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Strategies for Scaling Backend Architectures under High Transactional Load in Cloud Ecosystems

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Abstract

The article examines contemporary approaches to scaling backend architectures under conditions of high transactional load in cloud ecosystems. Particular attention is given to the challenges arising in multi-tenant environments, where large volumes of business transactions are simultaneously processed through distributed services, integration layers, and data processing systems. A comprehensive analysis of studies on autoscaling, computational resource management, microservice architectures, container orchestration, serverless computing, and high-throughput data ingestion pipelines was conducted. The findings indicate that mechanisms for early data validation, workload prediction, integration event management, and coordination of service interactions are becoming increasingly important. Based on the analysis, the author developed the Transaction-Aware Adaptive Backend Scaling Model. The proposed model expands current perspectives on the scaling of distributed backend platforms and can be applied in the design of high-load cloud systems, transactional services, and enterprise-level integration solutions. The article may be of interest to software developers, cloud platform architects, distributed systems specialists, and researchers in the field of cloud computing.

Keywords: backend architecture scaling; cloud computing; high transactional load; autoscaling; multi-tenant systems; transaction processing; data ingestion pipelines.

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1. Introduction

Processing large volumes of transactions is no longer a challenge faced exclusively by the largest technology companies. Today, payment services, subscription platforms, e-commerce marketplaces, telecommunications systems, and enterprise cloud solutions operate under similar conditions. The number of requests handled by such systems can fluctuate significantly even within a single day. Periods of moderate activity are often followed by sudden spikes in demand, during which the infrastructure must allocate additional resources within seconds while maintaining service stability. Any delay in this process leads to increased response times, growing request queues, and violations of service-level agreements.

At the same time, approaches to software system design are evolving. Large monolithic applications are increasingly being replaced by distributed architectures composed of interconnected services, container platforms, message queues, and automated resource management mechanisms. In such an environment, simply adding computational capacity is no longer sufficient. Greater importance is placed on understanding which services experience the highest load, how resources are distributed across system components, and how quickly the infrastructure can respond to changes in request volume. As a result, the attention of both researchers and practitioners is gradually shifting from individual scaling mechanisms toward integrated strategies that combine intelligent resource allocation, autoscaling, asynchronous data processing, and workload forecasting within a unified cloud architecture.

Despite the growing number of studies devoted to workload management and computational resource allocation, their combined application within a single architectural framework remains insufficiently explored. The existing literature is dominated by studies that examine autoscaling, resource management, or computational organization separately. The impact of their integrated interaction on the resilience and performance of high-load cloud systems has received considerably less attention. Previous studies can be divided into several related research directions. The first direction concerns general autoscaling, cloud task scheduling, and the configuration of container orchestration platforms. Alharthi and his colleagues [1] systematized reactive, proactive, and machine-learning-based auto scaling techniques and showed that their effectiveness depends on workload variability, monitoring accuracy, provisioning delay, and service-level requirements. Xiu and his colleagues. [2] developed a meta-reinforcement-learning method for cloud task scheduling. Their experiments showed that the method could adapt to new scheduling environments after a limited number of gradient updates while maintaining comparatively high server utilization. Augustyn and his colleagues [3] examined the configuration of the Kubernetes Horizontal Pod Autoscaler and proposed calculating limits on the maximum number of pods from observed workload fluctuations. Their results demonstrated that autoscaler configuration can reduce computational resource consumption while maintaining the required system performance. Tran and Kim [4] addressed the limitations of manually configured resource quotas in Kubernetes-based edge environments and proposed a hybrid mechanism for adapting quotas to changing demand. Kumar [5] demonstrated the applicability of horizontal autoscaling to latency-sensitive Open Radio Access Network workloads. These studies confirm the importance of adaptive capacity management, but their principal management objects remain computational tasks, pods, quotas, infrastructure utilization, and service-level performance indicators.

The second research direction focuses on intelligent resource allocation in distributed and multi-tenant cloud environments. Alatawi [6] formulated resource allocation in multi-tenant serverless environments as a reinforcement-learning problem that accounts for latency, resource utilization, and energy consumption. The proposed approach improved adaptation to changing workload conditions compared with static and heuristic allocation strategies. Dong [7] proposed an agent-based simulation model for evaluating service placement, migration, server consolidation, energy consumption, resource utilization, and service-level agreement violations. These studies demonstrate the potential of adaptive decision-making, but they primarily describe workloads as computational tasks or resource demands rather than as end-to-end business transactions passing through several dependent services.

The third research direction encompasses microservice and serverless architectures. Ninos and his colleagues [8] showed how compute-intensive applications can be decomposed into independently managed microservices and scaled through Kubernetes-based orchestration. Nkenyereye and his colleagues [9] emphasized that resource scheduling and offloading decisions can be improved by considering the functionality of containerized applications rather than relying exclusively on general infrastructure indicators. Golec and his colleagues [10] demonstrated that serverless elasticity is constrained by cold-start latency, which can affect end-to-end performance and quality of service. Mankala and Silva [11] illustrated the potential of serverless parallel processing for workload-specific real-time applications. Collectively, these studies indicate that architecture and workload characteristics influence scaling effectiveness, but they do not provide a unified mechanism for coordinating multiple stages of a business transaction.

The fourth research direction concerns data ingestion and cloud-based information processing. Pacella and his colleagues [12] developed a scalable data ingestion and real-time processing framework based on messaging and stream-processing technologies. Their findings demonstrated the importance of coordinating data ingestion, durable event transmission, and real-time analytical processing under high-volume workloads. Chen and Ge [13] combined cloud-native microservices, message queues, caching, forecasting, and anomaly detection within an application-specific information system. These studies show that scalable ingestion and computational resource management can be integrated within one architecture. However, they do not explicitly connect input data quality, transaction type, predicted service dependencies, and scaling decisions throughout the complete lifecycle of a business operation.

Taken together, previous studies provide well-developed mechanisms for infrastructure monitoring, pod scaling, serverless execution, task scheduling, and high-throughput data ingestion. Nevertheless, these mechanisms are generally examined at separate architectural levels. Limited attention has been given to their coordinated use when a single business transaction passes through multiple services, validation stages, integration layers, and resource allocation mechanisms. This gap provides the basis for the Transaction-Aware Adaptive Backend Scaling Model proposed in this study. The model treats the transactional flow as the primary management object and combines transaction classification, early data validation, workload prediction, resource-state monitoring, and feedback-based adaptation within one conceptual framework. The aim of this study is to develop and theoretically substantiate a model for scaling backend architectures under conditions of high transactional load based on contemporary approaches to autoscaling, computational resource management, and distributed computing. To

achieve this objective, the following research tasks were formulated:

– to analyze contemporary approaches to scaling backend architectures in cloud ecosystems;

– to examine mechanisms for managing computational resources and autoscaling under variable workloads;

– to assess the potential of serverless and distributed architectures for high-load systems;

– to identify effective architectural solutions for improving service performance and resilience.

The research hypothesis is that sustainable scaling of backend architectures under conditions of high transactional load cannot be achieved solely through increasing computational resources. It is assumed that stable and resilient performance is attained through a combination of resource allocation mechanisms, workload forecasting, and autoscaling strategies.

The scientific novelty of the study lies in shifting the focus of scaling from the infrastructure level to the transactional flow level. Unlike existing approaches that make scaling decisions based primarily on CPU utilization, memory consumption, and network activity, the proposed model incorporates business transaction characteristics, early validation results, and predictions of transactional workflow behavior.

2. Materials and Methods

The study was conducted as a review-analytical investigation followed by the development of an original model for scaling backend architectures under conditions of high transactional load. Particular attention was given to research on autoscaling, computational resource management, distributed computing, serverless architectures, container platforms, and approaches for ensuring the stable operation of cloud systems. The review included studies published between 2022 and 2025, allowing the analysis to focus on the most recent approaches and technological solutions.

The literature search was performed using Google Scholar, ScienceDirect, SpringerLink, and MDPI databases. Various combinations of the following keywords were used to construct the search strategy: “backend architecture scaling,” “high transactional load,” “autoscaling,” “resource allocation,” “microservices architecture,” “serverless computing,” “Kubernetes,” “load balancing,” “throughput,” and “latency.” The logical operators AND and OR were employed to refine the search process. The review included studies containing experimental findings, analytical reviews, or conceptual developments related to the scaling of backend systems and the maintenance of their reliable operation in cloud environments. Publications focused on highly specialized technical issues not directly associated with resource allocation, transaction processing, or architectural aspects of scaling were excluded from further consideration.

At the initial stage, more than 30 publications potentially relevant to the research topic were identified. Following an assessment of their content, scientific relevance, and alignment with the study objectives, the final sample consisted of 15 sources. Particular attention was paid to studies examining the effects of different scaling strategies

on system throughput, response time, computational resource efficiency, and compliance with service-level agreements. Research addressing intelligent resource allocation, workload forecasting, and the application of distributed architectures under conditions of intensive transactional activity was also analyzed.

Comparative, systemic, and content analysis methods were employed to process the collected materials. Comparative analysis was used to evaluate different scaling approaches and identify their strengths and limitations. Systemic analysis made it possible to examine the relationships between computational resources, workload management mechanisms, and architectural characteristics of cloud systems. Content analysis was applied to identify recurring patterns and trends characterizing the evolution of contemporary approaches to scaling high-load backend infrastructures.

The final stage of the study involved the development of an original backend scaling model. The model was constructed through the synthesis of findings from the reviewed studies and the identification of relationships among resource allocation, autoscaling mechanisms, workload forecasting, and transaction flow processing. The resulting model was used to generalize the identified patterns and formalize the interactions among the principal mechanisms responsible for scaling backend architectures under conditions of high transactional load.

3. Results

The growth of transactional workloads in cloud ecosystems is increasingly creating challenges that cannot be resolved simply by adding computational resources. This issue is particularly evident in multi-tenant platforms, where a shared infrastructure simultaneously serves numerous clients, applications, and business processes. Resources are continuously redistributed among competing operations. As the number of requests increases, workload distribution becomes less balanced, and local congestion within a single component begins to affect the performance of interconnected services.

These challenges arise because many operations pass through multiple processing stages. Subscription renewals, service modifications, cancellations, payment calculations, and data synchronization all require the participation of several services. A delay at any stage can increase the execution time of the entire operation and generate queues in subsequent processing phases. Consequently, the focus of scaling is gradually shifting from resource expansion toward managing operational flows within the system.

The primary factor limiting performance is the speed at which computational resources can be reallocated. When workload changes occur gradually, differences between scaling approaches remain relatively small. These differences become evident during sudden traffic spikes, when the infrastructure must rapidly adapt to new operating conditions [10]. The main weakness of reactive scaling is response latency. Additional resources are provisioned only after signs of overload have already appeared. A time gap exists between the increase in demand and the deployment of new service instances. During this interval, request queues grow, latency increases, and the risk of violating service-level agreements rises. The key limitation is therefore the speed of decision-making.

Predictive scaling reduces this gap [1,4]. Infrastructure resources are provisioned in anticipation of expected increases in activity, thereby lowering the risk of overload. However, this approach introduces another challenge.

Forecasting errors can result either in resource shortages or in excessive resource reservation. The more dynamic the workload, the greater the cost of such inaccuracies.

A different principle is employed in adaptive resource allocation systems. Decisions are made based on the current state of the infrastructure and the characteristics of the workload. As more operational data become available, management strategies are adjusted and computational resources are redistributed among competing processes. A similar pattern can be observed in multi-tenant cloud environments, where application stability depends directly on the effectiveness of resource allocation mechanisms [6].

Despite the differences among existing resource allocation approaches, their effectiveness is determined not only by the volume of available computational resources. In multi-tenant platforms, the critical factor is the ability of the infrastructure to redistribute resources among competing transactional flows in a timely manner. As workloads increase, performance issues arise less frequently from complete resource exhaustion and more often from delays in decision-making and insufficient adaptability of computational resource management mechanisms. Resource management alone is not sufficient. Most transactions pass through multiple services and several stages of data processing. Subscription renewals, service modifications, payment calculations, and information synchronization are rarely executed within a single component. Any delay tends to propagate further along the processing chain. This is one of the main reasons why distributed architectures have become so widely adopted [8]. Overloads are more likely to remain confined to individual services rather than affecting the entire platform. However, a new challenge emerges. The number of internal interactions grows rapidly, and the successful execution of operations becomes increasingly dependent on the coordinated functioning of numerous interconnected components [14]. Data integration flows generate a substantial workload within modern cloud environments. Events arrive simultaneously from multiple sources, and the intensity of these streams can change abruptly.

Under such conditions, both message ingestion speed and the ability to safely process data throughout the infrastructure become critical. High-throughput data processing pipelines are designed specifically to address these requirements [12]. Messages pass through sequential stages of routing, validation, and transmission between services. Message queues and asynchronous processing help absorb short-term traffic spikes and prevent individual system components from becoming overloaded [13].

As the number of integrations increases, the cost of errors also rises. Incomplete messages, duplicate events, or data structure inconsistencies can trigger failures across multiple interconnected services. Contemporary cloud architectures combine durable message transmission with real-time stream processing [12], while anomaly-detection mechanisms can identify abnormal data patterns [13]. Based on these findings, the proposed model moves message validation, data integrity checks, and exception handling to the earliest stage of processing. The stability of such environments is further supported by orchestration and functionality-aware scheduling mechanisms that redistribute workloads across containerized services [8,9]. Serverless computing addresses a different challenge by rapidly provisioning additional resources during periods of increased activity. However, its effectiveness varies considerably depending on the characteristics of transactional workloads and the structure of executed operations [11].

To identify directions for the further development of scaling mechanisms, a comparative analysis of existing approaches was conducted. Table 1 presents their principal advantages, limitations, and impact on the processing of transactional workloads under conditions of high demand.

Table 1: Limitations of Existing Scaling Approaches and Their Implications for Transaction Processing (Compiled by the author based on sources [1,6,10])

Approach	**Main Strength**	**Main Limitation**	**Impact on Transaction Flow**
Reactive Autoscaling	Simple implementation	Delayed response	Queue accumulation during spikes
Predictive Scaling	Early resource allocation	Forecast errors	Overprovisioning or resource shortages
RL-Based Resource Allocation	Adaptive decisions	High training complexity	Slow convergence under changing workloads
Serverless Scaling	Rapid elasticity	Cold-start latency	Increased response time for critical operations
Container-Based Scaling	Stable orchestration	Scaling lag	Delayed service availability
Proposed Transaction-Aware Model	Transaction-centric scaling	Higher monitoring requirements	End-to-end transaction continuity

The presented findings indicate that each existing approach effectively addresses specific scaling challenges but does not provide comprehensive management of the transaction lifecycle. The principal limitations are associated either with delayed responses to workload fluctuations or with insufficient consideration of the characteristics of processed operations [4]. This highlights the need for models that treat transactional flows as independent objects of management.

As cloud environments become increasingly complex, the primary burden gradually shifts from individual services to the interactions between them. For platforms processing large volumes of transactions and integration events, it is no longer sufficient to execute individual requests quickly. Equally important is maintaining coordinated operation across all system components, controlling data movement between services, and preventing the accumulation of errors within transactional workflows. It is at this level that architectural limitations most often become apparent as workloads continue to grow.

4. Discussion

The findings of the review indicate that the principal scaling challenge in high-load cloud systems is not limited to insufficient computational capacity. It also arises from a mismatch between the allocation of resources and the

structure of the operations that consume them. Infrastructure metrics can show that a service is overloaded, but they do not explain whether the workload consists of independent requests, repeated invalid events, or interdependent transactions that must pass through several services in a defined sequence. The proposed approach addresses this distinction by treating the transactional flow, rather than an isolated infrastructure component, as the primary object of scaling management.

This interpretation extends the conclusions of previous autoscaling studies. Alharthi and his colleagues [1] showed that reactive, proactive, and intelligent autoscaling mechanisms have different advantages and limitations depending on workload variability, monitoring accuracy, provisioning delay, and service-level requirements. Augustyn and his colleagues [3] demonstrated that the Kubernetes Horizontal Pod Autoscaler can be improved by configuring pod limits according to observed workload fluctuations. Tran and Kim [4] similarly showed that static resource quotas may prevent timely scaling under changing demand. These approaches improve infrastructure adaptation, but their decisions are principally driven by resource utilization, workload intensity, and predefined performance constraints. The results of the present study suggest that these indicators should be supplemented with information about the business operations generating the workload.

The distinction becomes important when two workloads produce similar CPU or memory utilization but have different transactional characteristics. A large number of independent read requests may be processed by horizontally scaling a single service. By contrast, subscription renewals, payment recalculations, service modifications, and cancellations may require coordinated execution across authentication, billing, integration, data storage, and notification services. Scaling only the component with the highest CPU utilization may not remove the actual bottleneck if another dependent service controls the completion of the entire workflow. Transaction-aware scaling therefore requires the system to identify the services involved in an operation and determine which stages constrain its end-to-end completion.

The comparison with intelligent resource allocation studies further clarifies this requirement. Alatawi [6] demonstrated that reinforcement learning can improve resource allocation in multi-tenant serverless environments by incorporating latency, resource utilization, and energy-related indicators. Xiu and his colleagues [2] showed that meta-reinforcement learning can accelerate adaptation to new cloud task-scheduling environments. Dong [7] demonstrated the value of fine-grained resource-state simulation for evaluating service placement, migration, server consolidation, resource utilization, and SLA violations. These approaches make resource management more adaptive, but their primary decision objects remain computational tasks, services, or infrastructure states. The proposed Transaction-Aware Adaptive Backend Scaling Model does not replace these mechanisms. Instead, it provides an additional analytical layer that supplies transaction-level information to reactive, predictive, or learning-based scaling engines.

Microservice and serverless architectures provide mechanisms through which transaction-aware decisions can be implemented. Ninos and his colleagues [8] demonstrated that microservice decomposition allows individual components to be managed and scaled independently. Nkenyereye and his colleagues [9] showed the importance of considering application functionality when making scheduling and offloading decisions for containerized workloads. These findings support differentiated scaling according to the role of a service within the processing

workflow. Nevertheless, independent scaling also increases the importance of coordinating service dependencies because a transaction remains incomplete if one component scales successfully while another dependent service becomes congested.

Serverless computing provides rapid elasticity for short-duration processing, but its applicability depends on workload characteristics. Golec and his colleagues [10] identified cold-start latency as an unresolved limitation that can affect end-to-end performance and quality of service. Mankala and Silva [11] demonstrated the applicability of serverless parallel processing to a specific real-time workload. These studies indicate that serverless resources should not be activated solely because the incoming request rate has increased. Transaction latency requirements, invocation frequency, execution duration, and the availability of warm instances must also be considered. Short asynchronous validation and transformation tasks may be suitable for serverless execution, whereas latency-sensitive transactional stages may require pre-warmed or continuously available capacity.

Workload pressure also emerges within data ingestion pipelines. Pacella and his colleagues [12] demonstrated that messaging and stream-processing technologies can support scalable ingestion and real-time data processing. However, high ingestion capacity does not by itself ensure that business transactions will be completed successfully. Alongside valid messages, integration environments may receive duplicate events, incomplete records, inconsistent payloads, and outdated information. If these events are transferred to core services without preliminary verification, computational resources are consumed by operations that may already be incapable of successful completion. The results therefore support the inclusion of input validation outcomes within the scaling decision process rather than treating validation exclusively as a separate data-quality procedure.

Based on the comparative and systemic analysis, the Transaction-Aware Adaptive Backend Scaling Model was developed. Figure 1 presents the structure of the proposed model and the relationships among transaction classification, runtime validation, workload prediction, adaptive scaling, and feedback-based adjustment.

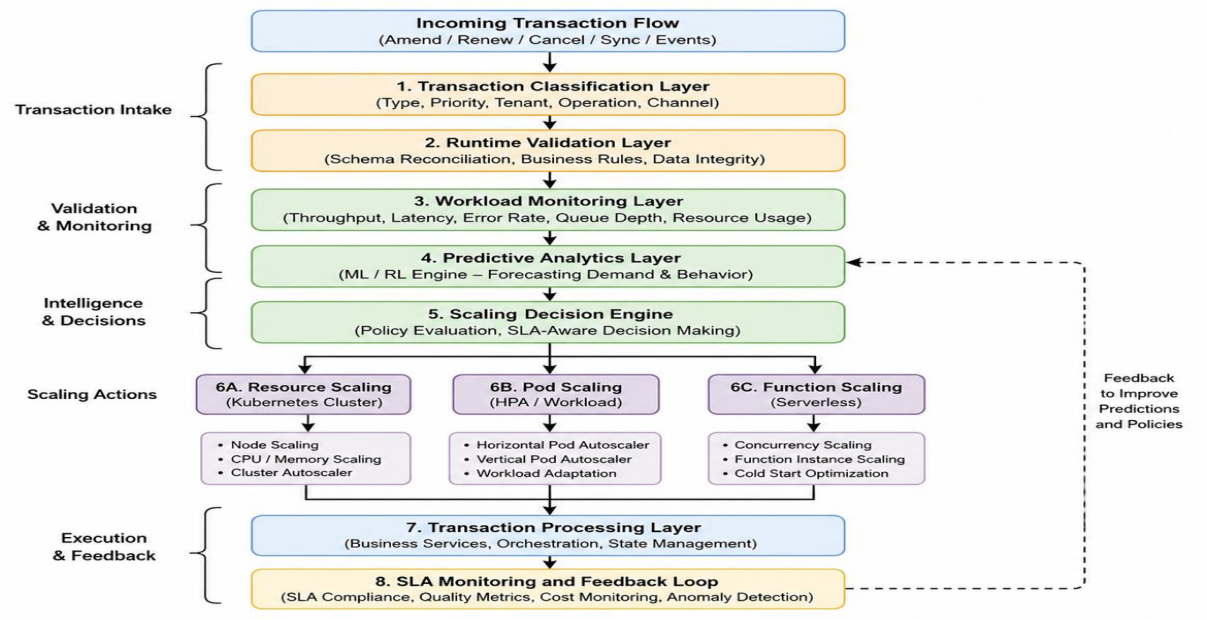

Figure 1: Transaction-Aware Adaptive Backend Scaling Model (Author's Development)

The principal distinction of the proposed model lies in the choice of the management object. Most existing solutions focus on the state of the infrastructure, including CPU utilization, memory consumption, network activity, queue length, and the number of active containers. In the proposed model, the central management object is the transactional flow itself. Scaling decisions are driven not only by changes in infrastructure conditions but also by changes in the composition, validity, priority, dependency structure, and expected behavior of operations passing through the system.

The decision-making logic of the model can be represented by the following functional relationship:

$S = f(T, R, L, V)$

where:

S – scaling decision;

T – characteristics of the transactional flow;

R – current state of computational resources;

L – predicted workload;

V – results of incoming data validation.

The variable T represents the characteristics of the transactional flow. These characteristics may include the transaction category, priority, expected execution path, number of dependent services, estimated computational demand, processing deadline, retry behavior, tenant affiliation, and applicable SLA. For example, a payment recalculation that must pass through several dependent services and satisfy a strict completion deadline should be treated differently from an independent background data synchronization operation.

The variable R describes the current state of the infrastructure. It may include CPU and memory utilization, queue length, replica availability, network conditions, service health, active container capacity, and the availability of warm serverless instances. These indicators show whether the current infrastructure can support the expected processing demand, but they do not independently explain where the workload will propagate within the architecture.

The variable L represents the predicted workload. Unlike a general request-volume forecast, this variable should describe the expected arrival rate and composition of transactional operations. The forecast should indicate which transaction categories are likely to dominate, which services will be involved, and where queues or resource shortages may emerge. This distinction makes it possible to allocate capacity to the services situated along the expected execution path rather than scaling all platform components uniformly.

The variable V reflects the results of incoming data validation. It may include the proportions of incomplete, duplicated, inconsistent, outdated, conflicting, or rejected events. Validation outcomes are important because an

increase in the number of incoming messages does not always correspond to an equal increase in valid business transactions. A traffic spike dominated by duplicate or malformed events should not automatically result in the expansion of all downstream business services.

The four variables perform different but complementary functions. Infrastructure state R indicates the current capacity of the system. Predicted workload L provides an estimate of near-future demand. Transaction characteristics T identify how the workload is expected to propagate and which services are critical to completing the operation. Validation results V determine how much of the incoming event stream should proceed to downstream processing. The scaling decision S is formed from the combined interpretation of these variables.

The model integrates five interconnected functional components. Each component is responsible for a distinct stage of transactional flow analysis and scaling decision-making. Unlike traditional architectures, where scaling is determined mainly by infrastructure thresholds, the proposed model relies on the sequential processing of transaction-related information, input data quality verification, workload forecasting, adaptive resource allocation, and feedback. Table 2 presents the functional components of the model.

Table 2: Functional Components of the Transaction-Aware Adaptive Backend Scaling Model (Author's Development)

Component	**Function**	**Input Data**	**Output**
Transaction Classification Layer	Classification of incoming business operations	Transaction events	Transaction category
Runtime Validation Layer	Validation and filtering of incoming data	Transaction payload	Validated transaction stream
Predictive Analytics Layer	Forecasting workload dynamics	Historical and current workload metrics	Predicted transaction load
Adaptive Scaling Engine	Dynamic resource allocation and scaling decisions	Forecast results, SLA indicators, resource status	Scaling actions
Feedback Layer	Continuous model adjustment and optimization	Runtime performance metrics	Updated scaling policies

Processing begins at the Transaction Classification Layer. The system identifies the type of incoming business operation and determines its role within the overall workflow. This stage distinguishes, for example, between subscription renewals, service modifications, cancellations, payment calculations, information synchronization, and background analytical operations. Classification provides the contextual information required to determine which services are likely to participate in processing and what completion requirements apply to the operation.

The transaction is subsequently transferred to the Runtime Validation Layer. At this stage, the message structure,

mandatory fields, identifiers, consistency conditions, and duplication status are verified. Erroneous, incomplete, or conflicting messages are rejected, isolated, or redirected before they reach core services. Only validated events are transferred to the following processing stages. This reduces the probability that downstream resources will be occupied by operations that cannot be completed successfully.

The Predictive Analytics Layer combines historical workload information with current transaction categories and runtime metrics. Its function is not limited to forecasting total traffic volume. It estimates the expected composition of the transactional flow, the services that will be involved, the likely distribution of processing demand, and the points at which congestion may occur. The prediction can therefore distinguish a general increase in requests from an expected increase in a specific category of multi-stage business operations.

The Adaptive Scaling Engine receives transaction characteristics, validation outcomes, workload predictions, SLA indicators, and information about current resource availability. Depending on these inputs, the engine may scale containerized services horizontally, adjust resource quotas, allocate additional computational capacity, or activate serverless functions for short-term workload spikes. The selected action should correspond to the expected execution path of valid transactions rather than to the state of a single infrastructure metric.

Several decision scenarios clarify this logic. If the model detects a predicted increase in valid, high-priority transactions with strict SLA requirements, it can allocate additional capacity to the services situated along their critical execution path before overload occurs. If an increase in traffic is primarily associated with invalid or duplicate messages, additional resources can be directed to the validation and ingestion layers without unnecessarily scaling core business services. If an unexpected workload spike produces local queue growth and resource saturation, the system can apply reactive scaling to the affected components. If the increase is predictable and recurrent, capacity can be provisioned before infrastructure thresholds are exceeded.

The Feedback Layer completes the management cycle. Information about actual transaction completion time, processing delays, queue accumulation, validation outcomes, scaling actions, resource consumption, and SLA compliance is returned to the predictive and decision-making components. Differences between predicted and actual behavior are used to update workload forecasts and scaling policies. The system therefore adapts not only to changes in workload intensity but also to changes in the structure and execution behavior of transactional flows.

A practical example illustrates the complete operation of the model. Consider a scheduled batch of subscription renewals in a multi-tenant platform. The Transaction Classification Layer identifies the incoming events as renewal operations and determines that they require validation, billing, subscription management, and notification services. The Runtime Validation Layer removes incomplete and duplicate events. The Predictive Analytics Layer estimates the number of valid renewals and the workload that will reach each dependent service. The Adaptive Scaling Engine allocates additional capacity to the services situated on the critical execution path before their queues exceed acceptable limits. Information about processing time, rejected events, queue growth, resource utilization, and SLA compliance is subsequently returned to the Feedback Layer.

A conventional reactive mechanism may also allocate additional resources in this scenario, but it will normally

act only after infrastructure thresholds have been exceeded. A purely predictive mechanism may act earlier, but it may overestimate the required capacity if a substantial proportion of incoming events fails validation. The proposed model combines these perspectives by evaluating both the anticipated workload and the proportion of transactions expected to proceed through the complete processing chain. Its potential advantage lies in improving the correspondence between allocated capacity and valid end-to-end operations rather than simply increasing the speed of resource provisioning.

The model also introduces additional implementation requirements. Transaction classification requires reliable metadata and an explicit representation of service dependencies. End-to-end monitoring may require distributed tracing and consistent transaction identifiers. Runtime validation consumes computational resources and may itself become a bottleneck during extreme traffic spikes. Incorrect classification can allocate resources to the wrong services, while forecasting errors may still result in insufficient or excessive capacity. In multi-tenant environments, transaction-level monitoring must also account for tenant isolation, information security, and privacy requirements, which are particularly important in serverless environments [15].

The proposed model should therefore be interpreted as a conceptual coordination framework rather than as an empirically validated replacement for existing autoscaling mechanisms. Its contribution lies in defining how transaction classification, validation outcomes, workload prediction, infrastructure status, SLA indicators, and feedback can be combined before a scaling action is selected. Reactive autoscaling, predictive models, Kubernetes orchestration, reinforcement-learning algorithms, and serverless execution remain implementation mechanisms within this broader decision structure.

The results provide theoretical support for shifting part of the scaling logic from infrastructure-level monitoring to transaction lifecycle management. However, the practical effectiveness of the model must be tested empirically. Future evaluation should compare it with reactive, predictive, and learning-based scaling approaches using end-to-end latency, throughput, queue length, transaction completion rate, SLA violations, resource consumption, infrastructure cost, forecasting error, and validation overhead as performance indicators.

5. Limitations of the Study

This study has several limitations. First, the review was limited to 15 publications identified through Google Scholar, ScienceDirect, SpringerLink, and MDPI and published between 2022 and 2025. Although this scope made it possible to focus on recent developments, the selected databases, keywords, inclusion criteria, and publication period may have excluded relevant studies, conference papers, and industry evaluations. The reviewed publications also examined heterogeneous systems, including Kubernetes environments, serverless platforms, edge systems, distributed applications, and data ingestion pipelines. Differences in workload characteristics, experimental configurations, and performance indicators prevented a direct quantitative comparison or meta-analysis of their findings.

Second, the Transaction-Aware Adaptive Backend Scaling Model remains conceptual. It was derived from the synthesis of previous research and was not implemented or evaluated within a production cloud platform. The

functional relationship S = f(T, R, L, V) defines the categories of information involved in decision-making but does not yet constitute an executable scaling algorithm. The study therefore does not provide empirical evidence regarding the model's effect on end-to-end latency, throughput, queue length, SLA violations, resource consumption, or infrastructure cost.

Third, the generalizability of the model has not been established. Its applicability may vary according to transaction duration, service dependency structure, workload predictability, tenant isolation requirements, and the use of containerized or serverless resources. Transaction classification and early validation may also introduce monitoring and processing overhead that was not quantified in the present study. Incorrect classification, incomplete dependency data, forecasting errors, and changes in transaction behavior may reduce the effectiveness of the resulting scaling decisions.

Future research should implement the proposed model in a controlled multi-tenant cloud environment and compare it with reactive, predictive, and reinforcement-learning-based scaling mechanisms. The evaluation should include both reproducible workload traces and real transactional scenarios. Relevant indicators should include median and tail latency, throughput, transaction completion rate, queue accumulation, SLA violations, resource-hours, infrastructure cost, scaling frequency, forecasting error, and validation overhead. Such testing is required before conclusions can be drawn regarding the model's practical superiority or applicability across different cloud ecosystems.

6. Conclusion

The analysis indicates that as transactional workloads increase, the principal limitations of modern cloud platforms may increasingly emerge at the level of business operation processing rather than solely at the level of computational capacity. Simply adding resources can temporarily improve performance, but it does not resolve issues associated with the execution of operations across distributed environments, integration layers, and interconnected services. As a result, the effectiveness of scaling is becoming increasingly dependent on the ability of an architecture to adapt promptly to changes in workload characteristics.

The principal outcome of the study was the development of the Transaction-Aware Adaptive Backend Scaling Model. Its fundamental distinction from traditional approaches lies in the fact that scaling decisions are based on transactional flow characteristics, data validation outcomes, and the predicted behavior of business operations within a distributed environment. In the proposed model, changes in scaling strategy are determined by the characteristics of incoming event streams, the results of data verification procedures, and the expected behavior of operations during subsequent stages of processing.

The practical value of the model is most evident in large-scale cloud environments where numerous operations involving updates, renewals, cancellations, and data synchronization are executed simultaneously. Under such conditions, early validation of incoming messages, workload forecasting, SLA monitoring, and the coordinated use of multiple resource adaptation mechanisms within a unified management framework become particularly important. These capabilities create conditions for maintaining platform stability even during abrupt changes in

the intensity of incoming event streams.

The conducted analysis provides theoretical support for the research hypothesis. Sustainable scaling appears to depend not only on the volume of available computational resources but also on the system's ability to analyze the structure of incoming operations, anticipate workload fluctuations, and account for the characteristics of the transactional flows being processed. However, empirical implementation and comparative testing are required before the hypothesis can be considered fully confirmed.

References

[1] S. Alharthi, A. Alshamsi, A. Alseiari, and A. Alwarafy, "Auto-scaling techniques in cloud computing: Issues and research directions," Sensors, vol. 24, no. 17, Art. no. 5551, 2024, doi: 10.3390/s24175551.

[2] X. Xiu, J. Li, Y. Long, and W. Wu, "MRLCC: An adaptive cloud task scheduling method based on meta reinforcement learning," J. Cloud Comput., vol. 12, Art. no. 75, 2023, doi: 10.1186/s13677-023-00440-8.

[3] D. R. Augustyn, Ł. Wyciślik, and M. Sojka, "Tuning a Kubernetes horizontal pod autoscaler for meeting performance and load demands in cloud deployments," Appl. Sci., vol. 14, no. 2, Art. no. 646, 2024, doi: 10.3390/app14020646.

[4] M.-N. Tran and Y. Kim, "Hybrid resource quota scaling for Kubernetes-based edge computing systems," Electronics, vol. 14, no. 16, Art. no. 3308, 2025, doi: 10.3390/electronics14163308.

[5] S. Kumar, "ORAN-HAutoScaling: A scalable and efficient resource optimization framework for open radio access networks with performance improvements," Information, vol. 16, no. 4, Art. no. 259, 2025, doi: 10.3390/info16040259.

[6] M. N. Alatawi, "Optimizing multitenancy: Adaptive resource allocation in serverless cloud environments using reinforcement learning," Electronics, vol. 14, no. 15, Art. no. 3004, 2025, doi: 10.3390/electronics14153004.

[7] D. Dong, "Agent-based cloud simulation model for resource management," J. Cloud Comput., vol. 12, Art. no. 156, 2023, doi: 10.1186/s13677-023-00540-5.

[8] F. Ninos, K. Karalas, D. Dechouniotis, and M. Polemis, "On microservice-based architecture for digital forensics applications: A competition policy perspective," Future Internet, vol. 17, no. 4, Art. no. 137, 2025, doi: 10.3390/fi17040137.

[9] L. Nkenyereye, B. G. Lee, and W. Y. Chung, "Functionality-aware offloading technique for scheduling containerized edge applications in IoT edge computing," J. Cloud Comput., vol. 14, Art. no. 13, 2025, doi: 10.1186/s13677-025-00737-w.

[10] M. Golec, G. K. Walia, M. Kumar, F. Cuadrado, S. S. Gill, and S. Uhlig, "Cold start latency in serverless computing: A systematic review, taxonomy, and future directions," arXiv:2310.08437, 2023. [Online]. Available: https://arxiv.org/abs/2310.08437.

[11] C. K. Mankala and R. J. Silva, "Sustainable real-time NLP with serverless parallel processing on AWS," Information, vol. 16, no. 10, Art. no. 903, 2025, doi: 10.3390/info16100903.

[12] M. Pacella, A. Papa, G. Papadia, and E. Fedeli, "A scalable framework for sensor data ingestion and real-time processing in cloud manufacturing," Algorithms, vol. 18, no. 1, Art. no. 22, 2025, doi: 10.3390/a18010022.

[13] B. Chen and W. Ge, "Design and optimization strategy of electricity marketing information system supported by cloud computing platform," Energy Inform., vol. 7, Art. no. 67, 2024, doi: 10.1186/s42162-024-00366-8.

[14] F. Dai, M. A. Hossain, and Y. Wang, "State of the art in parallel and distributed systems: Emerging trends and challenges," Electronics, vol. 14, no. 4, Art. no. 677, 2025, doi: 10.3390/electronics14040677.

[15] E. Marin, D. Perino, and R. Di Pietro, "Serverless computing: A security perspective," J. Cloud Comput., vol. 11, Art. no. 69, 2022, doi: 10.1186/s13677-022-00347-w.