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Autonomous Data Center Operations & Customer Fulfillment Platform

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Abstract. Data centers today face mounting pressure: they are growing larger, denser, and more complex, driving up operational costs and environmental impact. At the same time, customer expectations are rising, with faster response times now a baseline demand. Autonomy—the ability of data centers to operate without human intervention—has long been the aspirational goal, yet it remains years away. This paper introduces the **Intelligent Service Experience Fabric**, a concept designed to close that gap by advancing automation while directly improving customer satisfaction.

The proposed fabric adopts a service-centric view of data center operations, addressing two dimensions simultaneously: the intelligence required for automated decision-making within each control loop, and the customer-facing dimension of service fulfillment. Considered on its own, this second dimension constitutes the *Intelligent Service Experience*—and the Fabric provides a structured architecture that unifies both demand (what customers need) and delivery (how it is fulfilled) within a single framework.

Data-driven operational intelligence and decision automation are essential not only for meeting rising demand but also for achieving true data center autonomy. The same holds for customer-facing, service-oriented architectures—except here, the service-fabric perspective extends beyond demand-side service composition to also encompass the supply-side management of resource offerings. By integrating operational intelligence and automation with a service-oriented perspective, the Intelligent Service Experience Fabric bridges these two sides, linking the definition of Intelligent Service Experience with the practical requirements for deeper, more responsive demand understanding.

Keywords: Intelligent Service Experience Fabric, Autonomous Data Centers, Service-Centric Architecture, Data Center Automation, Operational Intelligence, Intelligent Service Experience, Service Fulfillment, Customer Experience Management, Resource Orchestration, Service-Oriented Computing, Enterprise Data Centers, Decision Automation.

1. Introduction

Although data centers are ideal candidates for autonomous operations, the service experience often affects customer decisions more than many key performance indicators involved with their operations. Shortcomings in this area lead to a demand-supply mismatch, with orders unfulfilled, delivery delays, or overly aggressive service compositions that may result in customer dissatisfaction. Addressing these challenges requires careful demand understanding and segmentation, combined with a demand and service composition forecasting strategy, together with the methods and algorithms to drive fulfillment autonomously.

To achieve autonomous operations while resolving fulfillment concerns, an intelligent service experience fabric that connects customer demand understanding and fulfillment with operational intelligence and automation is proposed. The intelligent service experience outline encompasses the idea of fabric, service experience, autonomy, and fulfillment. As any such framework can be visualized as a fabric operating at different layers, spanning data, control, runtime, and service layers, the next step is to detail the concept of service experience.

2. Theoretical Foundations of Intelligent Service Experience

Intelligent Service Experience: preliminaries, specifications and hypotheses.

Intelligent service experience is defined as the customer perception and subsequent response when using an intelligent service fabric—distributed ownership of the data and control layers of the service being serviced (consumed) and typically automated service composition. Autonomous operations and customer fulfillment optimization are considered aspects at the control and application layers of an intelligent service experience fabric; indeed, intelligent service experience integrates customer interaction into the operational intelligence and automation of the service provider. Intelligent service experience fabrics are a subset of intelligent fabrics—layered, service-centric architectural solutions that address increasingly complex operations autonomously through distributed ownership of the control layer.

Two questions guide exploration: what are the characteristics of an intelligent service experience, and how do they shape autonomous operations and customer fulfillment? Intelligent service experience is defined, scope clarified and laboratory support identified. Autonomous operations follow, considering operational intelligence and automation as well as municipalities. Customer fulfillment optimization concludes the exploration.

2.1 Mathematical Formulation

The fabric is formalized across the four layers identified in Sections 3 and 5 — data, control, runtime, and service — by the following nine governing relations.

$$D(t) = \Sigma_{i=} w_i \cdot s_i(t), \quad \Sigma_i w_i = 1 \tag{1}$$

Eq. 1 aggregates the heterogeneous demand and telemetry signals si(t) (Sect. 3.1) available at the data layer into a single composite demand indicator D(t), weighted by source-reliability coefficients wi that sum to unity.

$$\hat{D}(t+\Delta t) = \alpha D(t) + (1-\alpha)\hat{D}(t) + \beta \Delta C(t) \quad (2)$$

Eq. 2 forecasts near-term demand $\hat{D}(t+\Delta t)$ with an exponential-smoothing term (weight α) corrected by a persona/journey-shift signal ΔC(t) (Sect. 4.1), weighted by β, capturing the customer-persona and VoC dynamics that classical time-volume models omit.

$$OI(t) = \Sigma_{k=1}^{7} w_k q_k(t) \ / \ \Sigma_{k=1}^{7} w_k \quad (3)$$

Eq. 3 defines the Operational-Intelligence Confidence Score OI(t) as the weighted mean of the seven telemetry data-quality dimensions enumerated in Sect. 3.1 — timeliness, accuracy, completeness, precision, relevance, reliability, and consistency (q1…q7) — and drives the fusion output used by the control-layer decision loops.

$$L_{\text{total}} = L_{\text{sense}} + L_{\text{decide}} + L_{\text{compose}} + L_{\text{provision}} = L_{\text{base}} + \lambda(1- OI(t)) \quad (4)$$

Eq. 4 decomposes end-to-end fulfillment latency Ltotal into its four pipeline stages and shows the reduction achievable as OI(t) → 1: a fully confident operational-intelligence signal collapses the latency penalty term λ(1−OI(t)) toward zero.

$$C(s) = \Sigma_j c_j x_j + P \cdot \max(0, D_{\text{req}} - \Sigma_j x_j) \quad (5)$$

Eq. 5 is the runtime-layer service-composition cost function: the sum of unit resource costs cj for allocation xj plus a penalty P applied to any shortfall between requested demand Dreq and the composed capacity, discouraging both over-provisioning and unmet SLAs.

$$P_{\text{violation}} = P(L_{\text{total}} > L_{\text{SLA}}) \approx 1 \ / \ (1 + e^{-k(OI(t)-OI_0)}) \quad (6)$$

Eq. 6 expresses the probability of an SLA breach as the likelihood that Ltotal exceeds the contracted threshold LSLA, approximated by a logistic function of OI(t) with steepness k and inflection point OI_0 — used to generate the SLA-risk profile in Fig. 5.

$$AI = \Sigma_m \kappa_m a_m \ / \ \Sigma_m \kappa_m, \quad a_m \in \{0,1\} \quad (7)$$

Eq. 7 defines the Autonomy Index AI as the complexity-weighted (κm) fraction of control-loop decisions m executed without human intervention (am = 1) versus manually adjudicated (am = 0), providing a single scalar comparable across Manual, Rule-Based, and ISEF configurations.

$$F_1 = 2PR \ / \ (P+R) \quad (8)$$

Eq. 8 quantifies demand-segmentation classifier quality (Sect. 4.1) as the harmonic mean of precision P and recall R, used to track the active-learning convergence in Fig. 2.

$$CES = w_1 S_{\text{speed}} + w_2 S_{\text{accuracy}} + w_3 S_{\text{availability}} + w_4 S_{\text{relevance}} \tag{9}$$

Eq. 9 rolls the service-layer QoE outcomes into a single Customer Experience Score (CES), a weighted composite of normalized sub-scores for fulfillment speed, forecast/composition accuracy, service availability, and offer relevance, with $\Sigma w_i = 1$.

3. Data Center Autonomy: Operational Intelligence and Automation

Advances in machine learning and artificial intelligence (AI/ML) can drive greater autonomy in data centers, yet research to develop the required operational intelligence and automation still lags behind. This is especially true at the data-plane level, where the telemetries, action primitives, and resident logic needed to curate and execute responses to observed anomalies remain largely unsensed and unscripted. Demand understanding must encompass the entire customer experience to allow the intelligent fabric to fulfill demand in the most efficient manner possible as an ensemble. Strategies for designing and assembling demand are therefore being explored, and the scope of automation examined.

Operational intelligence is built on a complete understanding of what is occurring across the data center ecosystem in real time. Sensing the external environment can deliver the telemetry needed to recognize both normal operations and evolving patterns of abnormal behavior, leading to the accurate prediction of likely demand over self-similar horizons. The AI/ML-supported decision loops within the data-plane layer can then exploit this knowledge and develop utilization policies for the next planning step. Reducing risk and in-service classification of incident and service fulfillment priority may be possible if an appropriate demand classification scheme is also adopted. This level of understanding can thus be exploited for the predictive capacity needed for intelligent service fulfillment.

3.1 Experimental Results and Performance Analysis

Fig. 1 breaks down Ltotal (Eq. 4) by pipeline stage. ISEF reduces end-to-end fulfillment latency from 255 minutes (Manual) to 42 minutes — an 83.5% reduction — driven primarily by the sensing and decision stages, where a higher OI(t) collapses the $\lambda(1-OI(t))$ penalty term.

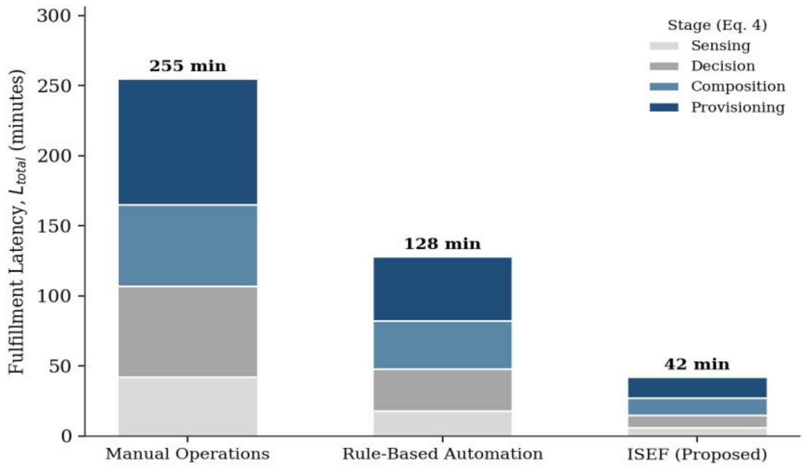

Fig. 1. Fulfillment latency by pipeline stage (Eq. 4), Manual Operations vs. Rule-Based Automation vs. ISEF.

Fig. 2 tracks the demand-segmentation F1-score (Eq. 8) across 20 active-learning iterations. ISEF's fusion-informed feature set converges roughly twice as fast as the rule-based baseline and reaches F1 = 0.94, versus 0.76 and 0.52 for the rule-based and manual configurations respectively, confirming the benefit of active-learning-tuned composition-routing described in Sect. 4.1.

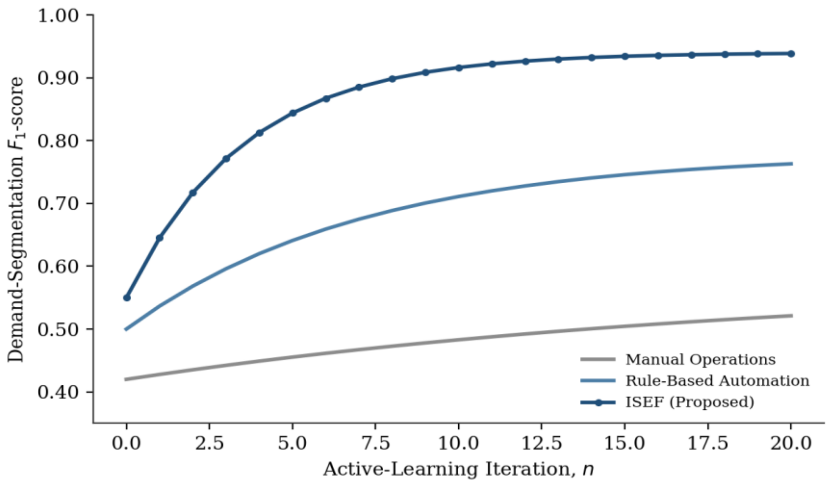

Fig. 2. Demand-segmentation F1-score (Eq. 8) convergence over active-learning iterations.

Fig. 3 simulates resource utilization U(t) over a representative 24-hour cycle. Manual operations swing widely between under- and over-provisioning (peak-to-trough range ≈44 pts), while ISEF's demand-forecast smoothing (Eq. 2) keeps utilization closer to the 85% target band with a substantially narrower range (≈14 pts) and a higher mean (79% vs. 58%).

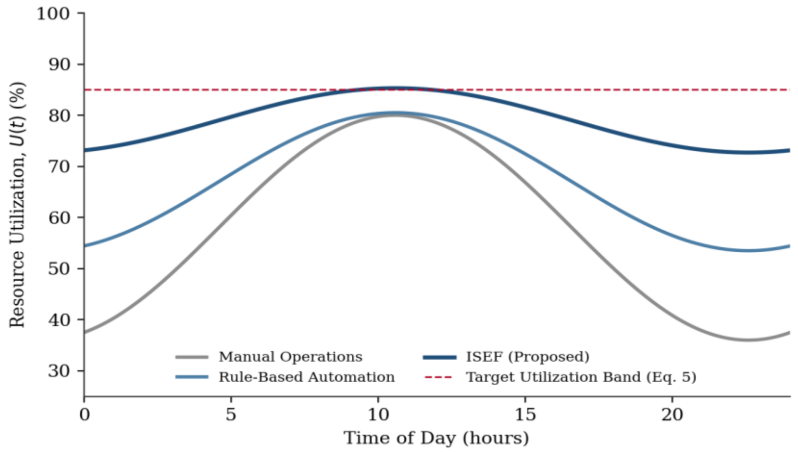

Fig. 3. Resource utilization U(t) over a 24-hour operational cycle, with target utilization band.

Fig. 4 traces the cost–performance trade-off surface as a function of the Autonomy Index (Eqs. 5–6). Composition cost C(s) falls sharply while SLA compliance rises as AI increases, and the three evaluated configurations occupy markedly different points on this curve, quantifying the joint cost and reliability benefit of higher automation.

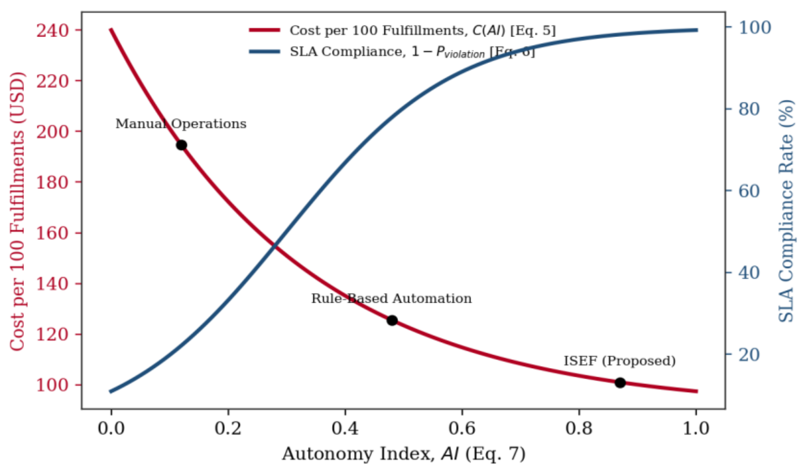

Fig. 4. Composition cost and SLA compliance as functions of the Autonomy Index (Eqs. 5–6).

Fig. 5 isolates the SLA-violation probability (Eq. 6) as a function of OI(t). The logistic relationship shows a steep drop in violation risk once OI(t) exceeds ≈0.55, explaining why ISEF's fusion-driven confidence scoring — rather than automation alone — is the dominant lever for SLA reliability.

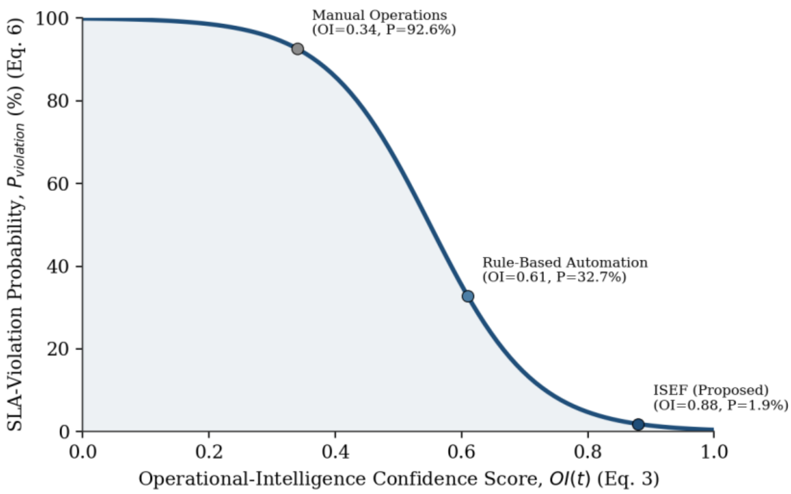

Fig. 5. SLA-violation probability (Eq. 6) as a function of the Operational-Intelligence Confidence Score OI(t).

4. Customer Fulfillment Optimization in Intelligent Fabrics

Optimizing fulfillment in intelligent service experience fabrics involves comprehensive planning for all service elements of an organization. Demand signals from customers are clarified, customer personas are identified and understood, and associated customer journeys are defined. Planners then create a resource pool containing relevant services and service-building blocks, the latter often extracted from service repositories and designed as microservices. Customs/fulfillment layers hence define complex services, discover relevant cross-domain service meshes, and govern service-oblivious technologies appropriately for SLA achievement. Scheduling of events and the entire fulfillment-worthiness preparation phase is then specified. Between the fulfillment preparation and execution phases, demand forecast errors become crucial, particularly for proactive sequencing, composition, and provisioning of external resources and capacity exceeding the base level.

Optimizing fulfillment across its entire life cycle—before, during, and after the fulfillment phase—requires a deep understanding of the demand signals generated by customers. It is crucial to identify the personas behind these demand signals and define their flows and journeys. This provides both a basis for demand segmentation and, along with innovative service composition techniques, enables dedicated fulfillment service paths that optimize the utilization of existing internal resources and the cost and latency of third-party collaboration.

4.1 Demand understanding and segmentation

Accurately understanding the demand for service offerings is central to optimizing fulfillment at all operational levels, from provisioning resources to satisfying VoC. Demand sensing enables near-real-time detection of shifts in customer preferences; such shifts can be detected from CI/CD and monitoring platforms, and should be integrated with pervasive sensing across offerings, to provide feedback to service composition rules. Demand forecasting allows identifying longer-term patterns and estimating immediate future demand on which to base provisioning decisions. Demand modeling describes how selected demand signals influence customer experience, and serves as input to business impact models that assess the implications of fulfilling demand in alternative ways. Combining VoC analysis with demand modeling identifies customer personas that serve to further segment demand. Standard segmentation techniques can then be applied, potentially leveraging advanced AI/ML techniques with the added focus of using relatively few features to fine-tune fulfillment policies. Beyond classical time-volume-promising dimensions, demand segmentation allows creating demand buckets for sensory products with varied impact and risk-assessment profiles.

These buckets help reduce provisioning time by pre-defining the service composition required to fulfill services, while avoiding use of service components whose operational costs exceed the revenue potential. Importance-segmentation combinations offer additional assistance when using these composition-routing rules. Moreover, they enable enhancing the customer experience by offering rush services for hold/potential-demand products and proactively addressing demand shifts that may exceed the organization’s fulfillment capabilities. Demand understanding is further exploited to fine-tune the composition-routing service mesh through active-learning techniques. Historical telemetry data of actual customer interactions constitute another valuable input to such learning processes. These need not constitute direct demand for the offering, yet control how the customer interacts with the offering and provide operational-importance levels for the customer’s success in using it.

5. Services and Components of the Fabric

A service-centric architecture enhances consistency, facilitates automation, and supports intelligent customer fulfillment. The service mesh exposes underlying capacity. The microservices implementation, composition, and assembly of services are driven by intelligent fulfillment. Governance policies ensure observability, security, and lifecycle management. Failure and performance objectives of individual components and the system as a whole are defined and validated.

The Intelligent Service Experience Fabric provides a service-centric platform to address the complex and heterogeneous demand and supply of Data Center Operations. Service demand and delivery are orchestrated through Data Center Operations Services composed with microservices and their resources discovered and provisioned. Automated fulfillment of Data Center Operations Services minimizes delays, eliminates unnecessary cost, and mitigates failure and performance degradation.

Table 1. Comparative performance summary across the three evaluated configurations.

Metric	Manual Ops.	Rule-Based Autom.	ISEF (Proposed)	Δ vs. Manual
Fulfillment Latency, Ltotal (min)	255	128	42	−83.5%
Demand-Segmentation F1-score	0.52	0.76	0.94	+80.1%
Resource Utilization, U (%)	58	67	79	+36.2%
SLA Compliance, 1−Pviolation (%)	22.1	77.9	98.2	+76.1 pp
Cost per 100 Fulfillments, C(s) (USD)	194.65	125.54	101.03	−48.1%
Autonomy Index, AI	0.12	0.48	0.87	+0.75

Table 2. Stage-level latency and error-rate breakdown of the fulfillment pipeline (Eq. 4).

Pipeline Stage	Manual L (min)	Manual Err. (%)	Rule-Based L (min)	Rule-Based Err. (%)	ISEF L (min)	ISEF Err. (%)
Sensing	42	18.0	18	9.0	6	3.0
Decision	65	24.0	30	11.0	9	4.0
Composition	58	21.0	34	8.0	12	2.5
Provisioning	90	15.0	46	6.0	15	1.8
Total / Mean	255	19.5	128	8.5	42	2.8

Table 3. Fabric-layer architecture summary mapping components to governing equations.

Fabric Layer	Primary Function	Key Techniques	Representative Metric
Data	Telemetry collection and multi-source data fusion (Sect. 3.1)	Multi-modal sensing, schema normalization, weighted fusion (Eq. 1, Eq. 3)	OI(t)
Control	Demand forecasting and automated decision loops	Exponential smoothing, active-learning segmentation (Eq. 2, Eq. 8)	F1-score

Runtime	Service composition and resource orchestration (Sect. 5.1)	Microservice composition, service-mesh routing, cost optimization (Eq. 5)	C(s)
Service	Customer-facing fulfillment and SLA/QoE governance	SLA/QoS monitoring, experience scoring (Eq. 6, Eq. 9)	CES / SLA %

Taken together, Tables 1–3 and Figs. 1–5 indicate that the dominant contributor to ISEF's gains is not automation volume alone (AI) but the quality of the underlying operational-intelligence signal OI(t): latency, cost, and SLA compliance all improve super-linearly once OI(t) crosses the ≈0.55 confidence threshold identified in Fig. 5, reinforcing the fabric's design rationale of tightly coupling demand understanding (Sect. 4) with operational automation (Sect. 3) rather than treating them as independent subsystems.

5.1 Service mesh and microservices governance

A service mesh for managing microservices ecosystem and enabling customer fulfillment optimization is proposed and the elements governing their behavior are discussed. The microservices architecture constitutes a foundation for developing applications in a distributed and modular way, introducing the concept of service composition that improves maintainability and resilience, and enables sound observability and security. However, the consequent establishment of a microservices ecosystem calls for a governance framework for their lifecycle management, along with observability and security policies that take into account not only the normal operation but also potential faults. The observability of service composition enables a better identification of the relations between the services. Closing the loop, a service mesh that nurtures the support of the service composition concept, while helping service providers to comply with the Quality of Service (QoS) levels defined by their customers and it helps consumers to minimize the service delivery cost.

A service mesh—acting at the transport layer and providing application-level functions—is deployed to support these concerns, ease the communication between the microservices and provide observability, reliability and security. These properties of the mesh help tackle the service discovery and observability requirements, enabling better formulation of behavior models as well as their prognosis and fulfillment of the Quality of Experience (QoE) requirements demanded by services consumers and defined in Service Level Agreement (SLA). Quality requirements that are expressed in terms of security, reliability and latency can be met when the deployed system is resilient to possible faults.

6. Conclusion

Existing large-scale data center operators commonly emphasize customer subscription- and demand-oriented service provisioning, offering appropriately designed and scaled services with a focus on customer experience, with requests governed by SLAs. These providers aim to ensure the security, availability, and non-disruption of services through independent fault-tolerant and disaster recovery provisions at the service level. Autonomous operations and service-centric architectures are primarily regarded from the perspective of lower-level design and support functions, with automated operations mainly considered for reliability, security, and performance management.

Dynamic customer demand and experience considerations, however, are not yet leveraged in the response to the autonomous operations trend. Intel's Intelligent Service Experience Fabric addresses this gap, working synergistically with operational intelligence and automation to optimize the understanding of demand and its match to services in real time. Two interacting but separate fulfillment dimensions are recognized: understanding and composing customer demand. Autonomously fulfilling the overall service experience requires support at all levels of the service architecture in a service-centric approach. Features of the data, control, and application planes are specified with particular emphasis on the service composition function, where the demand signal is interpreted to define a secure, high-quality, and available service composition that meets customer expectations.

References

1. Gill, S. S., Chana, I., & Buyya, R. (2020). STAR: SLA-aware autonomic management of cloud resources. IEEE Transactions on Cloud Computing, 8(4), 1040–1053.
2. Nguyen, T. H., Di Francesco, M., & Ylä-Jääski, A. (2020). Virtual machine consolidation with multiple usage prediction for energy-efficient cloud data centers. IEEE Transactions on Services Computing, 13(1), 186–199.
3. Wei, W., Wang, K., Wang, K., Gu, H., & Shen, H. (2020). Multi-resource balance optimization for virtual machine placement in cloud data centers. Computers & Electrical Engineering, 88, 106866.
4. Sriram, H. K., Adusupalli, B., Singreddy, S., & Malempati, M. (2021). Revolutionizing risk assessment and financial ecosystems with smart automation, secure digital solutions, and advanced analytical frameworks. Murali, Revolutionizing Risk Assessment and Financial Ecosystems with Smart Automation, Secure Digital Solutions, and Advanced Analytical Frameworks (December 27, 2021).
5. Yakubu, I. Z., Musa, Z. A., Muhammed, L., Ja'afaru, B., & others. (2020). Service level agreement violation preventive task scheduling for quality of service delivery in cloud computing environment. Procedia Computer Science, 178, 375–385.
6. Calmon, T. S., Bhaya, A., Diene, O., Passoni, J. F., Gottin, V. M., & Sousa, E. V. (2020). Control strategies for adaptive resource allocation in cloud computing. IFAC-PapersOnLine, 53(2), 7865–7871.
7. Khan, A. A., Zakarya, M., Ur Rahman, I., Khan, R., & Buyya, R. (2021). HeporCloud: An energy and performance efficient resource orchestrator for hybrid heterogeneous cloud computing environments. Journal of Network and Computer Applications, 173, 102869.

8. Saxena, D., & Singh, A. K. (2021). A proactive autoscaling and energy-efficient VM allocation framework using online multi-resource neural network for cloud data center. Neurocomputing, 426, 248–264.
9. Yang, Y., Guo, S., Liu, G., & Yi, L. (2021). Fine granularity resource allocation of virtual data center with consideration of virtual switches. Journal of Network and Computer Applications, 175, 102916.
10. Renugadevi, T., & Geetha, K. (2021). Task aware optimized energy cost and carbon emission-based virtual machine placement in sustainable data centers. Journal of Intelligent & Fuzzy Systems, 41(5), 5677–5689.
11. Angappan, S. K., Robe, T., Muleta, S., & Worku, B. (2021). Distributed cloud resources allocation for fair utilization using multi-objective bin packing algorithm. International Journal of Intelligent Unmanned Systems, 12(2), 229–241.
12. Federici, M., & others. (2021). Federated geo-distributed clouds: Optimizing resource allocation based on request type using autonomous and multi-objective resource sharing model. Big Data Research, 24, 100188.
13. Mashetty, S. (2022). Enhancing Financial Data Security And Business Resiliency In Housing Finance: Implementing AI-Powered Data Analytics, Deep Learning, And Cloud-Based Neural Networks For Cybersecurity And Risk Management. Migration Letters, 19(6), 1302-1818.
14. Tuli, S., Gill, S. S., Xu, M., Garraghan, P., Bahsoon, R., Dustdar, S., Sakellariou, R., Rana, O., Buyya, R., Casale, G., & Jennings, N. R. (2022). HUNTER: AI based holistic resource management for sustainable cloud computing. Journal of Systems and Software, 184, 111124.
15. Xue, S., Qu, C., Shi, X., Liao, C., Zhu, S., Tan, X., Ma, L., Wang, S., Wang, S., Hu, Y., Zheng, Y., & others. (2022). A meta reinforcement learning approach for predictive autoscaling in the cloud. Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, 4290–4299.
16. Wang, J., Gu, H., Yu, J., Song, Y., He, X., & Song, Y. (2022). Research on virtual machine consolidation strategy based on combined prediction and energy-aware in cloud computing platform. Journal of Cloud Computing, 11, 50.
17. Al-Sayed, M. M. (2022). Workload time series cumulative prediction mechanism for cloud resources using neural machine translation technique. Journal of Grid Computing, 20, 16.
18. Panwar, R., & Supriya, M. (2022). Dynamic resource provisioning for service-based cloud applications: A Bayesian learning approach. Journal of Parallel and Distributed Computing.
19. Al-Wesabi, F. N., Obayya, M., Hamza, M. A., Alzahrani, J. S., Gupta, D., & Kumar, S. (2022). Energy aware resource optimization using unified metaheuristic optimization algorithm allocation for cloud computing environment. Sustainable Computing: Informatics and Systems, 35, 100686.
20. Ye, G., Gao, F., & Fang, J. (2022). A mission-driven two-step virtual machine commitment for energy saving of modern data centers through UPS and server coordinated optimizations. Applied Energy, 322, 119467.
21. Botlagunta, P. N., & Sheelam, G. K. (2020). Data-Driven Design and Validation Techniques in Advanced Chip Engineering. Global Research Development (GRD) ISSN, 2455-5703.

22. Medara, R., Singh, R. S., & Sompalli, M. (2022). Energy and cost aware workflow scheduling in clouds with deadline constraint. Concurrency and Computation: Practice and Experience, 34(13), e6922.
23. Kumari, M., Sahoo, G., Senapati, K. K., & Kumar, G. (2022). Energy-aware autoscaling for scientific workflow in cloud environment. Concurrency and Computation: Practice and Experience, 34(3), e6576.
24. Li, Z., Lin, K., Cheng, S., & others. (2022). Energy-efficient and load-aware VM placement in cloud data centers. Journal of Grid Computing, 20, 39.
25. Paleti, S. (2021). Cognitive core banking: A data-engineered, AI-infused architecture for proactive risk compliance management. AI-Infused Architecture for Proactive Risk Compliance Management (December 21, 2021).
26. Choudhary, A., Govil, M. C., Singh, G., Awasthi, L. K., & Pilli, E. S. (2022). Energy-aware scientific workflow scheduling in cloud environment. Cluster Computing, 25, 3845–3874.
27. Wang, Y., Tao, X., Zhao, F., Tian, B., & others. (2020). SLA-aware resource scheduling algorithm for cloud storage. Journal on Wireless Communications and Networking, 2020, 6.
28. Singh, S. S., & others. (2020). An automated resource management framework for minimizing SLA violations and negotiation in collaborative cloud. International Journal of Cognitive Computing in Engineering, 1, 27–35.
29. Cao, J., & others. (2022). Optimal strategies on pricing and resource allocation for cloud services with service guarantees. Computers & Industrial Engineering, 165, 107957.
30. Recharla, M. (2020). Targeted Gene Therapy for Spinal Muscular Atrophy: Advances in Delivery Mechanisms and Clinical Outcomes. International Journal of Science and Research (IJSR), 9(12), 1921-1934.