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TOWARDS IMPROVING 5G QUALITY OF EXPERIENCE: FUZZY AS A MATHEMATICAL MODEL TO MIGRATE VIRTUAL MACHINE SERVER IN THE DEFINED TIME FRAME

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ABSTRACT
The industry and government have recently acknowledged and used virtual machines (VM) to promote their businesses. During the process of VM, some problems might occur. The issues, such as a heavy load of memory, a large load of CPU, a massive load of a disk, a high load of network and time-defined migration, might interrupt the business processes. This paper identifies the migration process among hosts for VM to overcome the problem within the defined time frame of migration. The introduction of VMs migration in a timely manner is to detect a problem earlier. There are workload parameters, such as network, CPU, disk and memory as our parameters. To overcome the issue, we have to follow the Model named Fuzzy rule. The rule follows the basic of tree model for decision-making. The application of the fuzzy Model for the study is to determine VMs allocation from busy VMs to vacant VMs for balancing purposes. The result of the study showed that the use of the fuzzy Model to forecast VMs migration based on the defined rule had 2 positive impacts. The positive impacts are (1) Time frame live migration of VMs can reduce workload by 80 %. This aims to reduce failures in performing a live migration of VMs to increase data center performance. (2) In testing, the fuzzy Model can provide results with an accuracy of 90 %, so this model can perform a live migration of VMs precisely in determining the execution time. Next, the workload could be balanced among VMs. This research could be used further to improve 5G Quality of Experience (QoE) shortly.
Keywords: *Virtual Machine Server, Fuzzy Model, Live Migration, Comparison Research*

1. Introduction

The development of VMs in the 4.0 era has significantly progressed well. VMs are widely used in data center (DC) to enhance business and non-business applications. Many companies utilize this server to optimize the physical server in their DC. VMs are outstanding because they are primary application resources (Haris et al., 2022a; Hossain et al., 2020). In its application, VMs are needed to serve and manage the operating system (OS), to run the application system, and many more. For many years, VMs have been operated and researched in many ways to see the better way of future VMs.

To see the better way of VMs, we can review the issues or find other better ways. This research will see through the issue that appeared on VMs. Many problems arising to the production must be solved well. The appeared matters can make the OS dying. Moreover, the existing problems are the high stressing of the CPU and full of memory, which reduces the server performance to support the application. Providing a high data rate to all users without considering the network access duration and location is identified as the primary requirement in 5G technology. Many past researches have already been done for VMs migration. A classic VMs migration is manually moving from a host to another host once the issue occurs (Guo et al., 2022; Moura et al., 2022; Satpathy et al., 2021).

In the earliest studies, some researchers attempted to reduce the risk that will be occurred soon. Research (Y. Kumar et al., 2022) said that Live migration of VMs targeting (1) reallocate resources between VMs in balancing data center workloads, (2) cluster-based genetic algorithms are able to display problematic VMs estimates, (3) genetic algorithms aim in selecting migration destinations Front VMs load on VMs. Research (Shao et al., 2020) said that managing the migration of VMs by scheduling aims to (1) place VMs that have hosts that are not too busy, and (2) schedule algorithms in placing VMs in live migration to reduce energy consumption in the

DC. Furthermore, an analysis on the VMs taking the workload of the VMs has been conducted. The migration of VMs is based on high Quality of Service (QoS). In fact, VM migration uses fuzzy to predict the workload of network traffic. The optimizing for problem resources (CPU, RAM, Bandwidth, etc.) is the primary problem using Dependability-based Distributed Virtual Machine Placement (D2VMP). Therefore, fuzzy to determine replication of VM has been conducted (Elsaid et al., 2021; Hu et al., 2013; Jin et al., 2009).

This study focuses on detecting problems in VMs so problems that often occur can be identified early and predicting the problem VMs with fuzzy analysis. Incident prediction using fuzzy was the primary research on VMs. In fact, the movement of a VM from one host to another host based on CPU, memory, network, and the disk has been done without a time frame definition. The early study highlighted no specific research on the time frame defining migrating the VMs (Silva Filho et al., 2018).

This study also extends the result of the conducted previous research. In reality, the previous research was focused on something other than the time of the migration process. A new 5G network with wide coverage needs to be developed to achieve wide coverage during communication. Thus, to overcome the problem, this study focuses on the migrating issue of VMs in a defined time frame (Ahmad et al., 2015). We, expect that the result of the study will improve the awareness of the problems that happen in VMs so that the application will run well every time (Mugisha & Zhang, 2017). We have several sections for this paper. The following section is our literature study about VMs. The next section outlines our method and research result and discusses the impact. The last is the conclusion and future work on VM migration (Gilesh et al., 2020; Kaur et al., 2018).

2. Literature Review

This section will analyze the literature to migrate the VMs from one host to another host. The workload analysis of VMs will focus on memory and CPU because they are required to allocate the VMs within the defined time frame. The first decision, the problems are full of memory, full load of CPU and high traffic. The second decision, the study on the migration time of VMs and the searched aspect for enhancing performance using the fuzzy Model, can boost the performance of VMs (Alharbe et al., 2022; Guo et al., 2023; Rukmini & Shridevi, 2023).

Migration of VMs

Based on the previous study on VM migration, they are determined that specific tasks should be completed. So we investigate VM migration and find that certain polls explain the challenges inherent to VM migration (Jin et al., 2011). VM allocation may be categorized depending on survey results. In fact, some requirements must be satisfied to migrate virtual machines, such as a high memory and CPU load. This research includes extra factors, such as a large disk load, a heavy network load, and a predetermined amount of time. The added time parameter will measure the incident in a time-based way, optimizing VM performance (Haris et al., 2022b; Hu et al., 2011; Ramanathan et al., 2021).

Priority during VM migration is timely migration and placement on an appropriate host. Calculating VM migration using the fuzzy Model in line with CPU-SLA and RAM-SLA (Farzai et al., 2020; Karmakar et al., 2022; Singh & Singh, 2020; Yin & Zhang, 2022) is helpful. The purpose of VM placement is to promote VM performance. CPU, RAM, disk, and network are used to determine VM migration, but QoS is the determining factor. The primary factor in VM migration utilizing the fuzzy Model is the network due to network host overload. Past research was demonstrated that network overload can affect CPU and memory (K. Kumar et al., 2022; Seddiki et al., 2022). Figure 2 describes VM migration utilizing factors such as CPU, RAM, disk, and network, where these variables indicated VM host high load (Le, 2020; Li et al., 2017; Svard et al., 2011; Tao et al., 2019).

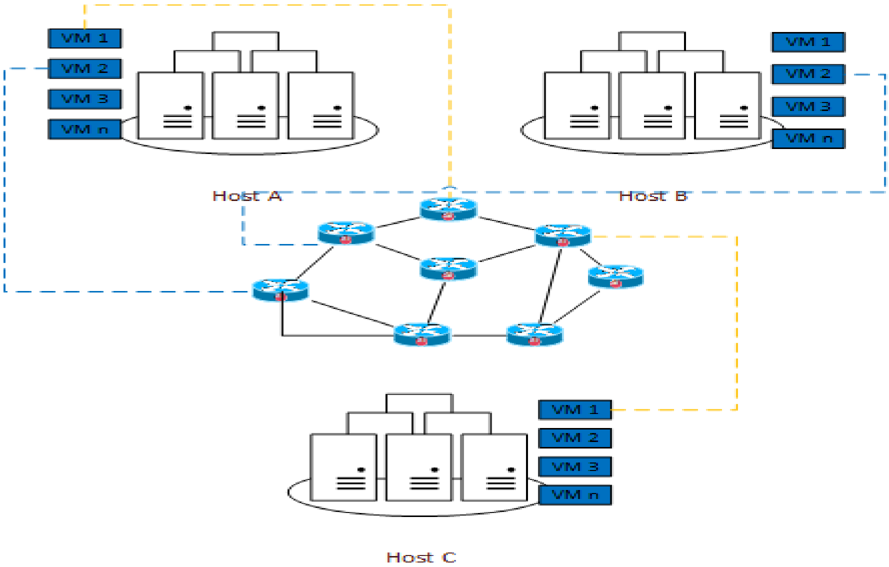

Fig. 1. Model of VM Migration (Hidayat & Alaydrus, 2019)

Classification Live Migration VMs

Live migration VMs is a way to optimize application performance during live migration VMs in terms of bandwidth usage. Migration VMs can be classified into three parts pre-copy, post-copy and hybrid-copy. We describe the classification in the next paragraph (Bhardwaj & Rama Krishna, 2019).

The pre-copy approach first duplicates all memory pages to the goal have, whereas the VM proceeds to run on the source have in a warm-up stage. After that, whereas the VM runs on the source have, the pre-copy strategy iteratively duplicates the adjusted memory pages of the VM to the goal have and stops after coming to a restrain that's characterized by cycles number edge or having a steady memory state of the VM at the goal have. The profoundly adjusted memory pages are replicated to the destination have alongside the VMs CPU state after ceasing the VM at the source have in a stage called halt and duplicate stage and then continuing the VM to proceed running at the goal have (Le, 2020).

Post-copy operates by (1) stopping the VM on the source host, (2) copying its CPU state and non-pageable memory pages, and (3) restarting on the destination host. After that, the source starts to push the memory pages to the destination during the memory transfer. If the VM applications need a particular memory page that has not been transferred yet, an on-demand memory page request will request the page from the source as apage fault trap. Then it copies that page to the destination host. This method has less downtime (Rukmini & Shridevi, 2023). However, requesting too many page faults degrade the performance of the applications that run on the VM due to requesting the pages. It copies them through the network, which increases migration downtime and decreases application performance. A comparison of various migration methods including Pre-copy (Wang et al., 2019).

In, a hybrid method that combines the Pre-Copy and Post-Copy methods is introduced. This method begins with a single Pre-copy migration iteration that copies the VM's memory to the destination host while the VM is still running on the source host. Following that iteration, the Post-copy method operates by pausing the VM, copying the CPU status to the destination host, and then restarting the VM's operation on the destination host. Following that, it begins to retrieve the remaining memory from the source host (Bhardwaj & Rama Krishna, 2019; Jamali et al., 2016). See figure 2 on live migration pre-copy and post-copy VMs.

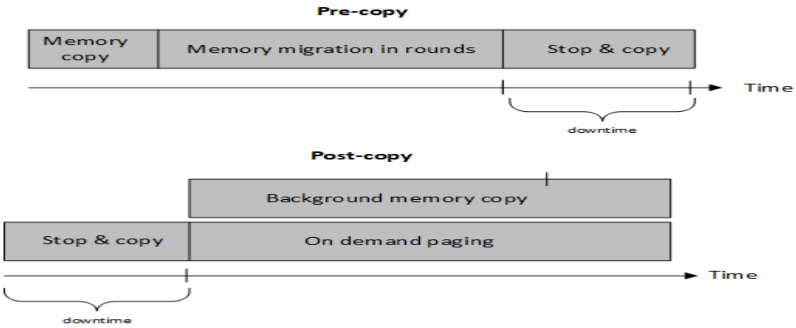

Fig. 2. Classification Live migration VMs Model (Kokkinos et al., 2016)

From this method, we, the authors, had an idea to improve the design using Fuzzy rule model. Hence, it will increase the possibility of moving VMs in a critical time or even better time.

3. Research Methods

Framework Data Study

In DC, the workload datasets were obtained via VM. We collected data using data mining in a month and have 7800 records. We collected data based on the operating hours of VM services using data mining. Observations were held at 9:00, 11:00, 13:00, 15:00, and 17:00. These hours served as filters for the data and performance of VMs. We forecasted which VMs should be transferred to another host based on a fuzzy model analysis of the total number of records (Katal et al., 2021; Rajakumari et al., 2022). Our analytical approach with datasets and fuzzy model processing is depicted in Figure 3.

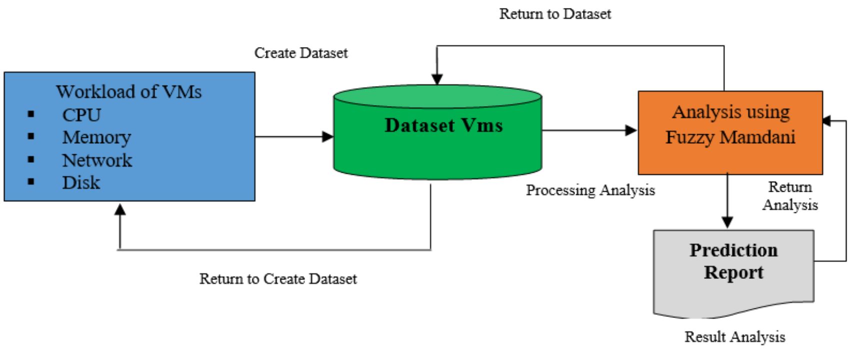

Fig. 3. Dataset Processing of VM Migration

From the fig. 3, we describe the methodology to collect the data for Fuzzy Model. We must have the workload data of VMs, such as: CPU load, Memory load, Network load, Disk load. If we use some VM software, it has a count on each variable. Then we have a full dataset of these workloads. The collection of workload data will then be analyzed using Fuzzy Model. Next, we have the value of prediction. Then we report it.

Data Workload Fuzzy Model

Fuzzy Model translates input to output as a fuzzy set. A fuzzy set is a group of membership function variables. MIN-MAX is another definition of Fuzzy Model used to assess migration status (small, medium, large). There were four steps: (1) formation of fuzzy sets, (2) implication, (3) rule component, and (4) confirmation. Figure 4 depicts the unclear fuzzy model process.

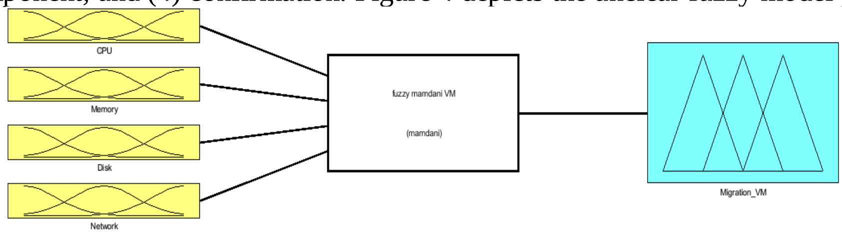

Fig. 4. Fuzzy Model Processing Data

This study used centroid and affirmation methods. The method was a crips solution using fuzzy area concentration. The data sources were datasets retrieved for problem analysis in VM.

We collected it for a month. Table 1 shows each variable's workload category (CPU, memory, network and disk). These four aspects were essential parts of the VM which interrelated with their functions. In this case, the authors would analyze the workload to achieve load development with the chosen method.

Table 1 - Dataset of VM Workload

Variable	Term Set	Workload percentage (%)
CPU	Small	[0– 40]
	Medium	[40– 60]
	Large	[60– 80]
Memory	Small	[0– 40]
	Medium	[40– 60]
	Large	[60– 80]
Disk	Small	[0– 40]
	Medium	[40– 60]
	Large	[60– 80]
Network	Small	[0– 40]
	Medium	[40– 60]
	Large	[60– 80]
Migration	No Migration VM	[0– 60]
	Migration VM	[60– 100]

Table 1 shows the unprocessed data and only the defined category. We create the migration science with CPU, memory, network and disk-based on type to improve the VM performance. The function of the fuzzy set was a curve showing intervals $0 - 1$ on data input mapping. The formula of the fuzzy set CPU, Memory, Disk, and Network is shown in Equation 1.

$$[C, M, D, N] = \begin{cases} 0; \quad ; & x \leq a \\ \frac{(x-a)}{(b-a)} & a \leq x \leq b \\ 1; & x \geq b \end{cases}$$

This research followed the min implication function (Rukmini & Shridevi, 2023) . The process had a group of premises and one conclusion. We used the process to understand the premise's and conclusion's relationship (K. Kumar et al., 2022). The formula of min implication is shown in Equation 2 where i is fuzzy rule i-th.

$$\propto = Predicate_i = \mu_{A_1}[x_1] \cap \ldots \cap_{A_n} [x_n] = Min\left(\mu_{A_1}[x_1], \ldots, \mu_{A_n}[x_n]\right)$$

Rule Fuzzy Model

We defined four parameters (disk, network, CPU and memory) and three classifications (small, medium, and large). We had 81 rule combinations. Chosen by the researcher.

Table 2 - Role Fuzzy VM Migration

No.	Migration Rule of VM
[R1]	IF (CPU is Small) and (Memory is Small) and (Disk is Small) and (Network is Small), then (No Migration VM)
[R2]	IF (CPU is Large) and (Memory is Small) and (Disk is Large) and (Network is Large), then (Migration VM)
[R3]	IF (CPU is Small) and (Memory is Small) and (Disk is Large) and (Network is Medium), then (Migration VM)
[R4]	IF (CPU is Medium) and (Memory is Medium) and (Disk is Large) and (Network is Small), then (No Migration VM)
…	...

…	…
[R80]	IF (CPU is Large) and (Memory is Large) and (Disk is Medium) and (Network is Large), then (Migration VM)
[R81]	IF (CPU is Medium) and (Memory is Large) and (Disk is Medium) and (Network is Medium), then (Migration VM)

Table 2 shows some of the Fuzzy model algorithm logic applied to share the load on the VM. This logic function rule would produce a condition that was the desired load balance in which the CPU, memory, disk, and network aspects will be balanced in each process.

Defuzzifier

We utilized this stage to interpret an ambiguous membership into a conclusion. We must return a crips value and transform the fuzzy output into a crips output depending on the membership function we had provided. Defuzzifier was required because undefined decision variables must be turned into crisp variables. The fuzzy set was an input for the defuzzifier received from the fuzzy rule. Meanwhile, the output is the fuzzy set's domain. This concept will yield precise results. Equation 3 depicts the defuzzifier formula.

$$\text{Defuzzifier} = \frac{\sum_{t=0}^{n} c_1 \min\{\mu_{cv_i}(C), \mu_{mv_i}(M), \mu_{dv_i}(D), \mu_{nv_i}(N)\}}{\sum_{t=0}^{n} \min\{\mu_{cv_i}(C), \mu_{mv_i}(M), \mu_{dv_i}(D), \mu_{nv_i}(N)\}}$$

Membership function performance depends on minimum Availability, CPU, Memory, Disk and Network membership values. Mathematical equations can be seen in the equation.

$$\mu_{per}(Y) = (\mu_{cv_i}(C), and\, \mu_{mv_i}(M), and\, \mu_{dv_i}(D), and\, \mu_{nv_i}(N)$$

Eq. (3) can also be written as

$$\mu_{per}(P) = (\mu_{cv_i}(C), and\, \mu_{mv_i}(M), and\, \mu_{dv_i}(D), and\, \mu_{nv_i}(N)$$

Similarly, Eq (4) can be written as shown in Eq (5).

$$\mu_{per}(P) = (\mu_{(cv \cap mv \cap dv \cap nv \cap}(Y)$$

4. Results and Discussions

The information was collected throughout a month of VM workload. The datasets consist of three hosts, including several VMs. These datasets consist of data mining on the workload of VMs using the specified parameter. The data were analyzed using Fuzzy Model. Table 3 summarizes the findings of the workload % experiment.

Table 3 - The Experiment of Fuzzy in Workload VM

CPU (%)	Memory (%)	Disk (%)	Network (%)	Defuzzification Result (%)
35.5	60.7	60.3	70.5	83.1
40.5	40.1	64.5	60.2	49
57.9	35.4	4.6	57.9	80.6
54.1	48.5	57.5	16.2	71.9
66.3	45.2	52.9	19	53.7

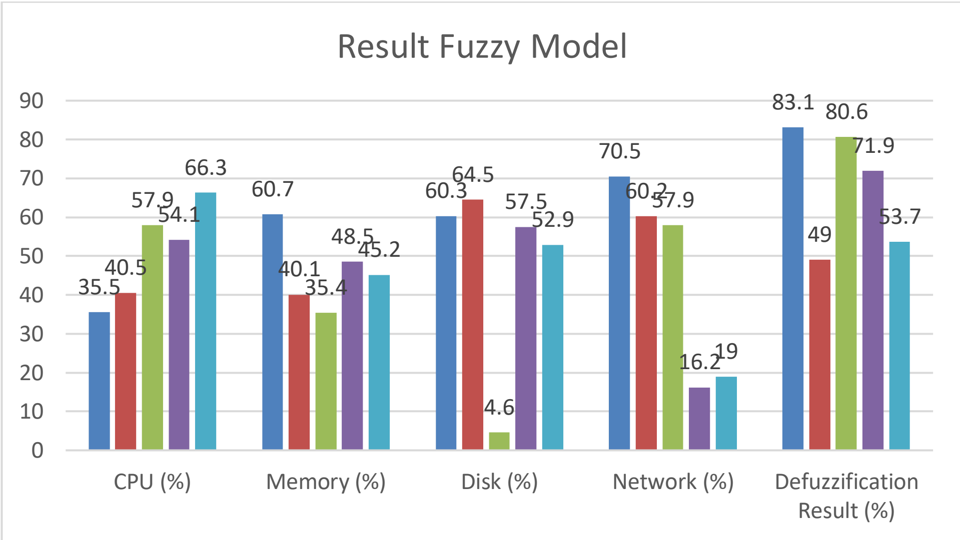

Fig. 5. Result Workload Data in Fuzzy Model

Table 3 is visually moved. A month was divided into five weeks. The defuzzifier result revealed that the highest impact, 83.1, is for the first week. The third week's performance of 80.6 is the next highest. This result indicated that a dynamic network (1st week) or the combination of an active network and a high CPU processing rate (3rd week) results in the most defuzzifier. To comprehensively understand VMs migration, we examine 7800 data and show them in Table 4.

Table 4 - Result Processing Dataset with Fuzzy Model

Time	Allocation Host	Status		
		Total	Migration	Normal
08:00 AM–8:00 PM	Host A	1500	201	1299
08:00 AM–8:00 PM	Host B	2400	574	1826
08:00 AM–8:00 PM	Host C	3900	225	3675

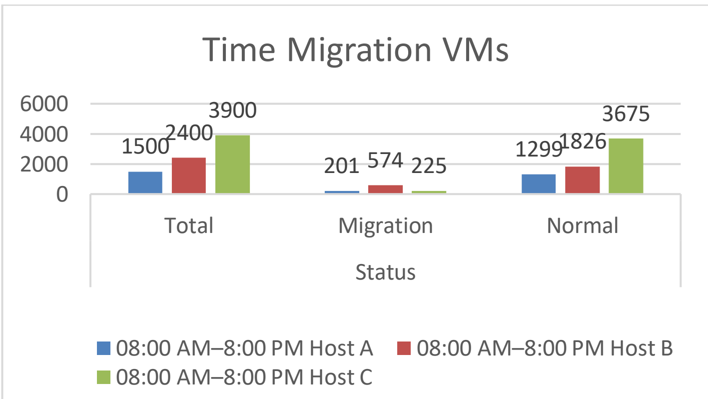

Fig 6. Workload VM in Processing Fuzzy Model

Figure 6 showed that host B contains more VMs migration than hosts A and C (24%). Other result showed that though host C has more VMs, it has less migration status of VMs (6%). Meanwhile, host A had 13% of the migration VMs. From the result, host B could be moved to host C from 8:00 AM to 20:00 AM to reduce VMs workload.

Research Findings

Referring to the results above, the author found some evidence that results are better than past research (Badem et al., 2017). The formulas that the author uses to get accuracy, precision and recall get the following results.

Table 5 - Comparison Method

Algorithm	Accuracy (%)	Precession (%)	Recall
k-NN	75.73	73.39	64.54
DSS	86.26	90,08	69,50
Fuzzy	90.22	91.10	80.21

From these results, it can be seen that the value of fuzzy is better than k-NN and DSS. From these results, the combination of 4 variables that the author uses brings better accuracy. With these results, it is hoped that better future research will be held (Gümüşçü et al., 2020).

Discussions

In the tests that have been carried out, the author observes network traffic at certain hours, gets information on busy times in the data center at 9:00, 11:00, 13:00, 15:00, and 17:00, this pattern is used as a benchmark for three-time frames of a month. The workload dataset for three months on VMs such as CPU to Memory, is used as a migration limit with the criteria specified in table 1.

The author also observes bandwidth patterns with the time frame, then this is used as the time to determine when the live migration of VMs is carried out. The purpose of this bandwidth pattern is a strategy in determining the right time to live migrate VMs. As a result, failure in live migration of VMs is low. In the tests carried out by the author, the network traffic is 83.1% defuzzifier with the combination in table 3.

5. Conclusion

The result of VM migration with fuzzy showed the positive impacts. First, VMs migration can be conducted within the defined time frame to reduce VMs workload. Second, the undefined method's application was periodically determining the overload VMs. With these results, the excellent performance of VMs can be continuously maintained, and the activity would run as it should. The goal of live migrating VMs within a period of time is to reduce network traffic on each VMs, where this can reduce failures in carrying out live migration of VMs, and can provide decisions in carrying out live migration of VMs, from the results of the comparison of the KNN and DSS algorithm models the need for additional data more and combining other algorithms, so the results will be better.

Future works are explained here. First future work, the use of several techniques can be applied to predict the VM overload and how to migrate to overcome this overload, one of which was the Markov chain method or other processes related to predicting a dominant problem. The Markov Chain method was used frequently. So, the problem occurring in VMs would be maintained well for the problem dictionary in VMs problem. Further, this VM migration with a fuzzy approach can reduce latency, as requested by 5G applications. Second future work, the use of other variable to complete the calculation will be appreciated. For 5G applications, the Base Station System (BTS) signal length can be input as calculation.

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