Mobile Games at the Edge: A Performance Evaluation to Guide Resource Capacity Planning

Gabriel Araújo[2], Carlos Brito[2], Leonel Correia[2], Tuan Anh Nguyen[1,*], Jae Woo Lee[1,*] and Francisco Airton Silva[2]

[1]*Konkuk Aerospace Design-Airworthiness Research Institute (KADA), Konkuk University, Seoul, South Korea*

[2]*Federal University of Piauí (UFPI), Picos, PI, Brazil*

Keywords: Mobile Edge Computing, Online Gaming Services, Queuing Models, Performance Evaluation, Quality of Service.

Abstract: Mobile games are very popular among young generations, especially during the worldwide Covid-19 pandemic. The pandemic has caused an enormous increase in data transactions and computation over the Internet. Computing for games often consumes a vast amount of computational resources. Nowadays, mobile devices require heavy computing tasks. For this reason, edge computing resources are essentially needed in the game industry for non-latency data transactions. However, edge computing involves many aspects that make its architecture highly complex to evaluate. Pure performance evaluation of such computing systems is necessary for real-world mobile edge computing systems (MEC) in the game industry. This paper proposes a closed queuing network to evaluate the performance of a game execution scenario in MEC. The model permits the evaluation of the following metrics: mean response time, drop rate, and utilization level. The results indicate that the variation in the number of physical machines (PM) and virtual machines (VM) has a similar impact on the system's overall performance. The results also show that dropped messages can be avoided by making small calibrations on the capabilities of the VM/PM resources. Finally, this study seeks to assist the development of game computing systems at MEC without the need for prior expenses with real infrastructures.

1 INTRODUCTION

Online games are extremely profitable in the entertainment industry nowadays. According to Statista[1] Mobile games are the most popular apps on mobile devices, with time spent on mobile devices growing by 26% in the year 2021. According to Newzoo's Global Games Market Report, the mobile games market generated revenue of $68.5 billion in 2019 and is expected to generate revenue of $95.4 billion in 2022 (Wijman, 2019). This billion-dollar market corresponds to one of the most active sectors in software development. The quality of service (QoS) requirements for software/hardware infrastructures to host online game services are stringent to secure game data transactions with uninterrupted availability and high performance. However, mobile devices are often featured by limited processing and storage capacity. Due to these constraints, mobile devices become rapidly obsolete, and hard to host state-of-the-art releases of new games. Therefore, emerging computing paradigms have come into play as alternative solutions for limited mobile devices' computational resources.

Mobile cloud computing (MCC) has been a dominant computing paradigm for mobile gaming in the past years. MCC has been permitted to render games remotely in the cloud and transmitted back to players (Zhang et al., 2019). This alternative allows players to start games immediately, without downloads and time-consuming software installations (Li et al., 2018). Besides, MCC brings advantages to game developers such as cost savings, platform independence, resource enhancement, and piracy prevention (Yates et al., 2017). Developing efficient gaming systems is required to diminish the latency of a player's gaming interaction from her gaming device to the end computing centers. To satisfy strict requirements to reduce gaming latency, mobile edge computing (MEC) comes into play to bring the computing and storage capabilities even closer to mobile devices (Carvalho

*Corresponding author

[1]https://www.statista.com/statistics/1272220/time-spent-mobile-apps-worldwide-by-category/

Araújo, G., Brito, C., Correia, L., Nguyen, T., Lee, J. and Silva, F.
Mobile Games at the Edge: A Performance Evaluation to Guide Resource Capacity Planning.
DOI: 10.5220/0011071200003200
In *Proceedings of the 12th International Conference on Cloud Computing and Services Science (CLOSER 2022)*, pages 238-245
ISBN: 978-989-758-570-8; ISSN: 2184-5042

et al., 2020).

Performance evaluation is essential to guarantee an optimized game system execution at the edge. MEC performance evaluation is often required even before developing the real-world system. However, carrying out real experiments is usually expensive, time-consuming, and often calls for a third-party organization involvement. Aiming to reduce costs in developing complex computational systems, here specifically for gaming, analytical models are often adopted to forecast the future system behaviors (Willig, 1999). Queuing models, for example, enable the assessment of different performance metrics of a targeted, practical system. More specifically, queuing modeling can predict the effect of resource containment and variation on system performance through different metrics, such as drop rate, the mean response time (MRT), mean number of users, and others (Cohen and Boxma, 1985).

Studies in the literature showed significant progress in the assessment of gaming cloud and edge infrastructures using analytical models (Hains et al., ; Lee et al., 2015; Li et al., 2017; Li et al., 2018; Marzolla et al., 2012; Wu et al., 2015; Yates et al., 2017). Among the studies mentioned above, exclusively the work (Hains et al.,) performed a game performance assessment at MEC considering only the MRT metric. The performance modeling and evaluation of the gaming system coupled with the edge computing paradigm is of paramount importance even in advance the real-world system development.

This paper proposes a **closed-loop queue-based performance evaluation model** that captures the fundamental pure-performance behaviors of data transactions in MEC. The model enables game designers at the edge to analyze the impact of changes in system performance even during design stages. The model is highly adjustable, allowing the configuration of several parameters such as transmission time, service time, queue size, and resource capacities. We have conducted a **sensitivity analysis** combining various factors to determine which ones have the most significant impact on the system's response time. The number of virtual machines (VMs) and physical machines (PMs) were the most sensitive factors, causing a significant impact on the system's response time. We have also explored a resource capacity variation that works as a practical guide for performance analysis in a gaming execution scenario at the edge with the proposed model. To the best of our knowledge, this study is unique in the research area on adopting queuing models for performance evaluation of a MEC-based gaming system.

2 RELATED WORK

This section presents the related work. The papers have proposed different analytical models (e.g., Petri net, Markov chain, queuing networks) to evaluate the performance of various architectures in the cloud or edge infrastructures. Table 1 details the comparison of selected works with our study.

Metrics - All papers used different performance metrics to evaluate their proposals. A wide number of metrics are important to understand how the system behaves. Yates et al., 2017 proposes a model for cloud gaming systems to optimize low latency video frame rate updates. Hains et al., features a client/server solution designed to improve network conditions with games online that use remote centralized servers to improve game connection stability. However, the papers by (Yates et al., 2017), and (Hains et al.,) only used the analysis metrics of mean age and MRT, respectively. While in (Li et al., 2017; Li et al., 2018), the authors have focused only on a normalized cost metric. The work (Wu et al., 2015) presented a new transmission programming structure to guarantee the quality of delivery of videos with high frame rates in mobile cloud gaming scenarios. Lee et al., 2015 proposed a speculative execution system for mobile cloud games. Wu et al., 2015 and Lee et al., 2015 have used metrics of service quality and processing time, respectively. However, the studies of Yates et al., 2017, Li et al., 2017, Li et al., 2017, Wu et al., 2015, and Lee et al., 2015 did not consider metrics such as resource utilization and the number of requests in their systems to optimize their performance. Jittawiriyanukoon, 2014 developed a queuing model that is considered a reliable data scheduler. However, the authors did not concern some other critical performance metrics such as drop rate. Our proposal assimilates critical performance metrics of a gaming system, including mean response time (MRT), resource utilization, number of requests in the system, and request drop rate. Such metrics were not investigated systematically and comprehensively by any related studies.

Load Balance - The vast majority of related studies in literature did not consider essential techniques to balance the workload of their architectures. Only two studies (Marzolla et al., 2012) and (Song et al., 2016) used load balancing in their proposals. Marzolla et al., 2012 used load balance to evenly distribute requests between servers in a zone controller, which is a software component responsible for handling all interactions between players and the virtual world. Song et al., 2016 proposed an approach based on queuing theory for task management and a heuristic algorithm for resource management. Song et al., 2016 com-

Table 1: Comparison of selected works.

Title	Application Context	Metrics	Architecture	Load Balance	Capacity Evaluation
(Marzolla et al., 2012)	Games	Mean response time and number of users online	Cloud	✓	✗
(Nan et al., 2014)	Multimedia	Mean response time and resource cost	Cloud	✗	✓
(Jittawiriyanukoon, 2014)	Multimedia	Mean queue length, utilization, mean waiting time in queue, throughput and mean traversal time	Cloud	✗	✗
(Song et al., 2016)	Multimedia	Average task waiting time and Cumulative Cost	Cloud	✓	✗
(Wu et al., 2015)	Games	Peak signalto-ratio, output and end-to-end delay	Cloud	✗	✓
(Lee et al., 2015)	Games	Client frame time, throughput and processing time	Cloud	✗	✗
(Yates et al., 2017)	Games	Average age	Cloud	✗	✗
(Li et al., 2017)	Games	Monetary Cost	Cloud	✗	✓
(Li et al., 2018)	Games	Monetary Cost	Cloud	✗	✓
(Hains et al.,)	Games	Mean response time	MEC	✗	✗
Our Work	Games	Mean response time, utilization, system number of messages, throughput and drop rate	MEC	✓	✓

pared load balancing with three other approaches to show the effectiveness of their approach. Our work uses load balance to control the workload among the queues.

Capacity Evaluation - Li et al., 2017 addressed the problem of server provisioning for the cloud in the gaming context. This work assessed the server's ability to discover its influence on the performance of the proposed algorithms. Li et al., 2018 used the capacity assessment to determine which of the servers has enough residual capacity to host a game instance. As we observed, these works focused on evaluating performance, focusing only on cost. Our work used capacity assessment in conjunction with load balancing to better system resources distribution.

3 AN MEC-BASED GAMING SCENARIO

Figure 1 shows an overview of the scenario for executing games at the MEC. The proposed scenario is based on the architectures presented in (El Kafhali et al., 2020) and (Carvalho et al., 2020).

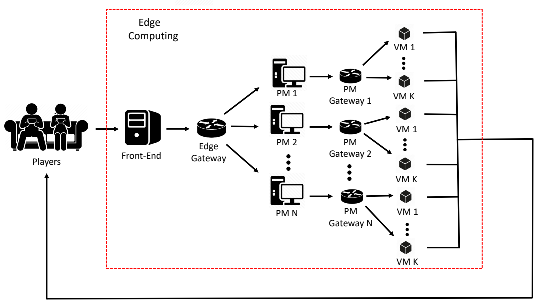


Figure 1: Evaluated scenario: executing games on mobile edge computing.

Players request gaming services for the Front-End machine, which distributes gaming requests among the edge components. Requests are generated by games executing on mobile devices and may vary according to the game context and the user's number. Therefore, low proximity to servers is required to provide efficient resource availability and a low mean response time.

The Front-End machine receives gaming requests from mobile devices. The Front-End re-transmit the requests to the physical machines (PMs) through an edge gateway. These requests can be, for example, gaming character movement commands. In addition to efficiently redirecting traffic to PMs, the gateway is responsible for data aggregation and load balancing. The PMs, in turn, offer a high level of processing and storage, with several virtual machines (VMs) allocated for the requests processing. Each PM is associated with a gateway that distributes and performs load balancing to respective VM nodes. Each VM receives and processes a request and then forwards it back to the players. Some assumptions were traced regarding the evaluated scenario.

- Edge
  - **[e1]:** Some details about communication between devices are not our main focus to simplify the modeling drawbacks. For instance, hand-shaking mechanisms, communication protocols, or other minor data transfer times between internal components. These times can be encompassed by the transmission and service times of the most general system components.
  - **[e2]:** Requests are independent from each other, and therefore the requests arrival complies with exponential distribution with an specific arrival rate λ (Song et al., 2016; Li et al., 2018; Jittawiriyanukoon, 2014; Lee

et al., 2015; Li et al., 2017). Our model can be extended and adopted when other non-exponential types of arrival distribution are considered, such as Erlang or Weibull distributions (Azaron et al., 2006; Grottke et al., 2010). In these cases, the assumption can be relaxed since the arrival time can be split into multi-phases of exponential distribution (Castet and Saleh, 2009).

  - **[e3]:** Different load balancing techniques in this layer are not taken into account. Since load balancing is not the focus of the assessment, requests received through the edge gateways and PMs are equally distributed to each PM and VM node, respectively.
  - **[e4]:** A homogeneous scenario was considered. All PMs and VMs have identical resources and processing capacities, while data processing is independent of each other. Each PM and VM node can have a multi-core CPU for parallel processing. The role of data storage in the border layer was not considered.
  - **[e5]:** Edge-layer virtual machines can have multiple cores for parallel processing similarly in modern cloud centers. The edge layer can scale elastically and balance the access load of several remote customers on a multi-core VM.
- Evaluation
  - **[s1]:** The pure performance of executing games on edge is the main focus of the modeling. Therefore, the involvement of physical components and their operational availability is minimized. Component failure and recovery behaviors are not considered in modeling for performance evaluation.
  - **[s2]:** The goal of this work is twofold: (i) exploring the bottleneck of supportive game architectures considered in real-time player data transmission, (ii) exploring the impact of changing the configuration of PMs and VMs on the edge layer for performance metrics and (iii) to realize the performance-related trade-offs between local players and distant players. Therefore, the complexity of the proposed general scenario is reduced to simplify the performance models using the queuing network theory.

4 QUEUING MODEL

This section presents the closed queue model to represent data transactions throughout the gaming system in the scenario presented in the previous section. In a cyclic queuing model, the number of requests N is fixed since requests go through the N stages repeatedly with no allowed entries or exits. There are Ni parallel exponential servers at the nth stage, all with the same mean service time μi (Gordon and Newell, 1967). When the service is completed at the i stage, a request proceeds directly to the j stage with probability p_{ij}. These cyclical models are stochastically equivalent to open systems in which the number of requests cannot exceed N. Equilibrium equations for the joint probability distribution of requests are solved by a variable separation technique (Gordon and Newell, 1967).

Figure 2 illustrates the proposed model for the evaluated scenario. All model components follow the same name standards used to describe the gaming scenario. The data flow occurs from left to right. Players generate requests within a predefined time interval following a particular exponential distribution. These requests are sent to the Front-End queue and then to PMs with a uniform distribution through the edge gateways. Since the random distribution is extremely fast, such time is not considered in this paper.

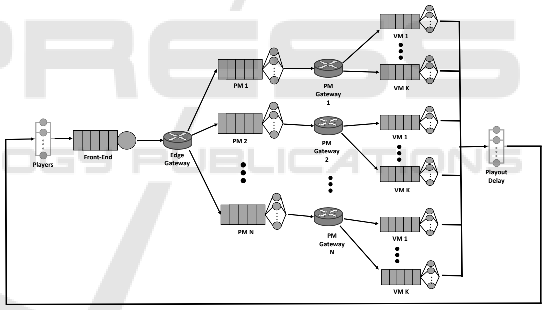


Figure 2: Queuing model for executing games on mobile edge computing.

In each PM has K VM queues that will carry out requests. There are also N gateways for each PM. These gateways transmit the requests to the VMs, then they are forwarded back to the players. The play-out delay simulates the time taken by the player to decode and display the frame on his screen. It has no specific service; it is only one component that causes a delay in transmitting a request. After the response reaches the client, new requests are generated in a cyclic scheme. It is assumed that the received data will be processed considering a queue rule Fist-In-First-Out (FIFO). The Front-End, PM, and VM queues are modeled considering the M/M/c/K queue model. The main parameters of such stations are queue size, service time, and the number of internal servers, which, in this work, correspond to the number of processing cores. The M/M/c/K queue model means the queue size is K shared by c service stations.

5 PERFORMANCE EVALUATION

This section presents a performance evaluation of the proposed queuing model. The section is divided into two parts. Section 5.1 presents a sensitivity analysis to identify the parameters with the greatest impact on the system. Finally, based on the variation of the parameters with the greatest impact, several performance metrics are observed in Section 5.2.

5.1 Sensitivity Analysis

This section presents a study of sensitivity analysis using the DoE method. The execution of the Design of Experiments (DoE) seeks to identify the factors that most influence the system. The MRT has been chosen as the dependent variable in this analysis because it is the most perceptive aspect to the final user. The analysis was performed using the system parameters as factors. Therefore, the adopted factors were: VMs number, PMs number, VM queue size, and VM service time. Table 2 presents the fixed parameters. Table 3 shows the DoE factors and levels. According to the previous analysis, the minimum (level 1) and maximum (level 2) values have been changed, looking for levels with the greatest impact on the MRT. Table 4 show all combinations of factors and respective levels. Sixteen combinations were generated (2-level design). Every combination was executed thirteen times. The MRT means of each combination is also identified in Table 4.

Table 2: Fixed parameters used in DoE.

Parameters	Values
Number of Requests	400
Front-End Queue Size	1000
PM Queue Size	1000
Front-End Service Time	10 ms
PM Service Time	20 ms
Users Service Time	10 ms
Playout Service Time	23 ms
Number of Front-End Cores	16
Number of PM Cores	16
Number of VMs Cores	6

Figure 3 presents the Pareto chart, which analyzes the impact of each factor on the MRT. The higher the bar, the greater the impact of that factor on the dependent metric. The Pareto chart shows the non-standardized effects and uses Lenth's method to draw a red reference line for statistical significance. The Pareto chart identifies important effects using Lenth's pseudo standard error (PSE). The red line of the Pareto chart is drawn at the margin of error, which is: $ME = t \times PSE$ where t is the $(1-\alpha/2)$ quantile of a t-distribution with degrees of freedom equal to the (number of effects/3) (Mathews, 2005). The number of VMs is the factor with the greatest impact, followed by the number of PMs. The number of VMs and PMs significantly impacts MRT with statistical confidence, as both go beyond the red line. The VM service time and the VM queue size have a lower impact than the number of PMs and VMs. The interaction between the factors (e.g., AB and AC) was not highly significant.

Table 3: Factors and respective levels.

Factors	Level 1	Level 2
VM Service Time	32 (ms)	42 (ms)
VM Queue Size	150	250
Number of PM	1	2
Number of VMs	1	4

Table 4: Combination of factors and levels.

Combinations	VM Service Time (ms)	VM Queue Size	Number of VMs	Number of PMs	Calculated MRT (ms)
#1	32	150	1	1	289.40
#2	32	150	4	1	293.62
#3	32	150	1	2	555.97
#4	32	150	4	2	917.54
#5	32	250	1	1	274.09
#6	32	250	4	1	1333.07
#7	32	250	1	2	1750.64
#8	32	250	4	2	251.97
#9	42	150	1	1	802.58
#10	42	150	4	1	480.93
#11	42	150	1	2	475.93
#12	42	150	4	2	342.82
#13	42	250	1	1	316.89
#14	42	250	4	1	1051.26
#15	42	250	1	2	698.01
#16	42	250	4	2	434.56

Figure 4 shows the main effects graph. The mean values obtained in the main effects graph allow us to know the results considering all possible factor combinations. Thus, the evaluator can better design the system in anticipation of any scenario. The y-axis represents the MRTs means for each level. The number of VMs factor has the greatest impact, with the most inclined line. The VMs factor obtained an MRT of 942.95 ms in its first level (1 VM). In the second

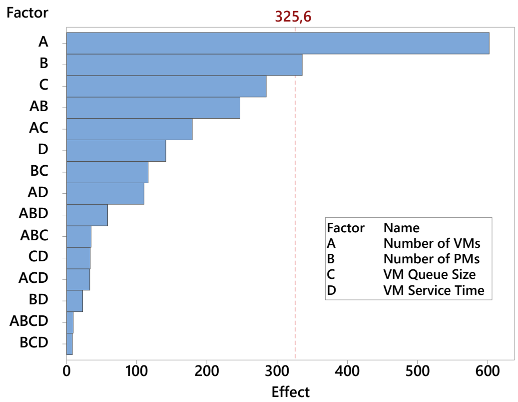


Figure 3: Impact of system factors on MRT.

level (4 VMs), the MRT was 340.72 ms. The variation in the number of VMs resulted in a considerable change to the system's MRT, with a difference of approximately 602.22 ms. The variation of the other factors was relatively small. The VM service time, for example, obtained a variation of 180 ms.

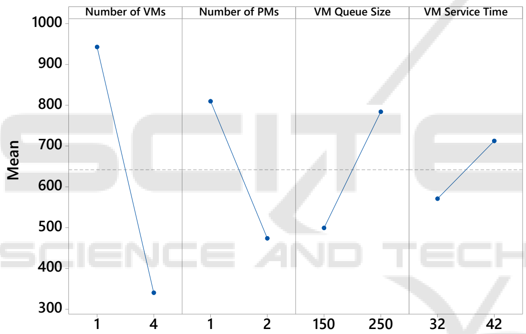


Figure 4: Main effect of system factors.

The DoE has evidenced that the number of processing nodes (VMs and PMs) is the most relevant aspect of the architecture. Therefore, the following section considers such information and performs two groups of numerical analyses by varying PMs and VMs numbers according to different arrival rates.

5.2 Numerical Analysis - VM Capacity Variation

This section presents a set of analyses using the proposed model to evaluate the following scenario: variation of the VM nodes. The Java Modeling Tools (JMT) (Bertoli et al., 2009) tool was used to model and evaluate the proposed scenario. JMT is an open-source toolkit for analyzing and evaluating the performance of communication systems, based mainly on the queue theory (Fishman, 2013). We consider the system's parameters used in (Gopika Premsankar and Taleb, 2018) as input parameters for our model. Gopika's work evaluated a MEC architecture with a single mobile device as a client and containers executing the services. Still, they evaluated a 3D game called *Neverball*, where the player must tilt the floor to control the ball to collect the coins and reach an exit point before time runs out. Table 5 shows the input parameters used for each component of the model, including queuing capacity. The **X** indicates that the component does not have a capacity definition for the station in turn. The number of requests was varied from 10 to 750 in the simulations.

Table 5: Fixed Input parameters.

Component Type	Component	Time (ms)	Queue Size	Number of Cores
Machine	Front-End	10.0	1000	16
	PM	20.0	1000	16
	VM	32.0	250	6
Delay	Users	10.0	X	x
	Playout	23.0	X	x

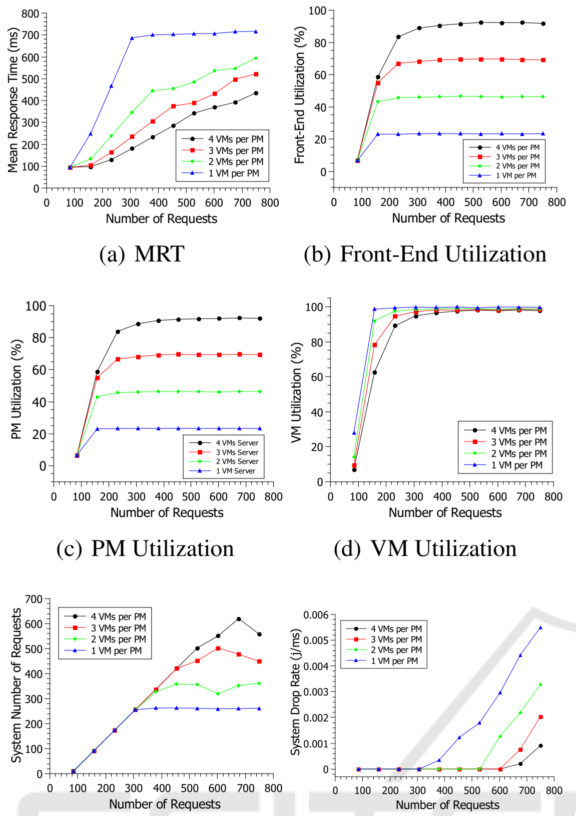
This scenario analyzes the model, varying the number of resources in the VM layer. Table 6 presents the configuration used in the experiments in scenario A. VMs varied from 1 to 4 nodes, keeping the values fixed for the other components. We use 2 PMs in this scenario. Figure 5 presents the results considering different numbers of VM nodes.

Table 6: Varied Parameters - Scenario A.

Component	Number of Machines
FrontEnd	1
PM	2
VM	1/2/3/4

Figure 5(a) shows the results as a function of the mean response time (MRT). Although the MRT has similar behavior for 2, 3, and 4 VMs, the greater the VMs, the lower the MRT to process the same number of requests in a homogeneous scenario. We observed a variation of 90ms of difference for 750 requests. Already considering a single VM, we have a discrepant behavior, with an MRT close to 720ms, due to the VM's low level of resource at this point. With this saturation, the loss of messages begins (see drop rate in Figure 5(f)). In other cases, the variation was from about 390ms (4 VMs) to about 575ms (2 VMs). Therefore, the increase in the number of VMs positively impacts response time.

Figures 5(b) and 5(c) show the use of Front-End and PMs, respectively. They showed an identical behavior: the greater the number of requests processed, the greater the utilization percentage. Therefore, a



(a) MRT (b) Front-End Utilization

(c) PM Utilization (d) VM Utilization

(e) Number of requisitions in the system (f) Drop Rate

Figure 5: Results for the analysis of the variation of the VM nodes.

smaller number of VMs implies a smaller number of requests processed and, consequently, less use and greater drop of messages (see Figure 5(f)). After 200 requests, all scenarios were saturated. It is important to note that such saturation does not represent the maximum utilization of the node's capacity. Only the node with 4 VMs approached the maximum capacity, while the others had their utilization rate varying from 22% to 64%.

Figure 5(d) shows the use of VMs. Again, the greater the number of requests, the greater the utilization. However, unlike Front-End and PMs, as the amount of resources increases, usage decreases. VMs only process requests that have passed through the Front-End and the PMs; fewer requests arrive and process everything that arrives. Besides, the processing capacity of VMs is less than Front-End and PMs. All nodes approach the maximum utilization capacity (100%) up to 500 requests, where nodes with fewer resources reach this capacity faster. After 500 requests, all nodes remain saturated and constant.

Figure 5(e) shows the number of requests within the system. The greater the capacity of the nodes, the greater the number of requests within the system. Therefore, the node with 4 VMs can handle a maximum number of requests equal to 640, dropping more than 100. While the node with 1 VM serves a maximum of 280 requests. Therefore, although many VMs increase the number of requests in the system, many losses still occur.

Finally, Figure 5(f) shows the rate of system request drops. The increase in the drop rate is directly proportional to the arrival of requests. The smaller the number of VMs, the higher the drop rate. Initially, everything that arrives is attended by all nodes, however, when the number of requests exceeds 300, losses start to occur. The node with 1 VM (worst case) reaches a drop rate of almost 0.006 j/ms. In the best case (4 VMs), the drop rate is less than 0.001 j/ms. The increase in the drop rate is caused by the depletion of resources on the VM nodes and is reflected in several system metrics. Nodes with 3 and 4 VMs have dropped requests from 600 requests. These nodes have a similar drop rate. Therefore, the node with 3 VMs may be a more advantageous option than the one with four concerning the drop rate in this scenario.

6 CONCLUSION AND FUTURE WORKS

This work proposed a closed queue model to represent and evaluate the performance of a game execution scenario in mobile edge computing. The relationship between the number of players and the VM/PM capacity variation is evidenced from different perspectives. The results show that the variation of PMs and VMs has a significant impact on the system's overall performance. The results also show that dropped messages can be avoided by making small calibrations on the capabilities of the VM/PM resources. As future work, we intend to extend the model to explore different types of communication between the components. More elements can also be included, such as cloud components for creating a hybrid model with a border layer and a cloud layer.

ACKNOWLEDGMENTS

This research was supported by Basic Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education (No. 2020R1A6A1A03046811).

REFERENCES

Azaron, A., Katagiri, H., Kato, K., and Sakawa, M. (2006). Reliability evaluation of multi-component cold-standby redundant systems. *Applied Mathematics and Computation*, 173(1):137–149.

Bertoli, M., Casale, G., and Serazzi, G. (2009). Jmt: performance engineering tools for system modeling. *ACM SIGMETRICS Performance Evaluation Review*, 36(4):10–15.

Carvalho, D., Rodrigues, L., Endo, P. T., Kosta, S., and Silva, F. A. (2020). Mobile edge computing performance evaluation using stochastic petri nets. In *2020 IEEE Symposium on Computers and Communications (ISCC)*, pages 1–6. IEEE.

Castet, J.-F. and Saleh, J. H. (2009). Satellite and satellite subsystems reliability: Statistical data analysis and modeling. *Reliability Engineering & System Safety*, 94(11):1718–1728.

Cohen, J. and Boxma, O. (1985). A survey of the evolution of queueing theory. *Statistica neerlandica*, 39(2):143–158.

El Kafhali, S., El Mir, I., Salah, K., and Hanini, M. (2020). Dynamic scalability model for containerized cloud services. *Arabian Journal for Science and Engineering*, 45(12):10693–10708.

Fishman, G. S. (2013). *Discrete-event simulation: modeling, programming, and analysis*. Springer Science & Business Media.

Gopika Premsankar, M. d. F. and Taleb, T. (2018). Edge computing for the internet of things: A case study. 5:1275–1284.

Gordon, W. J. and Newell, G. F. (1967). Closed queuing systems with exponential servers. *Operations research*, 15(2):254–265.

Grottke, M., Nikora, A. P., and Trivedi, K. S. (2010). An empirical investigation of fault types in space mission system software. In *2010 IEEE/IFIP international conference on dependable systems & networks (DSN)*, pages 447–456. IEEE.

Hains, G., Mazur, C., Ayers, J., Humphrey, J., Khmelevsky, Y., and Sutherland, T. The wtfast's gamers private network (gpn®) performance evaluation results. In *2020 IEEE International Systems Conference (SysCon)*, pages 1–6. IEEE.

Jittawiriyanukoon, C. (2014). Performance evaluation of reliable data scheduling for erlang multimedia in cloud computing. In *Ninth International Conference on Digital Information Management (ICDIM 2014)*, pages 39–44. IEEE.

Lee, K., Chu, D., Cuervo, E., Kopf, J., Degtyarev, Y., Grizan, S., Wolman, A., and Flinn, J. (2015). Outatime: Using speculation to enable low-latency continuous interaction for mobile cloud gaming. In *Proceedings of the 13th Annual International Conference on Mobile Systems, Applications, and Services*, pages 151–165.

Li, Y., Deng, Y., Tang, X., Cai, W., Liu, X., and Wang, G. (2017). On server provisioning for cloud gaming. In *Proceedings of the 25th ACM international conference on Multimedia*, pages 492–500.

Li, Y., Deng, Y., Tang, X., Cai, W., Liu, X., and Wang, G. (2018). Cost-efficient server provisioning for cloud gaming. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, 14(3s):1–22.

Marzolla, M., Ferretti, S., and D'angelo, G. (2012). Dynamic resource provisioning for cloud-based gaming infrastructures. *Computers in Entertainment (CIE)*, 10(1):1–20.

Mathews, P. G. (2005). *Design of Experiments with MINITAB*. ASQ Quality Press Milwaukee, WI, USA:.

Nan, X., He, Y., and Guan, L. (2014). Queueing model based resource optimization for multimedia cloud. *Journal of Visual Communication and Image Representation*, 25(5):928–942.

Song, B., Hassan, M. M., Alamri, A., Alelaiwi, A., Tian, Y., Pathan, M., and Almogren, A. (2016). A two-stage approach for task and resource management in multimedia cloud environment. *Computing*, 98(1-2):119–145.

Wijman, T. (2019). The global games market will generate $152.1 billion in 2019 as the us overtakes china as the biggest market. *Newzoo) Abgerufen am*, 1(3):2020.

Willig, A. (1999). A short introduction to queueing theory. *Technical University Berlin, Telecommunication Networks Group*, 21.

Wu, J., Yuen, C., Cheung, N.-M., Chen, J., and Chen, C. W. (2015). Enabling adaptive high-frame-rate video streaming in mobile cloud gaming applications. *IEEE Transactions on Circuits and Systems for Video Technology*, 25(12):1988–2001.

Yates, R. D., Tavan, M., Hu, Y., and Raychaudhuri, D. (2017). Timely cloud gaming. In *IEEE INFOCOM 2017-IEEE Conference on Computer Communications*, pages 1–9. IEEE.

Zhang, X., Chen, H., Zhao, Y., Ma, Z., Xu, Y., Huang, H., Yin, H., and Wu, D. O. (2019). Improving cloud gaming experience through mobile edge computing. *IEEE Wireless Communications*, 26(4):178–183.