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Monitoring Resource Usage of Digital Learning Platforms for Online and Onsite Learning

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Technology development brings numerous benefits and transforms the landscape of education. As digital learning has become popular in Taiwan, various digital platforms have been developed. As online services on such digital platforms are diversified according to the increase in the number of digital platforms, the competitiveness of professionals in related industries is demanded more than before. Thus, it is necessary to estimate and decide on an optimal load of resource usage. In this study, we analyzed the data from TronClass of University A in Taiwan to determine the maximum load for resource usage. Data were collected from September 13 to November 7, 2021. The period for a comparative analysis was defined as the online learning period (from September 13 to October 10) and the onsite teaching period (from October 11 to November 7). During the online and onsite learning periods, the highest average CPU usage rate of TronClass was observed on Thursdays, whereas the lowest usage was on Mondays. The highest average CPU and memory usage of the web and database servers was observed also on Thursdays. 1143 and 839 users accessed the Web, while 609 and 473 used mobile devices, and the peak numbers of concurrent web users were 5284 and 2076, while those of mobile device users were 4748 and 2933 during the online and onsite learning periods, respectively. The CPU usage rate of the web server during the online teaching period was 13% higher than that during the onsite teaching period. The CPU usage rate of the database server during the online teaching period was 2–3% higher than that during the onsite teaching period.

1. Introduction

The Internet has brought the concept of the knowledge economy to the public. Accordingly, the traditional book-centric approach in education is not the only way to learn. With the advent of digital learning on the Internet, individuals can be empowered to navigate innovative knowledge and valuable information. Consequently, schools have adopted the instructional

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model of digital learning to ensure that students can obtain knowledge anytime, anywhere.[1] Khan stated that knowledge is the continuous accumulation and constant updating of information.[2] The advent of digital learning enables a significant milestone in education. Since COVID-19, online learning has been a prevailing trend, transforming students from passive recipients into active contributors to knowledge sharing. Teachers, traditionally seen as educators imparting course content, have been transformed into facilitators who guide student learning. The challenge for teachers is, therefore, how to appropriately use technology to develop teaching materials, instructional methods, and interaction with students. In addition, the effective and efficient utilization of online resources has become a common challenge.[3] For the utilization, diverse needs and formats in learning must be considered as e-commerce plays an important role in education using online platforms, and traditional education has been transitioning to digital learning. Therefore, it is essential to cautiously develop platforms with appropriate procedures and teaching methods to achieve high learning effectiveness.

In 1997, the Ministry of Education in Taiwan (MOET) announced the Mid-term Development Plan for Distance Learning. To cultivate professionals for the development of technology in digital learning, the National Science Council of the Executive Yuan launched the National Program of e-Learning in 2003. This initiative aimed at providing more opportunities for lifelong learning, developing the digital learning industry, and advancing academic research. In 2008, the National Science Council amalgamated the National e-Learning Program and the National Digital Archives Program to launch the Taiwan e-Learning and Digital Archives Program for five years. The initiative was formulated to integrate expertise across various disciplines, establish excellent research teams and centers, and enhance the growth of the digital-learning-related industry. To improve digital learning in Taiwan to an international level, MOET initiated a four-year E-Learning Program in 2004 with four primary objectives: enhancing the efficiency of the backbone network bandwidth for education and academic research, elevating the quality of campus wireless networks, digitizing teaching materials, and promoting Massive Open Online Courses (MOOCs). The British Academy pointed out the long-term impact of the new coronavirus on society in 2020 to cope with the changes in the mode of learning during the pandemic. Distance learning has become a tool for teachers to impart knowledge.[4]

Distance learning impacts the learning status of children and adolescents. It is not easy for teachers to choose online learning and an appropriate digital learning platform. Teachers need to record teaching materials on camera so they need to familiarize themselves with various tools on the platform to edit and use teaching materials. It is also difficult for students to adapt to the change of the learning method used. During COVID-19, schools had to adopt online teaching, which increased the use of digital learning platforms within a short period. The increasing use of the platforms required sufficient resources for effective online education, which caused various problems in the management of the resources and digital learning platforms. Therefore, it is vital to estimate and predict the exact usage of the resources precisely to correspond to the continuous increase in using digital learning platforms.

To monitor the usage of resources, various sensor technologies are used. For a CPU to predict bottlenecks, optimize resource allocation, and prevent performance degradation, sensors with a simple network management protocol (SNMP) are used. The sensors monitor the load of all CPU cores. Randon access memory can be monitored for efficient utilization to prevent out-of-memory issues using SNMP, windows memory, Linux/Unix memory, or application-specific sensors to track memory usage.[5]

In this study, we analyzed the usage data of TronClass of University A in Taiwan. The usage patterns of TronClass were analyzed before and during COVID-19 to propose a way of optimizing the allocation of resources.[6] Additionally, the distribution of host resources between the server and users was analyzed for the effective adjustment of the resource allocation based on usage rates. The difference in the resource usage of onsite and online teaching was also explored during the COVID-19 pandemic. The result of this study helps the system administrator to allocate resources effectively on the basis of usage rates and respond to the anticipated increase in resource usage to prevent server problems. Such efficient management helps to enhance the efficiency of learning and save related resources and develop an appropriate sensor to monitor the usage of resources.

2. Literature Review

Although digital learning resources were used, the majority of the teaching materials were textbooks before the outbreak of COVID-19. During the pandemic, schools had to adapt to a new way of digital education using various equipment and cloud-based operations. Digital content was essential and online tests had to be provided. Students had to engage in online activities for discussions, questions and answers, and homework. With the experience in digital education, even in onsite learning, digital learning materials are widely used as digital learning becomes a new normal in education.

2.1 Digital learning platforms

There are digital learning platforms that are widely used as follows.

2.1.1 Zuvio Teaching Platform[7]

The Zuvio Teaching Platform (Zuvio) was developed by Xueyue Technology Co., Ltd. to address the communication gap among students in learning. Zuvio enables real-time cloud-based interaction and allows for class attendance and random student questioning, making it well-suited for a large number of students and allowing teachers to monitor students' learning progress in real time.

2.1.2 Moodle Learning Platform[8]

The Moodle Learning Platform (Moodle) is the most widely used open-source learning management system. With a global presence in over 150 countries and support for more than 70 languages, Moodle is used in various sectors, including government agencies, private enterprises, nonprofit organizations, and educational institutions. Students can access teaching resources such as electronic ddocuments, PowerPoint presentations, and audiovisual materials. Owing to the convenience of the Internet, students can participate in courses anytime, anywhere through the platform.[6] The design principles of Moodle include (1) fostering idea exchange among individuals, (2) developing teaching resources through human creativity, (3) enabling teachers to adjust the course on the basis of student reactions during lectures, and (4) providing a highly flexible learning environment that allows learning anytime, anywhere.

2.1.3. Small Private Online Course Teaching Platform (SPOC)[9]

POC combines online teaching platforms with mobile courses, resembling a compact version of a MOOC POC on a small scale. In SPOC, the number of students is limited to fewer than one hundred in a hosting institution. A course on SPOC is not available for the public. SPOC combines face-to-face interaction with online self-study, making it different from MOOCs. SPOC follows a "MOOC + Classroom" model, representing flipped learning with MOOC resources.

2.1.4 MOOCs Teaching Platform[10,11]

MOOCs is an online open-course platform. It allows users to segment the course content with video lectures. Each learning module of MOOCs incorporates real-time online discussions and feedback to increase interaction among students. Whether through collaborative learning or problem discussions, students can manage their learning progress. Currently, MOOCs are the basis of Coursera,[12] a collaboration framework of MIT and Harvard University. Khan Academy[13] and Udacity[14] are also based on MOOCs.

2.1.5 TronClass

TronClass integrates cloud computing and big data analytics.[6] It employs interactive and flipped learning for innovative instruction to improve the quality of teaching and enhance students' enjoyment of classes. The initial version of TronClass is traced back to the QuanKeYun 1.0 intelligent education platform introduced by Guangdong QuanTong Education Company in 2015, which is considered the first generation of the TronClass system. As a hybrid teaching platform, TronClass provides flexibility in class time and location. Teachers can organize various teaching contents online, including videos, Word documents, PowerPoint files, and others. Instructors can edit questions online, and test results can be displayed immediately after students finish answering. Students can ask questions and provide feedback on their learning experience on their mobile devices. TronClass offers functions such as attendance checking, course-related messages, class scheduling, pre-class previews, post-class assignments, and online quizzes. It allows for communicating with teachers or peers through text messages. For flipped learning, TronClass facilitates group interactions and allows photo uploads for assignment submissions to enhance course participation. Immediate teaching feedback is attainable through surveys and other feedback mechanisms.

2.2. Analysis of resource usage

2.2.1 Load balancing and performance[15]

In Internet-related services, the reliability of servers is crucial, especially for peak use time. It is challenging to distribute the resources of a server in cloud technology and ensure stable and uninterrupted services. Building cluster architectures for high feasibility demands considerable time and costs, limiting its widespread adoption. For the real-time monitoring of single-server operations, a cluster-based approach is used. Performance analysis in different architectures is conducted with experimental results to identify a cost-effective, threshold-friendly, and performance-oriented deployment structure.

2.2.2 Energy saving[16]

On the Internet, big data is widely used with cloud computing. Many cloud architectures have been developed to enhance services in cloud computing. The construction of such cloud architectures needs substantial costs so resource allocation and energy saving are critical.

2.2.3 Cloud queue performance[17]

Cloud computing offers convenience in research and business. Public cloud servers enable developers to construct applications on the server. Applications are accessed through queuing, which requires users to wait until they become accessible. In a server, each user requests resource usage. If the server is busy, the user must wait until the current user completes their operation, potentially increasing the waiting time. To reduce the waiting time, a finite multiple-server queue model is used. For example, the **Certified Cloud Security Professional** queue model employs multiple servers to find available servers on the basis of the queue.

2.2.4 CPU usage rate[18]

Resource usage can be monitored using metrics such as CPU usage rates. The continuous monitoring of CPU usage rate over a specific period provides data to estimate server load. Higher usage rates demand increased user engagement. The CPU usage rate directly correlates with the server load.[19,20]

3. Architecture of TronClass

University A transitioned its digital learning platform from Moodle to TronClass on February 1, 2021. Its Moodle was designed to support 3,500 concurrent users. Owing to increased online teaching during COVID-19 and the transition, Moodle was overloaded. To determine an appropriate resource usage, we reviewed the structure and analyzed the data obtained from the learning platform.

The architecture of TronClass of University A is depicted in Fig. 1. The TronClass comprised 12 virtual machines (VMs), including one frontend load balancing server (VM01), five frontend web servers (VM02-04, VM11, VM12), one database load balancing server (VM05), three database servers (VM06-08), one media conversion server (VM09), and one management server (VM10). The TronClass could accommodate 6500 concurrent users for optimal efficiency.

Server virtualization is widely adopted for convenience and cost- and time-saving. Virtual machine software integrates host resources and allocates resources to VMs. The TronClass platform featured the following: the front-end load balancing server (01) with 12 cores and 24 GB of memory, five front-end web servers (02, 03, 04, 11, and 12) with 24 cores and 48 GB of memory, the database load balancing server (05) with 24 cores and 48 GB of memory, three database servers (06–08) with 24 cores and 64 GB of memory each, the media conversion server (09) with 16 cores and 32 GB of memory, and a management server (10) with eight cores and 32 GB of memory. In the media conversion server (09), teaching materials and video files were stored with a maximum disk capacity of 10 TB. The front-end web servers were responsible for the computation of front-end users and the disk capacity was 150 GB for the system and program management (Table 1). The TronClass of University A was equipped with 252 CPU cores, 568 GB of memory, and 13,740 GB of disk capacity to support 6,500 concurrent users. Since February 2021, 86.907 million user interactions have been observed and 10,383 courses were offered for 20,974 user accounts.

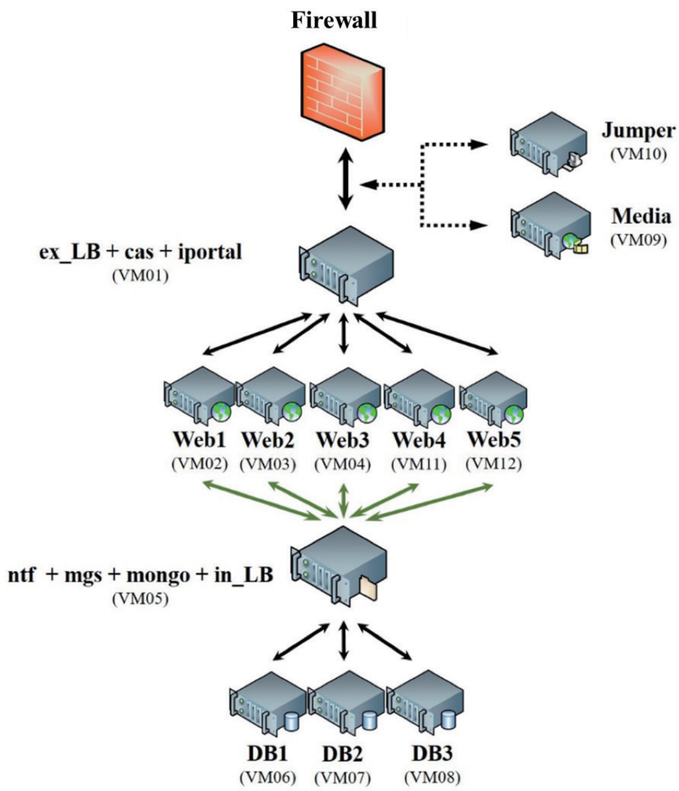

Fig. 1. (Color online) Architecture of TronClass learning platform.

Table 1
Web server resource configuration of TronClass.

VM Name	CPU cores	Memory capacity (GB)	Storage (Used/Total) (GB)	Remarks (servers)
TronClass-01	12	24	32.1 / 150	ex_LB + cas + iportal
TronClass-02	24	48	20.3 / 150	web01
TronClass-03	24	48	21.1 / 150	web02
TronClass-04	24	48	21.3 / 150	web03
TronClass-05	24	48	49 / 250	ntf + mgs + mongo + in_LB
TronClass-06	24	64	168.3 / 550	db01
TronClass-07	24	64	696.5 / 1050	db02
TronClass-08	24	64	205.7 / 550	db03
TronClass-09	16	32	4333.6 / 10290	media
TronClass-10	8	32	75.6 / 150	Jumper
TronClass-11	24	48	23.5 / 150	web04
TronClass-12	24	48	18.1 / 150	web05

4. Results and Discussion

We collected data on the CPU, memory, and I/O usage of each VM from the TronClass from September 13 to November 7, 2021. Data were integrated and analyzed using Excel and Power BI. The online learning period was defined from September 13 to October 10, whereas the onsite teaching period was from October 11 to November 7, 2021.

4.1 Resource usage during online teaching period

Figure 2 shows the average CPU usage rate of the web server during the online teaching period. The highest CPU usage rate (33%) on weekdays was observed on Thursdays. The maximum usage within a single time interval in a day was 78% on Thursdays, whereas the lowest average usage was 25% on Mondays. The majority of courses were provided on Thursdays with fewer courses on Mondays. Daily courses were scheduled between 9 AM and 3 PM. The average CPU usage rates were 33, 27, 26, 26, and 25% on Thursdays, Wednesdays, Fridays, Tuesdays, and Mondays, respectively. Figure 3 shows the memory usage of the web server during the online teaching period. The highest average usage (56%) was observed on Thursdays, and the lowest average usage (45%) occurred on Mondays. There was a correlation between the CPU and memory usage of the web server. Figure 4 shows the CPU usage rate of the database server during the online teaching period. On Thursdays, the highest average usage was 11%. During the online teaching period, 1143 users accessed the Web, while 609 users used mobile devices. The peak number of concurrent web users at the same time reached 5284, while that of mobile devices was 4748 (Fig. 5).

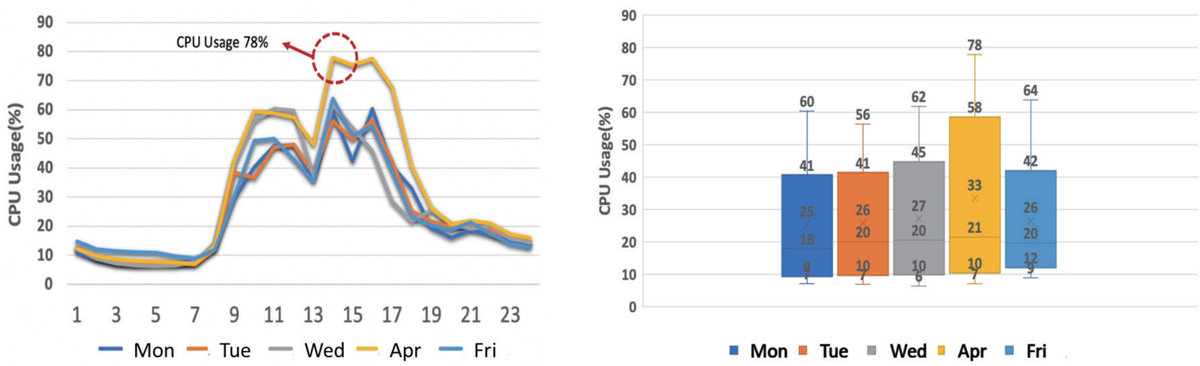

Fig. 2. (Color online) CPU usage rate of web server during online teaching period.

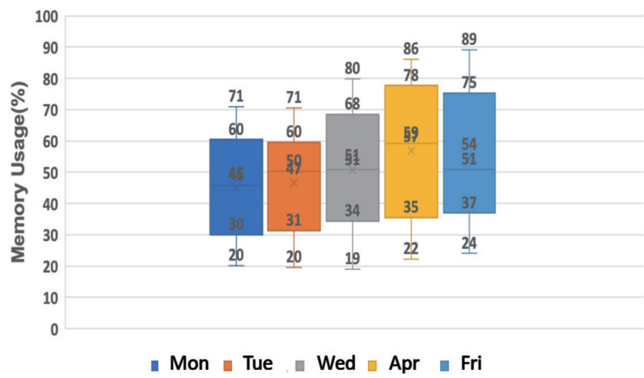

Fig. 3. (Color online) Memory usage of web server during online teaching period.

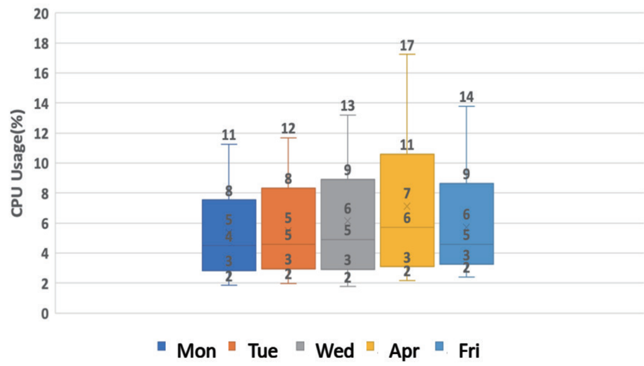

Fig. 4. (Color online) CPU usage rate of database server during online teaching period.

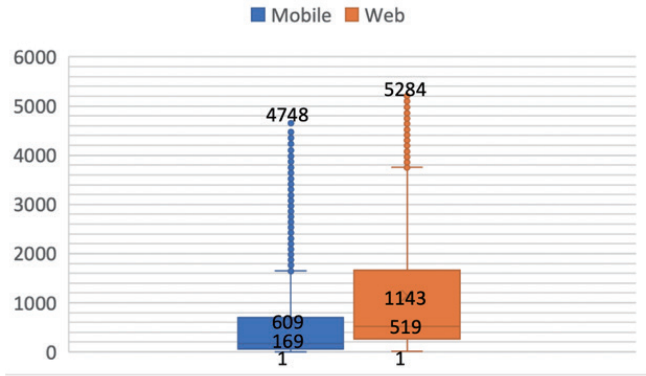

Fig. 5. (Color online) Number of concurrent users during online teaching period.

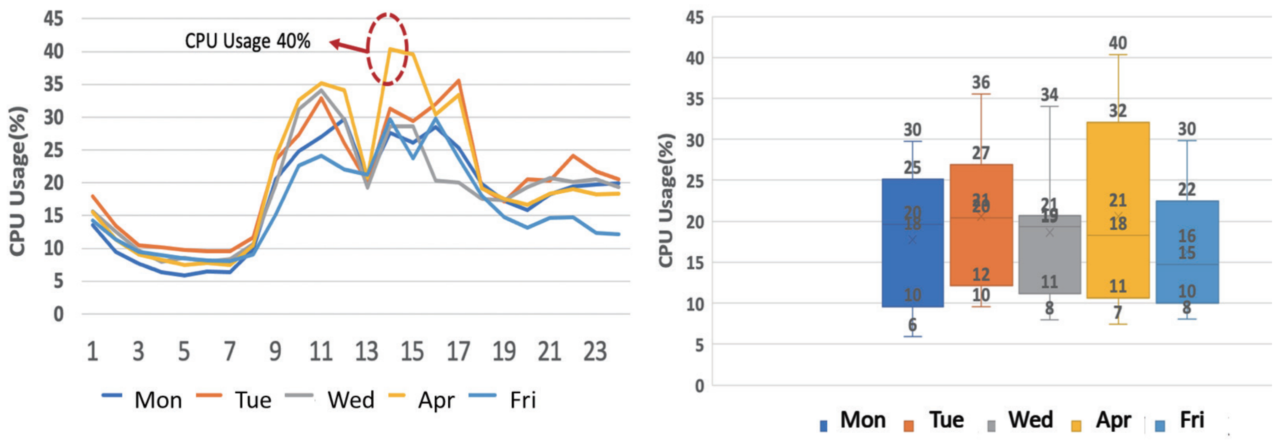

Fig. 6. (Color online) CPU usage rate of web server during onsite teaching period.

4.2 Resource usage during onsite teaching period

Figure 6 shows the average CPU usage rate of the web server during the onsite teaching period. The highest average CPU usage rate (20%) was observed on Thursdays. The peak daily usage (40%) was also observed on Thursdays. On Tuesdays, Wednesdays, Mondays, and Fridays, the usage rates were 20, 18, 17, and 16%, respectively. A correlation between the resource usage of the Web and CPU was observed. In memory usage (Fig. 7), the highest average usage of 54% occurred on Thursdays. The CPU usage rate of the database server was also the highest (5%) on Thursdays (Fig. 8). Figure 9 shows the number of concurrent server users during the onsite teaching period. The average numbers of users were 839 on the Web and 473 on mobile devices. The peak number of concurrent users on the Web was 2076, while that of mobile devices was 2933.

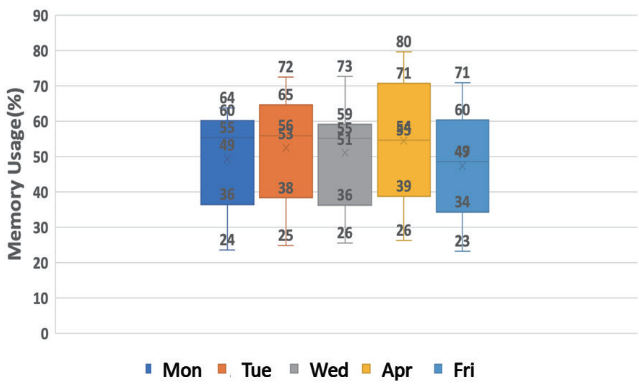

Fig. 7. (Color online) CPU usage rate of database server during onsite teaching period.

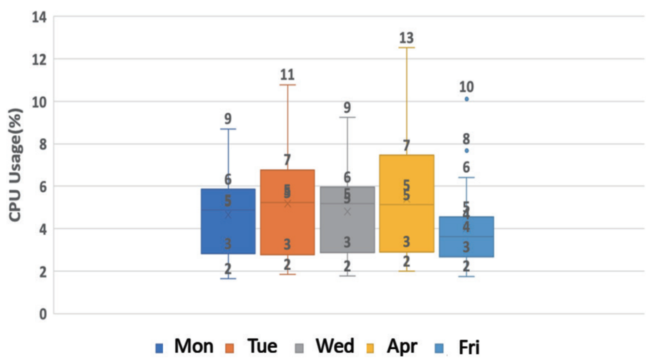

Fig. 8. (Color online) CPU usage rate of database server during online teaching period.

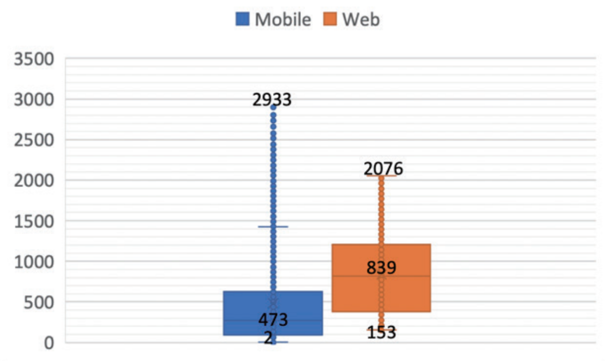

Fig. 9. (Color online) Number of concurrent users during online teaching period.

The CPU usage rate of the web server during the online teaching period increased by 13% compared with that of the onsite teaching period (Fig. 10). The memory usage of the web server for online teaching reached 64.36%. Even with the significant increase in CPU usage rate during the online teaching period, the usage did not exceed the maximum load of TronClass nor caused system paralysis or operational issues (Fig. 11). The CPU usage rate of the database server during the online teaching period increased by 2–3%, compared with that during the onsite teaching period (Fig. 12).

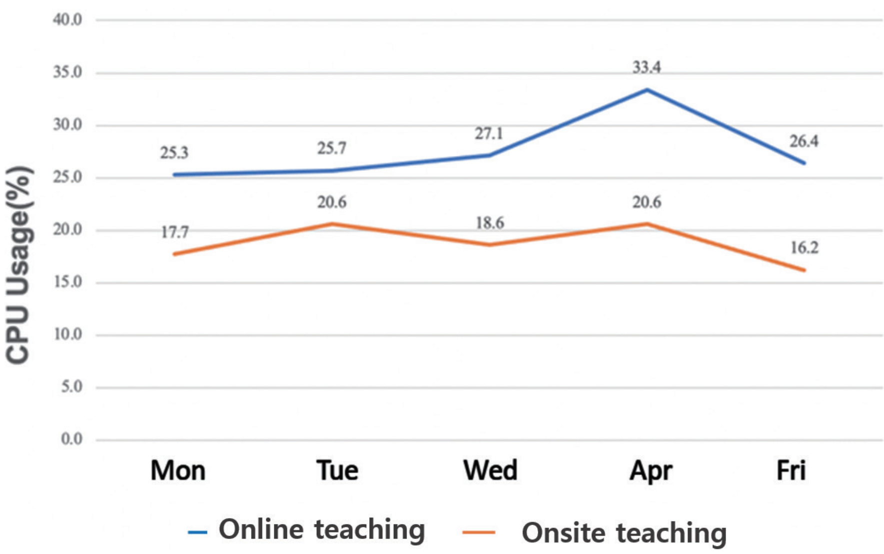

Fig. 10. (Color online) Comparison of CPU usage rate of web server between online and onsite teaching periods.

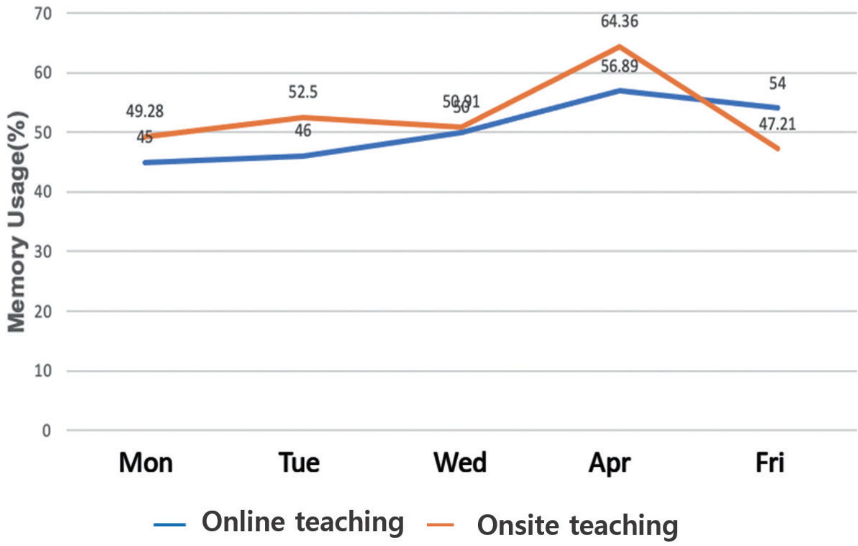

Fig. 11. (Color online) Comparison of memory usage of web server between online and onsite teaching periods.

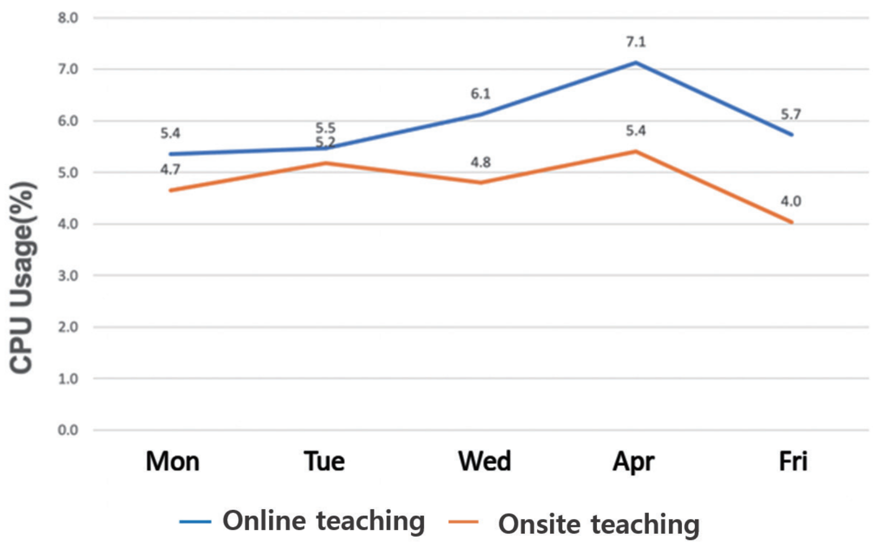

Fig. 12. (Color online) Comparison of CPU usage rate of database server between online and onsite teaching periods.

5. Conclusions

Since COVID-19, online teaching has become a new standard in education, increasing the utilization of digital learning platforms. Owing to the increasing demand for the platforms, the ability to effectively manage a large number of concurrent users and resource usage is crucial. In this study, we analyzed the data from the digital learning platform of University A in Taiwan to determine the maximum load for system resource usage. The platform used was TronClass, and data from September 13 to November 7, 2021 were obtained. The data were integrated and analyzed using Excel and Power BI. The period was defined as the online learning period (from September 13 to October 10) and the onsite teaching period (from October 11 to November 7).

During the online learning period, the highest average CPU usage rate (33%) was observed on Thursdays, whereas the lowest usage (25%) was on Mondays. The highest average usage (56%) of the web server was observed on Thursdays, and the lowest average usage (45%) was on Mondays. The highest average CPU usage rate of the database server was 7%. During the online teaching period, 1143 users accessed the Web while 609 users used mobile devices. The peak number of Web users at the same time reached 5284, while that of mobile devices was 4748. The highest average CPU usage rate of the web server (20%) during the onsite teaching period was observed on Thursdays. On Tuesdays, Wednesdays, Mondays, and Fridays, the usage rates were 20, 18, 17, and 16%, respectively. The highest memory usage of the web server (54%) occurred on Thursdays. The CPU usage rate of the database server was the highest (5%) on Thursdays. The average numbers of concurrent users were 839 and 473 on the Web and mobile devices, respectively. The peak number of concurrent users on the Web was 2076, while that of mobile devices was 2933. The CPU usage rate of the web server during the online teaching period was 13% higher than that during the onsite teaching period. The CPU usage rate of the database server during the online teaching period was 2–3% higher than that during the onsite teaching period. The results of this study can be used to predict the maximum load of the server of an online learning platform for the effective and efficient management of the platform.

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