ELASTICITY CONTROL FOR LATENCY-INTOLERANT MOBILE EDGE APPLICATIONS

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ELASTICITY IN CLOUD

- What is Elasticity?
- How does Cloud Computing Control Elasticity?
 - Re-active.
 - Pro-active.
 - Hybrid.



ELASTICITY CONTROL IN MEC GOAL

Operator cost Resource utilization ↓ Stability ↓

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User SLOs

Rejection rate \uparrow Response time \uparrow

Reactive

An interesting story - Hotstar OTT app

- Autoscaling doesn't work
- Cross-app API calls
- Battle-tested scaling strategy
- 1M+ requests/sec
- 10 Tbps+ peak bandwidth





ELASTICITY IN MOBILE EDGE CLOUD – A NECESSITY

- Most MECs applications are latency-sensitive applications.
- Limited resources with higher resource costs at the edge data centers (EDCs).
- The stochastic nature of user mobility causes resource demand fluctuated.
- Actuation delays allocated resources are not ready to be used immediately.

Overview of the paper

- Objective
 - Allocated Resources = Current Demand
- Idea
 - Proactive scaling based on location-aware workload prediction
 - Redistribute workload from under-provisioned EDC to close by EDCs
- Contributions
 - Implementation of location-aware elastic controller
 - Evaluation on simulated topology
- Key results
 - State-of-the-art controller: 69% utilization, 0.04% rejection rate
 - Elastic controller: 85% utilization, 0.02% rejection rate

Idea: workload cross-correlation between EDCs



PRO-ACTIVE ELASTIC CONTROL FRAMEWORK

Location-aware Workload Predictor

• Multi-variate LSTM networks.

• Performance Modeler

 $_{\odot}~$ Resources are abstracted at Pod modelled as a M/M/1/k FIFO ~ queue.

Resource Provisioner

 $\circ~$ cross-evaluating the resource requirements of EDCs in a group and determine a final number of desired resources for each EDC.

Group Load-balancer

• Weight round-robin load balancing approach.

PRO-ACTIVE ELASTIC CONTROL FRAMEWORK



Figure 1: Components of the proposed controller.

How it builds on previous works

- Prediction: Multivariate LSTM-based Location-aware Workload Prediction for EDCs
- Modeler: Queuing theory
- Provisioner: Extends Kubernetes auto-scaling

EXPERIMENT SETTING

- Emulated MEC:
 - $_{\odot}~$ MEC with EDCs distributed over a metropolitan area.
- Application:
 - Extremely latency-intolerant AR application.
- Workload:
 - $_{\circ}~$ Real taxi mobility traces.



EXPERIMENT SETTING

- Predefined Service Level Objectives:
 - Average Utilization = 80%.
 - Rejection rate = 1%.
- Controller settings:
 - Pro-active Auto Scaler.
 - Pro-active Auto Scaler + Group Load Balancer.
 - Re-active Auto Scaler: Kubernetes HPA*.

TABLE I: Group settings.

GroupID	EDCs		
#1	#1, #2, #3, #5, #10		
#2	#8, #12, #15		
#3	#11, #14		
#4	#4, #6, #7, #9, #13		

*https://kubernetes.io/docs/tasks/run-application/horizontal-pod-autoscale/

EXPERIMENT SETTING



EVALUATION - PERFORMANCE METRIC

- System and user-oriented metrics: recommend by SPEC*
 - \circ Under-provisioning accuracy,
 - $_{\circ}~$ Over-provisioning accuracy,
 - Under-provisioning timeshare,
 - \circ Over-provisioning timeshare,
 - \circ Instability.

*Nikolas Herbst et al., Ready for rain? A view from SPEC research on the future of cloud metrics

How does the proposed pro-acitve controller perform when compared to the re-active controller?

Metric	Pro-active AS + LB	Pro-active AS	Re-active AS
$ heta_U$	13.6	41.2	5.4
θ_O	14.2	39.5	305.6
$ au_U$	4%	43%	5.3%
τ_O	2.5%	46.7%	94.1%
υ	2.44%	2.8%	3.9%
Avg. resource uti- lization	85.9%	80.5%	68.4%
Rejection rate	0.02%	0.26%	0.04%
total Pods	3154	4405	5337
Avg. Pod lifetime (minute)	73.3	35.2	29.6

Table II: The performance of the three controllers based on the elasticity metrics.

How does the proposed pro-acitve controller perform when compared to the re-active controller?



Figure 5: The scaling behavior of three controllers on EDC#1.

How does the proposed pro-acitve controller perform when compared to the re-active controller?



Figure 6: Cumulative density of response times of the application in three elastic controller settings.

To what degree does location-awareness improve scaling?

- Conduct another experiment which a group is set with different size k
 - \circ k = 1
 - \circ k = 15



What is the decision time of the elastic controller?



Figure 8: Average Decision Time of the three controllers.

What is the impact of the two predefined threshold on the controller's scaling behavior?



(a) The targeted resource utilization is changed, while the targeted rejection rate is held constant at 1%.

(b) The targeted rejection rate is changed, while the targeted resource utilization is held constant at 80%.

CONCLUSION

- The correlation of workload variation in physically neighboring EDCs help improve the resource estimation.
- The Group Load-balancer further helps minimize the request rejection rate.
- The proposed controller achieves a significant better scaling behavior as compared against the state-of-the-art re-active controller.

Discussion

- Positive points
 - Clean and novel approach
 - Locative-aware approach may be applicable to use cases other than elasticity
 - Uses conventional approaches for application deployment
- Negative points
 - Low # of EDCs for evaluation (cell towers)
 - · Communication delay may not be found empirically
 - 2.5ms is impractical
 - If head movement > 100° ; latency < 2.5ms [1]
 - Arbitrary grouping of EDCs
 - Too many unknowns in evaluation (uniform distribution)

[1] Randall E Bailey, Jarvis James Arthur III, and Steven P Williams. Latency requirements for head-worn display s/evs applications. In Enhanced and Synthetic Vision 2004, volume 5424, pages 98–109. International Society for Optics and Photonics, 2004.