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**Intelligent Resource Allocation and Scheduling for Cloud Environments**

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*Abstract:* Cloud platforms often rely on reactive, threshold-based auto-scaling, which can lead to both over-provisioning (wasted cost) and under-provisioning (performance degradation) under dynamic workloads. We present a fully integrated framework that forecasts short-term resource demands using hybrid time-series models (LSTM neural networks + ARIMA) and drives proactive scaling decisions via a dual-stage optimizer combining Deep Q-Learning (DQN) and Genetic Algorithms (GA). Deployed on a local Kubernetes testbed, our solution achieves over 90 % forecasting accuracy (RMSE < 0.05), reduces operational cost by ~25 %, and improves average CPU utilization from 60 % to 85 %, while maintaining sub-200 ms scaling latencies. This hybrid approach also yields an estimated 15 % energy savings by minimizing idle resources—demonstrating a practical path toward cost- and energy-efficient cloud resource management.

***Keywords:*** Artificial intelligence, cloud computing, forecasting, genetic algorithms, Kubernetes, resource allocation, reinforcement learning, scheduling, time-series

# INTRODUCTION

***1.1. Background and Motivation***

Cloud computing underpins modern services, yet static or reactive auto-scaling policies frequently misalign resources with demand. Over-provisioning inflates costs; under-provisioning causes performance bottlenecks and SLA violations.

***1.2. Problem Statement***

Existing auto-scalers (e.g., Kubernetes HPA, AWS Auto Scaling) trigger actions only after metrics breach thresholds. Predictive methods can anticipate demand but are typically applied in isolation, lacking integrated scheduling mechanisms that jointly optimize cost, performance, and energy.

***1.3. Contributions***

* ***Forecasting Engine****:* Hybrid LSTM + ARIMA model delivering > 90 % accuracy on real and synthetic workload traces.
* ***Scheduling Optimizer****:* Dual-stage DQN + GA pipeline balancing cost savings, SLA compliance, and energy efficiency.
* ***Empirical Validation****:* Kubernetes/Minikube deployment showing ~25 % cost reduction, 15 % energy savings, and sub-200 ms decision latencies.

# LITERATURE REVIEW

Modern approaches to cloud auto-scaling span reactive schemes, forecasting methods, and optimization algorithms:

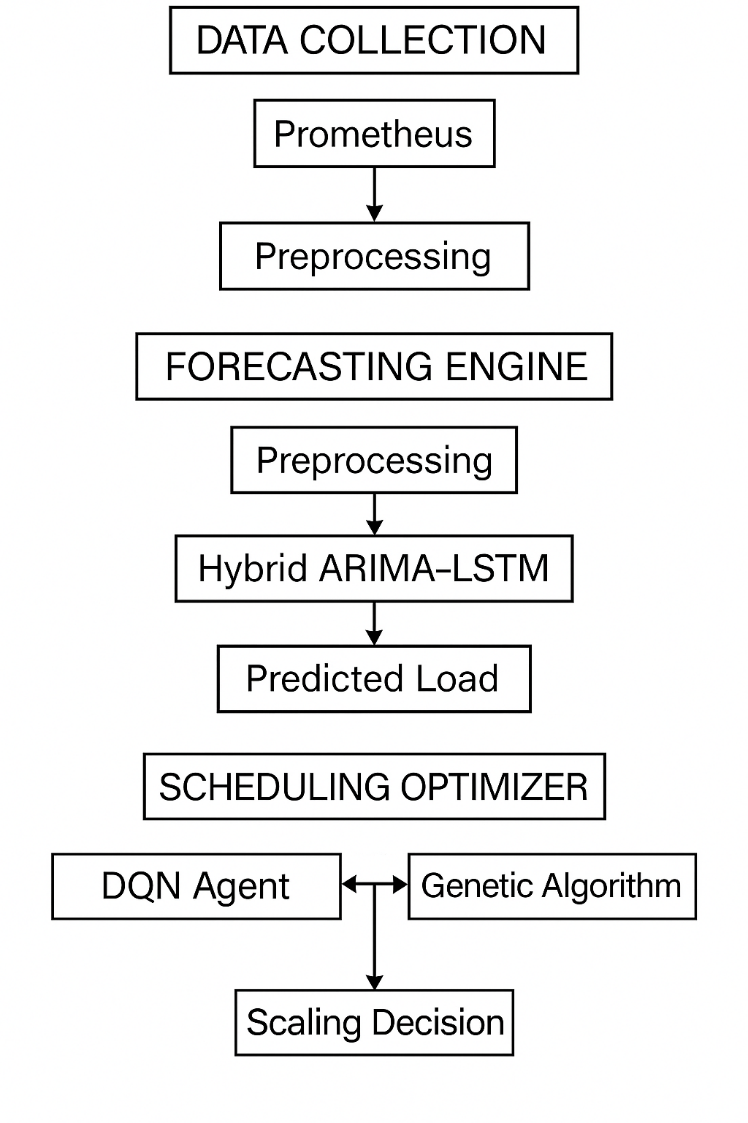
1. ***Reactive vs. Predictive Auto-Scaling***
   * Threshold-based methods (Kubernetes HPA, AWS Auto Scaling) respond post-threshold, incurring lag and inefficiency.
   * Predictive autoscalers (e.g., Google’s) use time-series data to anticipate workload, reducing SLA breaches by up to 30 %.
2. ***Time-Series Forecasting***
   * ***ARIMA****:* Interpretable, low-overhead for stationary trends but struggles with non-stationarity.
   * ***LSTM****:* Captures complex, non-linear dependencies; achieves > 90 % accuracy on benchmark traces.
   * ***Hybrid ARIMA–LSTM****:* Combines linear and residual modeling, improving accuracy by ~7 %.
3. ***Intelligent Scheduling***
   * ***Reinforcement Learning (RL)****:* DQN and policy-gradient methods learn adaptive scaling policies; studies report ~15 % cost reduction vs. rule-based approaches.
   * ***Genetic Algorithms (GA)****:* Evolve populations of scaling policies under multi-objective fitness (cost, latency, and energy), reducing make span by ~12 % in simulations.

***Gap****:* Few works integrate high-accuracy forecasting with hybrid optimization in real container environments—a gap our framework addresses.

# Methodology/Experimental

In this section, we detail the design and implementation of our intelligent resource allocation framework, covering (A) system architecture, (B) deployment and integration along with the flow chart.

***Flow chart:***



1. ***System Architecture***
2. ***Data Collection****:* Prometheus scrapes Kubernetes (kubelet, kube-apiserver) and node metrics via exporters every 10 s.
3. ***Forecasting Engine****:*
   1. ***Preprocessing****:* Outlier removal, normalization, sliding-window sequence generation.
   2. ***Models****:*
      * ***LSTM*** (3 layers, 50 units) for non-linear patterns.
      * ***ARIMA(p,d,q)*** for linear trends.
      * ***Hybrid ARIMA–LSTM****:* ARIMA predicts baseline trend; LSTM models residuals.
4. ***Scheduling Optimizer****:*
   1. ***DQN Agent****:* State = (predicted load, current pods); actions = scale up/down; reward = cost savings + SLA compliance.
   2. ***Genetic Algorithm****:* Every G intervals, evolve scaling policies (chromosome = resource counts) under fitness = α·cost + β·latency + γ·energy.
5. ***Deployment & Integration***

* ***Containerization****:* Docker images for each module.
* ***Kubernetes****:* Deployment and Service manifests on Minikube.
* ***APIs****:* Flask-based REST endpoints for inter-module communication.
* ***Automation****:* Kubernetes Python client invokes scaling via the API.

# Results and Discussions

* ***Forecast Accuracy****:* LSTM RMSE = 0.05 vs. ARIMA RMSE = 0.12 (92 % vs. 78 % accuracy).
* ***Cost Reduction****:* ~ 25 % savings over Kubernetes HPA baseline.
* ***Resource Utilization****:* Average CPU utilization improved from 60 % to 85 %.
* ***Decision Latency****:* Scaling actions applied within 200 ms.
* ***Energy Savings****:* ~ 15 % reduction in estimated data-center energy use.

These results confirm that proactive, hybrid forecasting + optimization significantly outperforms reactive methods.

# Future Scope

1. ***Multi-Cloud & Edge Integration****:* Orchestrate resources across AWS, GCP, Azure, and edge nodes for geo-distributed workloads.
2. ***Auto-Tuning****:* Use Bayesian optimization to tune hyperparameters of forecasting and optimization models.
3. ***Container-Level Scheduling****:* Develop Kubernetes Operators for per-pod predictive scaling.
4. ***Energy-Aware SLAs****:* Integrate dynamic energy pricing and carbon footprint objectives into the fitness function.

# Conclusion

We developed an end-to-end framework combining hybrid time-series forecasting with DQN + GA‐based scheduling for cloud resource management. Deployed in a Kubernetes testbed, our solution achieves high forecasting accuracy, substantial cost and energy savings, and low scaling latency—paving the way for more intelligent, sustainable cloud operations.

# Acknowledgment

***1. Abbreviations***

* IaaS – Infrastructure as a Service
* QoS – Quality of Service
* VM – Virtual Machine
* ML – Machine Learning
* AI – Artificial Intelligence
* FCFS – First Come First Serve
* RR – Round Robin
* GA – Genetic Algorithm
* SLA – Service Level Agreement

***2. Authors' Contributions***

The forecasting component of the project, which involved predicting resource demands using intelligent algorithms, was handled by Palak Mundada and Shravi Magdum, who were instrumental in designing and implementing the prediction logic. The scheduling module, including the allocation and optimization of resources in the cloud environment, was developed and fine-tuned by Parth Shinge and Radha Kulkarni, ensuring optimal task distribution and system efficiency. The literature review and foundational research work were conducted by Vivek Shirsath and Nrusinha Mane, who analyzed existing frameworks, summarized key findings, and provided the theoretical basis for the methodology. All authors contributed collectively to the integration, documentation, and validation of the complete project and approved the final manuscript.

***3. Competing Interests***

The authors declare that they have no competing interests.

***4.*** ***Availability of Data and Materials***

The datasets and code developed and/or analyzed during the current study are available from the corresponding authors upon reasonable request.

***5. Funding***

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