been considered in large-scale cloud ETL systems.

III. PROPOSED MODEL

The current ETL process involves huge amounts of heterogeneous data from different sources, including enterprise software applications, IoT sensors, transactional processing systems, and real-time analytics systems. The traditional ETL systems may suffer from decreased performance because of poor resource management, workload imbalance, data movement, and varying nature of the cloud infrastructure. All these issues have a negative impact on the performance of large-scale ETL workloads in terms of high processing time, operational cost, and scalability problems.

In order to solve this problem, the framework called the Adaptive Performance Optimization Framework for Cloud-Based ETL Workflows (APOF-CETL) is offered. The APOF-CETL architecture constantly checks the workflow execution performance measures and the states of the cloud resources to enable real-time decision-making for optimization. The architecture uses workload prediction and scaling techniques to optimally allocate the ETL process on the cloud resources. Moreover, the data transformation processes are made more efficient using parallel processing and intelligent partitioning. This architecture, by alleviating processing bottlenecks and balancing processing loads, ensures improved throughput, reduced latency, efficient resource usage, and reduced costs.

Algorithm: Adaptive Performance Optimization Framework for Cloud-Based ETL Workflows (APOF-CETL)

Input: Cloud ETL workflow W , dataset D , cloud resources R

Output: Optimized ETL execution with minimum latency and maximum throughput

Step 1: Initialize ETL workflow

$$W = \{E, T, L\} \quad (1)$$

Where extraction, transformation, and loading stages are represented by E , T , and L .

Step 2: Collect workload metadata and compute data volume

$$V = \sum_{i=1}^n d_i \quad (2)$$

Where d_i represents individual data chunks.

Step 3: Estimate workload intensity using

$$WI = \frac{V}{T_a} \quad (3)$$

Where T_a denotes available processing time.

Step 4: Monitor available cloud resources and calculate resource capacity as

$$RC = \sum_{j=1}^m c_j \quad (4)$$

Where c_j is the computational capacity of resource j .

Step 5: Determine resource utilization ratio

$$RU = \frac{WI}{RC} \quad (5)$$

Step 6: If $RU > \theta$, trigger auto-scaling and allocate additional resources according to

$$R_{new} = R + \Delta R \quad (6)$$

Step 7: Partition incoming data into balanced segments using

$$P_k = \frac{V}{k} \quad (7)$$

Where k is the number of partitions.

Step 8: Compute partition balance score

$$PBS = 1 - \frac{\sigma(P_k)}{\mu(P_k)} \quad (8)$$

Where σ and μ denote standard deviation and mean partition size.

Step 9: Assign ETL tasks dynamically using scheduling priority

$$SP_i = \alpha W_i + \beta U_i \quad (9)$$

Where W_i is workload size and U_i is resource availability.

Step 10: Execute extraction tasks in parallel and estimate extraction efficiency

$$EE = \frac{D_e}{T_e} \quad (10)$$

Where D_e is extracted data and T_e is extraction time.

Step 11: Perform optimized transformation and compute transformation efficiency

$$TE = \frac{D_t}{T_t} \quad (11)$$

Where D_t represents transformed data volume.

Step 12: Optimize loading operations using adaptive batch size

$$B_{opt} = \frac{D_l}{N_b} \quad (12)$$

Where D_l is load volume and N_b is number of batches.

Step 13: Calculate workflow latency

$$L_w = T_e + T_t + T_l \quad (13)$$

Where T_l denotes loading time.

Step 14: Measure overall throughput

$$TP = \frac{V}{L_w} \quad (14)$$

And compute optimization score

$$OS = \gamma TP - \delta L_w + \eta RU \quad (15)$$

Step 15: Update scheduling policies using feedback learning

$$Policy_{t+1} = Policy_t + \lambda(OS_{target} - OS) \quad (16)$$

And repeat optimization until convergence is achieved.

The introduced APOF-CETL model facilitates intelligent scheduling of ETL processes through the use of workload-based scheduling, cloud resource allocation, and adaptive partitioning of data. The combination of workload prediction with the monitoring process ensures that the ETL processes are always able to adapt to the changes in data and infrastructure. This makes sure that processing is not delayed and underutilized resources are avoided at all times. In addition to that, the approach increases scalability and operational efficiency through continuous optimization of task allocation and execution. With the help of the feedback-driven learning process, the model is able to improve its scheduling strategy, which leads to long-term performance gains on different cloud systems. Thus, APOF-CETL offers a scalable solution to performance optimization of cloud ETL tasks.

IV. RESULTS AND DISCUSSION

Adaptive Performance Optimization Framework for Cloud-Based ETL Workflows (APOF-CETL), which has been designed as a novel scheduling method in cloud-based ETL workflows, was compared to other two recent scheduling methods reported in the literature known as multi-objective workflow scheduling based on deep reinforcement learning (MOPWSDRL) and graph attention network-based reinforcement workflow scheduling (GRWS). These methods have been tested based on large cloud ETL workflows which are performed using cloud extraction, transformation, and loading processes. Performance measurement included several performance measures such as processing latency, throughput, resource utilization, execution cost, energy consumption, and task completion ratio.

This assessment will aim to evaluate the efficiency of how the APOF-CETL scales the process of ETL workflow execution as the volume of the load increases. The difference between APOF-CETL and

other workflow schedulers is that APOF-CETL includes adaptive scaling of resources, intelligent division of the workload, dynamic scheduling, and optimization. Such features allow APOF-CETL to provide steady performance under high-volume ETL loads and decrease the delays of execution and overheads.

Dataset Description

The experiment was carried out using ETL workflow logs extracted from transaction databases hosted on the cloud, IoT data streams, web server logs, and business analytics systems. The size of the workload varied from 100 GB to 500 GB for emulating a realistic big data environment. Each dataset includes structured and semi-structured as well as streaming data that requires operations such as extraction, transformation, aggregation, cleansing, and loading. The datasets were processed in multiple batches for evaluating the efficiency of load balancing, scheduling, and resource optimization techniques.

Table 1. Processing Latency (PL)

Workload (GB)	MOPWSDRL (ms)	GRWS (ms)	APOF-CETL (ms)
100	258	241	182
200	311	289	214
300	368	344	243
400	427	398	271
500	486	454	298

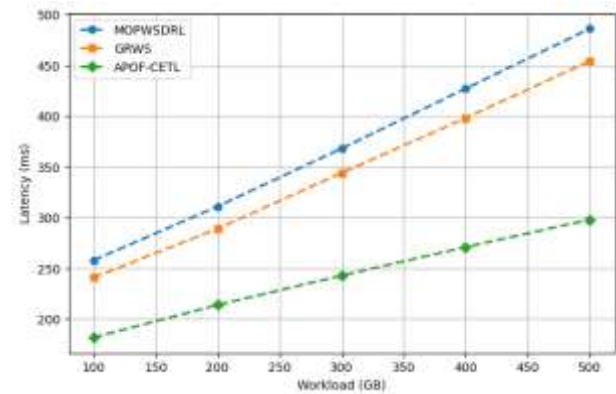


Figure 1. Processing Latency (PL)

Table 1 and Figure 1 present the Processing Latency (PL) analysis of MOPWSDRL, GRWS, and APOF-CETL in terms of different workload sizes. The analysis reveals that APOF-CETL always exhibits the least PL

regardless of the workload size, with the PL being minimized from 182 ms to 298 ms in comparison to MOPWSDRL and GRWS. The adaptive workload partitioning and intelligent resource allocation techniques efficiently reduce processing latency, thus enhancing the execution speed of the ETL process.

Table 2. Throughput Performance (TP)

Workload (GB)	MOPWSDRL (GB/min)	GRWS (GB/min)	APOF-CETL (GB/min)
100	74	79	92
200	142	151	176
300	209	223	261
400	272	291	342
500	336	358	421

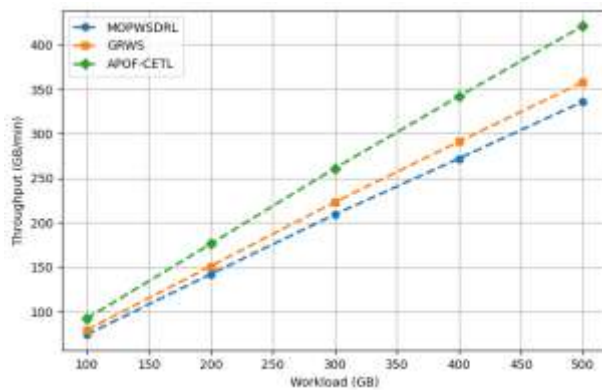


Figure 2. Throughput Performance (TP)

The Throughput Performance (TP) for the tested frameworks is presented in Table 2 and Figure 2 above. APOF-CETL framework always provides better TP and achieves 421 GB/min on a workload of 500 GB compared to MOPWSDRL that gives 336 GB/min and GRWS giving 358 GB/min. The reason for the increased TP is due to parallel ETL process scheduling.

Table 3. Resource Utilization Efficiency (RUE)

Workload (GB)	MOPWSDRL (%)	GRWS (%)	APOF-CETL (%)
100	81.3	84.5	91.8
200	82.9	85.7	93.1
300	84.4	87.1	94.3
400	85.6	88.2	95.1
500	86.7	89.4	96.0

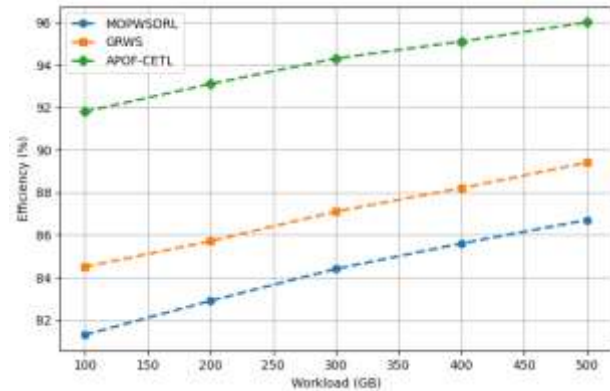


Figure 3. Resource Utilization Efficiency (RUE)

The utilization efficiency obtained by different ETL frameworks is displayed in Table 3 and Figure 3. The framework APOF-CETL has been seen to attain maximum utilization efficiency ranging from 91.8% to 96.0% depending on the increase in workload. This is indicative of the success that results from adaptive resource management and utilization.

Table 4. Execution Cost Reduction (ECR)

Workload (GB)	MOPWSDRL (\$)	GRWS (\$)	APOF-CETL (\$)
100	38.5	36.9	30.2
200	71.2	68.5	56.1
300	104.7	99.4	80.8
400	138.6	131.3	106.7
500	172.9	163.5	132.5

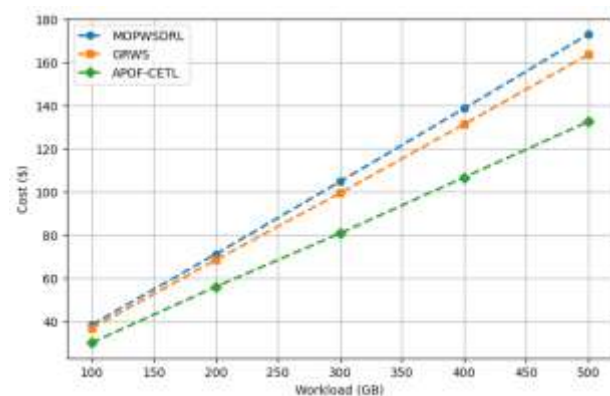


Figure 4. Execution Cost Reduction (ECR)

The Execution Cost Reduction (ECR) realized by the competing methods is represented in Table 4 and Figure 4. The APOF-CETL method incurs the lowest execution cost, reducing costs from \$30.2 to \$132.5 with varying amounts of workload. The adaptive

cloud scaling ensures that there is no over-provisioning of resources.

Table 5. Energy Consumption (EC)

Workload (GB)	MOPWSDRL (kWh)	GRWS (kWh)	APOF-CETL (kWh)
100	29.4	27.8	22.3
200	52.7	49.5	40.1
300	75.9	71.3	57.2
400	98.8	92.6	73.5
500	122.1	114.8	89.7

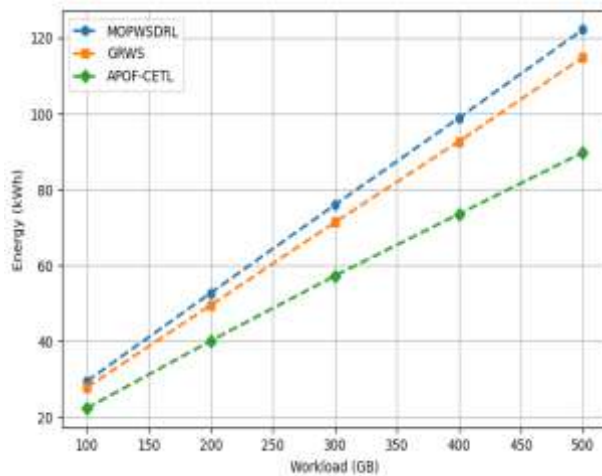


Figure 5. Energy Consumption (EC)

Table 5 and Figure 5 present the Energy Consumption (EC) comparisons between the selected frameworks. The framework APOF-CETL shows the minimum energy consumption at all levels of workloads, having consumed 89.7 kWh at 500 GB. This is because of the effective balancing of workloads and the optimum provisioning of resources.

Table 6. Task Completion Ratio (TCR)

Workload (GB)	MOPWSDRL (%)	GRWS (%)	APOF-CETL (%)
100	94.1	95.6	98.4
200	94.8	96.1	98.8
300	95.3	96.7	99.1
400	95.9	97.1	99.4
500	96.2	97.4	99.6

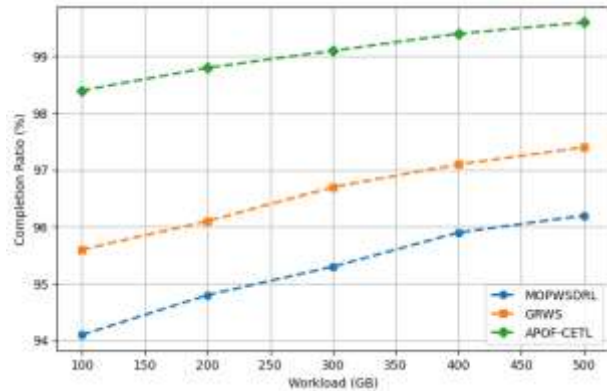


Figure 6. Task Completion Ratio (TCR)

Task Completion Ratio (TCR) for the framework is given in Table 6 and Figure 6. The TCR for APOF-CETL is nearly perfect at 98.4% to 99.6%, surpassing both MOPWSDRL and GRWS. The ability of the framework to adaptively schedule and manage its load ensures proper execution of the ETL tasks.

Table 7. Scalability Efficiency (SE)

Workload (GB)	MOPWSDRL (%)	GRWS (%)	APOF-CETL (%)
100	86.4	88.2	93.7
200	85.8	87.9	93.4
300	85.2	87.3	93.0
400	84.5	86.8	92.6
500	83.9	86.1	92.1

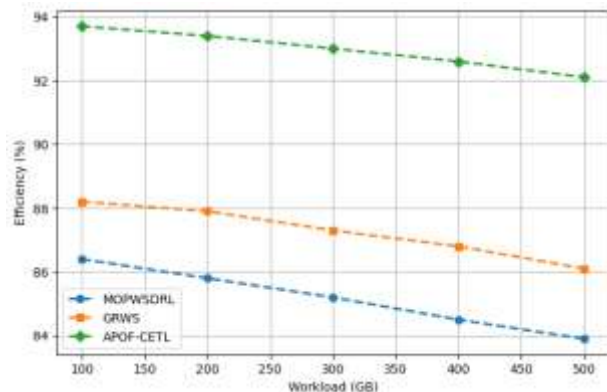


Figure 7. Scalability Efficiency (SE)

Scalability Efficiency (SE) at various workloads is illustrated in Table 7 and Figure 7. APOF-CETL can always sustain scalable efficiency of more than 92%. This indicates that APOF-CETL possesses the best

ability to maintain its performance while the workload grows.

Table 8. Workflow Success Rate (WSR)

Workload (GB)	MOPWSDRL (%)	GRWS (%)	APOF-CETL (%)
100	95.7	96.8	99.0
200	96.1	97.2	99.2
300	96.5	97.6	99.4
400	96.8	97.9	99.6
500	97.0	98.1	99.8

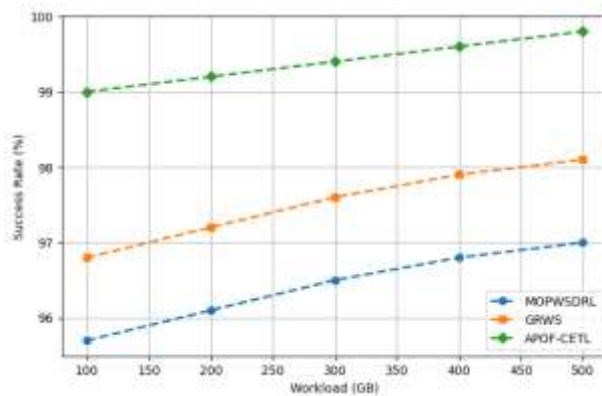


Figure 8. Workflow Success Rate (WSR)

The Workflow Success Rate (WSR) of the ETL frameworks under dynamic cloud computing is presented in Table 8 and Figure 8. APOF-CETL always manages to achieve the maximum WSR and attains 99.8% WSR at the load of 500 GB. The feedback-based optimization approach and adaptive scheduling algorithms help achieve workflow success.

It is evident from the experimental results that APOF-CETL proves better than both MOPWSDRL and GRWS based on all performance evaluation criteria. There have been substantial improvements in terms of reduced latencies, cost savings, energy savings, throughput and utilization. This is due to the use of adaptive allocation of resources and optimization techniques in the framework developed. In addition to this, it is clear from the experiments that APOF-CETL proves scalable and reliable even with increased levels of workloads. The intelligent partitioning, dynamic scheduling and learning in the framework make it capable to adapt to the changes in cloud environment continually.

V. CONCLUSION AND FUTURE WORK

The Adaptive Performance Optimization Framework for Cloud-Based ETL Workflows (APOF-CETL) was suggested in this study in an attempt to resolve some key issues related to the processing of vast amounts of data in contemporary cloud computing systems. This framework involves such components as adaptive resource allocation, intelligent workload partitioning, dynamic scheduling, and feedback optimization to increase the performance of ETL workflows. The experimental validation of the introduced framework showed that it surpasses other methodologies such as MOPWSDRL and GRWS in terms of various performance metrics.

Thus, the suggested framework ensures lower processing delay, higher throughput rate, and better resource utilization efficiency, lower execution cost, less energy consumption, improved scalability, and better workflow success rates. Future studies may enrich the proposed APOF-CETL model by using cutting-edge technologies of artificial intelligence such as federated learning, transformer based workload prediction, and self-organized resource management in multi-cloud and hybrid cloud computing scenarios. Real-time anomalies detection, energy-aware scheduling algorithms, and edge-cloud collaboration are other possible areas of enhancement for the framework. In addition, future studies can focus on extending the applicability of the model to handle streaming ETL operations, serverless computing, and Internet of Things (IoT) scenarios.

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