

A COMPREHENSIVE REVIEW OF PREDICTIVE VM MIGRATION SCHEMES USING FORECASTING TECHNIQUES IN CLOUD COMPUTING

Manjunatha S ¹ , Dr. Suresh L ² .

Abstract

More efficient VM management approaches have arisen from numerous researches that have been undertaken due high cost of data centres' energy consumption and its environmental effects such as CO2 emissions. VM migration is one of the critical VM management activities whose performance has a direct effect on the energy efficiency of cloud data centers (DCs). To conduct a more effective migration process and reduce the number of VM migrations, some of the VM management frameworks apply prediction algorithms to forecast various migration and VM-related factors. This paper presents an extensive survey and taxonomy of the predictive VM migration approaches adapted for the cloud DCs. For this purpose, it first provides the key issues regarding the VM migration and then classifies them based on their applied prediction algorithm. It illustrates the main contributions of each scheme and describes how prediction methods are integrated into the VM migration process, to make it more effective. Moreover, a comparison of the predictive migration schemes is provided.

Keywords: Efficient, Migration, Management, Prediction, and Taxonomy

1. Introduction

Cloud computing is an important technology aimed to present unlimited virtual resources to remote customers, based on the pay for use model. Various types of cloud computing such as mobile clouds, hybrid clouds, and cloud federations are designed and provided to deal with users' various functional and non-functional requirements [1-4]. Effective resource management in the cloud data centers (DCs) has a direct effect on their energy efficiency, scalability, performance, and reliability. Moreover, it can reduce the costs incurred to the cloud users and increase the cloud service providers' (CSPs) profit. Figure 1 indicates the energy-consuming units in the cloud DCs [5]. As shown in this figure, servers or PMs consume much of the energy in a DC. Reducing power consumption by optimal resource management is very challenging in green cloud DCs. Consequently, a lot of attention has been paid for dealing with the energy efficiency of PMs. Virtualization is one of the baseline techniques used to improve resource management in the cloud DCs. It applies a software layer denoted as the hypervisor, VMM or virtual machine monitor to manage several virtual machines (VMs) on each server or physical machine (PM) [6]. In the virtualized cloud DCs, two common problems affecting the power consumption are the hot-spot and cold-spot problems. Generally, a hotspot problem happens when the VMs hosted on a PM, issue requests for its resources which exceed a specific threshold and the PM cannot provide them. On the other hand, in the cold-spot problem, the resource consumption of a PM drops below a specific threshold and the PM becomes under-loaded. Both of these problems can be handled by migrating one or more VMs from the source PM to the other PMs [7]. To handle the outlined problems, hypervisors support non-live and live VM migrations [8, 9] which the latter can be further classified into pre-copy, post-copy and hybrid migration methods. In the non-

¹ Associate. Professor, Dept of CSE, Cambridge Institute of Technology, Bangalore and
² is Professor and Principal, Cambridge Institute of Technology, Bangalore.

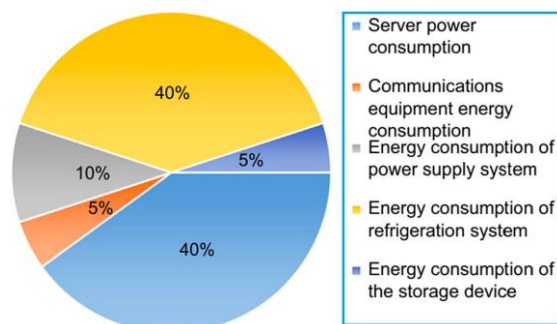


Fig. 1 Energy consumption units in a DC

live VM migrations, the application will be stopped throughout the VM migration process, but service downtime and VM migration are predictable. However, in live VM migration, the migrating VM continues to provide its service without disconnecting its client during the migration time and prevents SLAV [10], but regarding the type of application hosted on the VM, this migration method incurs higher overheads than the non-live migration method. Although VM migration can be used to deal with the hot-spot and clod-spot problems, inefficient migration of VMs can increase the processing overheads, energy consumption, and delay in the virtualized DCs [11, 12]. Thus, it must be handled very cautiously and at least as possible.

2. Research background

As shown in Fig. 2, ideally the following objectives can be achieved by conducting predictive VM migrations in the cloud DCs [20]:



Fig. 2. Objectives of the VM migration schemes

- *Reducing the number of PMs:* Consolidation of VMs can be used to solve the cold-spot problem, which puts some PMs into a sleep state and reducing the total number of PMs. By mitigating the number of PMs and making VM migrations more efficient, the energy consumption of CSP's decreases. Consequently, the profit of CSP's increases. Also, by better resource management, more users' requests can be handled and more profit can be achieved.
- *Reducing the number of VM migrations:* By accurate prediction of forecasting the future workload the unnecessary and premature VM migrations can be prevented.
- *Improving CSP's profit:*

- *Decreasing the DC's network traffic*: By efficient VM migrations, the retransmitted pages of the migrating VMs can be reduced which results in less incurred traffic to the DCs network and then can improve the performance of applications and prevents SLAV.
- *Preventing SLAV*: by reducing the downtime of migrating VMs the SLAV penalties can be prevented.
- *Improving QoS*: Efficient migration scheme incurs low downtime to the cloud system and improves QoS.
- *Reducing energy consumption in DC network*: By accurate forecasting of the application's workload on a VM, the future pages which will be accessed can be found. As a result, the number of pages transmitted can be reduced as well as the energy consumption of the DC network.

4 Predictive VM migration schemes

Various predictive VM migration schemes such as [30-38] are provided in the literature which tries to reduce the VM migration's side effects by forecasting near future load in various resources. This subsection presents a comprehensive overview of the predictive VM migration approaches designed and proposed for Cloud DCs. It tries to illuminate the main contributions of each scheme and describes how prediction algorithms are used in combination with the VM migration methods. Figure 3 depicts the taxonomy of the predictive VM migration schemes, based on their applied prediction algorithms

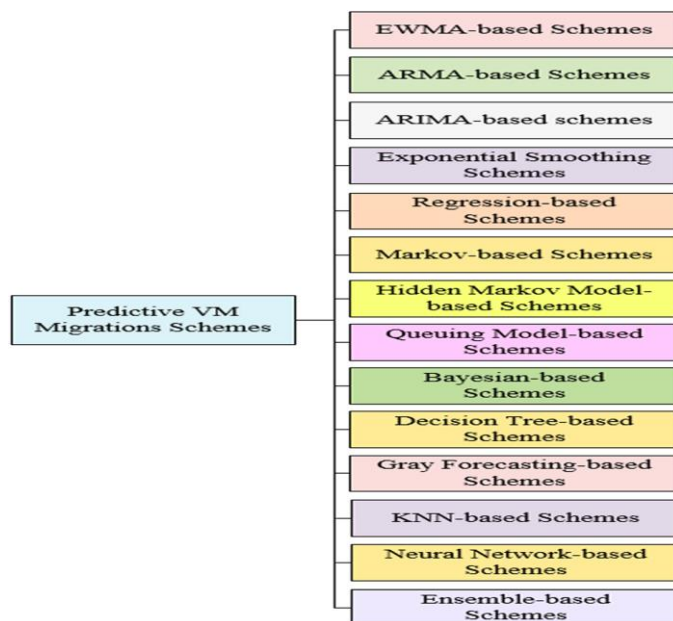


Fig. 3 Classification of the predictive VM migration schemes

4.1 EWMA-based schemes

The VM migration solution presented in [39], provides two techniques to balance the system workload in multiple live migrations which complement each other, and each of them produces better results under some kinds of load.

4.2 ARMA-based schemes

The approach provided in [40], proposes an energy-aware VM management scheme using ARMA-based prediction model to forecast the resource needed by the VMs as well as detecting the status of PM for initiating migrations. This scheme proposes a migration cost matrix and provides a set of migrations with the best performance.

4.3 ARIMA-based schemes

ARIMA is a popular statistical model for forecasting and time series analysis. It originates from the autoregressive model, the moving average model, and the ARMA model [41, 42]. This subsection provides a review on the ARIMA based VM migration schemes designed for cloud DCs.

4.4 Exponential smoothing-based schemes

In [49], Choudhary et al. are aimed to decrease the power usage and VM migration in the DCs, but at the cost of increased SLAV. For this purpose, it does not immediately migrate the VMs from the hotspot and cold spot PMs and check whether the migration is required or not. This approach detects a proper destination PM on which the VM will be migrated. They have conducted their simulations using CloudSim software and indicated that the migration decisions depend on the performance of the applied prediction models. However, only the CPU utilization is predicted in this approach and other resources are neglected. The approach provided in [50], presents a workload forecasting solution for deciding the proper destination PM to host the VM with the aim of reducing the VM migrations during the VM consolidation.

4.5 Regression-based schemes

Various regression-based migration schemes such as [54- 59] are provided in the literature. The Authors et al attempts to provide a review of the regression based VM migration schemes proposed in the literature. The authors have used VM clustering to introduce three improved migration approaches regarding the migration traffic factor. These approaches apply VM clustering for minimizing migration costs and the number of VM migrations. They also mitigated the required power for migration, at the cost of a small increase in the SLAV. The approach provides a presented a pre-copy live migration algorithm that operates in multiple stages to reduce downtime, number of transferred pages and total migration time. In the first stage, it transfers all memory pages and then, it keeps the history of each page and makes a transmission decision. They applied the auto-regression algorithm to forecast the pages' behaviour in the next interval to decide about page transmission. The authors have verified the performance of their scheme using simulations conducted via the Cloudsim software. Figure 4 depicts the architecture of this scheme.

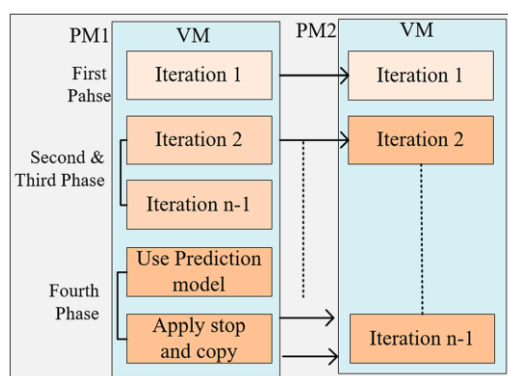


Fig. 4 Iterations in the pre-copy method

4.6 Markov-based schemes

Markov chains (MCs) are directed graphs used in modelling the applications [70]. Several Markov-based VM migration schemes such as [71], are provided in the literature. For instance, in [72], Melhem et al. provided a Markov-based forecasting approach to predict the PMs' workload and avoid premature VM migrations with forecasting the near future CPU utilization of the PMs. In this scheme, the CPU utilization of PM is compared with the upper and lower thresholds to determine the PM's state and then its future state of PM will be forecasted using the Markov-based forecasting model. Their algorithm

determines the VMs migration time to achieve load balancing and server consolidation. The evaluations are conducted on the Planet Lab dataset and random loads which indicate a reduction in the SLAV and the number of VM migrations. Figure 5 indicates the architecture of this predictive VM migration approach.

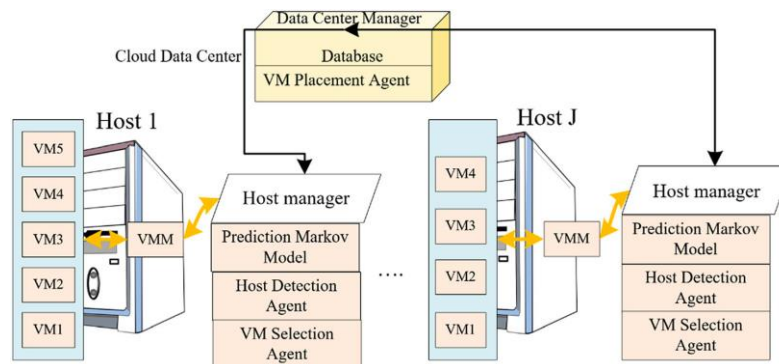


Figure 5 Architecture of this predictive VM migration approach

4.7 Hidden Markov model-based schemes

In [80], Xia et al. provided a status prediction-driven architecture, which considers VM migration cost and optimum VM migration time. They focused on a resource scheduling approach, by introducing a status forecasting model for PMs. For this purpose, they applied an HMM model for status prediction and forecasted the PMs. The authors indicated that their algorithm can reduce SLAV and power usage.

4.8 Queueing model-based schemes

This subsection tries to discuss the Queueing model-based VM migration schemes. In these schemes, the queueing theory is used for the mathematical study of the queues, created in the VM migration process. The approach presented in [81], provides a post-copy migration-based enhanced serial migration method and design queueing models for analyzing and reducing the migration time and the downtime of serial multiple migrations of VMs. To analyze the blocking rate, they modelled the arrival request by utilizing the M/M/C/C and the arrival request by the M/M/C queueing models. Table 1 compares the environments and workloads applied in the simulation of the Markov-based, HMM-based, and queueing- based predictive migration schemes.

Simulators/Environments					Workloads dataset/Software				
Schem e	Cloudsi m	XE N	KV M	MATLA B	PlanetLa b	Rando m	TPC -C	Kernel Compilati on	Unixbenc h
[72]	--				--	--			
[73]		--					--	--	--
[74]		--							
[75]	--								
[76]			--						
[77]	--								
[78]				--					
[81]		--							

Table 1 Properties of the Markov-based, HMM-based, and Queueing Model-based predictive VM migration schemes

4.9 Bayesian-based schemes

This subsection is going to provide a review of the Bayesian VM migration schemes. In [82], the authors focused on the cost-aware VM placement in distributed DCs using a multi-criteria decision-making method. They presented an algorithm for solving this problem using Bayesian networks and introduced two solutions for VMs consolidation and assignment. This scheme builds the Bayesian network regarding the probabilistic dependencies and the extracts expert knowledge among parameters for making decisions regarding cost-aware VM placement across the distributed DCs, which may face with energy outages. However, in comparison to other migrating schemes, it slightly increases the SLVs. The approach provided in [84], Jian et al. applied an online coloring bin packing for modelling the VM consolidation in the cloud DCs and puts forward an application-aware approximation method for finding a near-optimum solution. They used a Bayesian model for identifying load patterns and adjusting resource provisioning. They indicated that their approach can reduce power consumption and operation costs.

4.10 Decision tree-based schemes

The migration scheme presented in [85], proposes a predictive and power-aware assignment of VMs. Migrations are conducted through the prediction of the future computational required for each VM, to a proper assignment of them on the PMs. It applies the decision tree to forecast the next computational needs of each VM, to allocate them on the PMs efficiently and by conducting some experiments, it is shown that this scheme is able to reduce power usage. But, this scheme is not compared with the other VM migration solutions to indicate its effectiveness.

Table 2 indicates the simulator software, environments, and workloads applied in the simulation of the decision tree and Bayesian-based predictive migration schemes. Also, Table 3 presents a comparison of the simulation factors and prediction metrics in these schemes.

Simulators/environments	Workload datasets/generator						
Scheme	Cloudsim	XEN	JAVA	Netem	Clou Net	WebServer	FTP Server
[82]			--				
[83]				--		--	--
[84]					--		
[85]	--						
[86]		--					

Table 2 Properties of the Bayesian and decision tree based predictive VM migration schemes

Simulation factors						
Schemes	Energy consumption	Downtime	SLAV	Total migration time	No of migration	No of active servers
[82]	--		--			
[83]		--		--		
[84]	--				--	

[85]	--					
[86]						--

Simulation factors		Prediction metrics						
Success rate	Failure rate	VM failure	Load	VM resource	CPU Utilisation	Memory	Disk	Bandwidth
				--	--			
					--	--	--	--
			--					
--	--	--						
				--				

Table 3 Comparison of the decision tree and Bayesian-based predictive VM migration schemes

4.11 Gray forecasting-based schemes

In [87], Hong and Boyan provided a prediction model according to gray and credibility ant colony scheduling solution for the VM migration scheduling strategy. This model is able to predict the future usage of CPU in the VM and decides about the VM migrations by using a dual threshold method to prevent frequent migration caused by temporary oscillation of CPU usage. However, to achieve a better image of the DC status in the near future, other resources should be taken into account.

4.12 KNN-based schemes

This subsection focuses on the various KNN-based VM migration schemes. For example, in [89], Farahnakian et al. presented an adaptive VM consolidation approach to reduce the number of active PMs and minimize the power consumption of DC. They conducted consolidation using the K-NN regression to estimate resource utilization in the PMs. To enhance the performance of this consolidation scheme, they have considered a prediction method for resource utilization using KNN-UP or the k-nearest neighbour regression. Because, the power consumption of the CPU is high in general, they applied the KNN-UP to forecast CPU utilization in PMs and find the over-utilized PMs and under-utilized ones in the near future. The authors have conducted experiments and showed that their scheme can mitigate power usage and SLAV.

Table 4 presents a comparison of the software, environments, and workloads applied in the simulation of the Gray Forecasting and KNN-based predictive migration schemes. Also, Table 5 indicates the simulation factors and prediction metrics used in these schemes.

Simulators/Environments		Workload Datasets/Generators		
Scheme	Cloudsim	CoMon project	Planetlab	Random
[87]	--			
[88]	--			
[89]	--			--
[90]	--	--	--	--

Table 4 Properties of the gray forecasting and KNN-based predictive VM migration schemes

Simulation Factors								Prediction Metrics		
Scheme	Energy consumption	RMS E	MAP E	No of migrations	MA E	Load Balance Degree	Average SLAV	Host	Load	Availability
[87]	--						--	--		

[88]		--	--					--		
[89]				--					--	
[90]		--			--					--

Table 5 Comparison of the gray forecasting and KNN-based predictive VM migration schemes

4.13 Artificial Neural Network-based schemes

This subsection is going to provide a review of the ANN based VM migration schemes. In [91], the authors tried to evaluate linear and nonlinear predicting techniques with recurrent neural networks (RNN) to forecast network bandwidth utilization and CPU utilization for live migration. They minimize bandwidth usage and enhance the overall efficiency of DC. They evaluated their scheme by simulations on the workload of 600 PMs from Google clustering data and indicated that RNN is able to provide accurate forecasting of bandwidth usage and CPU utilization. By having this information, this scheme can reduce traffic, SLAV, and enhance DC efficiency. Table 6 determines the workloads and simulation software applied for simulation of the ANN-based predictive migration schemes. Moreover, Table 6 compares the simulation factors and prediction metrics in the ANN based VM migration approaches.

Simulators / Environments								Workload dataset/software	
Scheme	MAE	MSE	RMSE	MAPE	CPU Time Taken	SLAV	No of VM Migrations	Load	CPU Utilisation
[91]						--	--		--
[92]	--	--	--	--					--
[93]	--	--							--
[94]	--	--							--
[95]	--				--			--	

Table 6: Comparison of the ANN-based predictive VM migration schemes

4.14 Ensemble-based schemes

Ensembles are sets of learning machines that integrate their decisions, or their learning approaches, or various views of data to achieve more accurate predictions in unsupervised and supervised learning issues [96]. This subsection tries to discuss the ensemble-based VM migration schemes.

Table 7 indicates the simulation software and workloads applied for the simulation of the ensemble-based predictive migration schemes. Moreover, Table 8 compares the simulation and prediction metrics in the outlined approaches.

Simulation Factors									
Scheme	CPU Utilisation	Memory utilisation	Disk Utilisation	Migration Probability	Total Migration Latency	Energy Consumption	No of VM Migrations	Message Overhead	Total Migration Latency
[97]						--	--	--	
[98]									--

Prediction Metrics	
VM Resource	Migration Latency
--	
	--

Table 7 : Comparison of the ensemble-based predictive VM migration schemes

Simulators/Environments		Workload Datasets / Generators		
Scheme	CloudSim	KVM	Random	Google Trace
[97]	--		--	--
[98]		--		--

Table 8 : Properties of the ensemble-based predictive VM migration Schemes

6 Conclusion

Virtualization is one of the fundamental techniques utilized in the cloud DCs which enables effective resource management. However, it suffers from the hot-spot and cold spot problems which can diminish its merits. To mitigate these problems, the hosted VMs should be migrated from the over-loaded or under-loaded PMs to the more appropriate PMs. Consequently, the efficiency of the VM migration process is of high importance in cloud DCs. Predictive VM migrations try to conduct more effective migrations based on the current resources status and the predicted status of the cloud resources. Various predictive VM migration schemes are proposed in the literature which try to enhance migration process in the cloud DCs and by forecasting the future workloads of VMs they can reduce the number of VM migrations, reduce the migration time by improving various types of migration methods, or by preventing transferring pages that will be dirty in the near future.

This paper presents a comprehensive survey of the predictive migration approaches and classifies them based on the prediction methods applied to forecast future resource demands or workloads. It summarizes the major contributions of each studied VM migration scheme and specifies which advantages are achieved by using forecasting methods in the VM migration schemes as well as their possible limitations. Furthermore, it discusses their applied workloads, evaluated factors, simulator software, and hypervisors environments as well as factors predicted in the studied schemes.

For future researches in the predictive VM migration schemes, the following issues can be considered:

- Creating more accurate predictive migration solutions should be considered in the future to achieve better results.
- Better algorithms for training the applied classifier in the predictive VM migration schemes can be investigated in the next studies.
- A few numbers of the studied schemes have focused on security issues. However, considering the growing number of security attacks, providing secure predictive VM migration solutions is of high importance.
- Regarding the growing virtualization-based technologies such as edge computing, fog computing, cloudlets, and vehicular clouds, fast and low overhead prediction solutions are needed to run with less need for historical data.
- Most of the VM migration schemes have only considered resources such as CPU and memory in their predictions, while other factors such as disk I/O and network access are neglected.
- Considering the possibility of failures of communication links and PMs, fault-tolerant VM migration should be explored in the following researches.
- Because, conducted simulations cannot truly reveal the possible shortcomings of the proposed migration schemes, conducting experiments in the real environments such as OpenStack and hypervisors such as Xen and KVM can be addressed in the next studies.
- Since the performance of VM migration approaches mainly depends on the application's type and their workloads, using different types of workloads for evaluation of the predictive VM migration schemes is needed to fully illuminate their true capabilities and limitations.

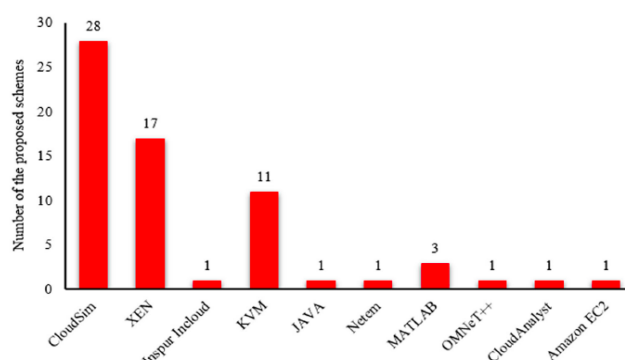


Fig. 6 : Applied simulators, environments, and hypervisors

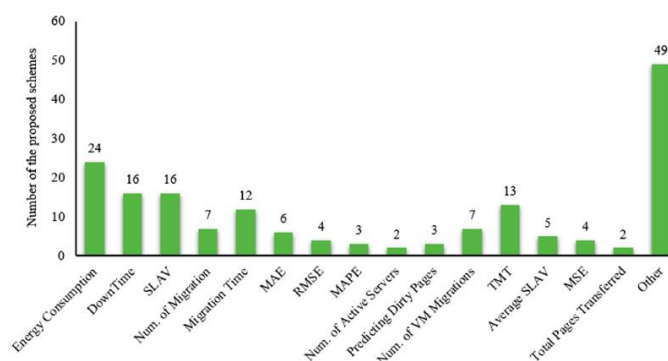


Fig. 7 : Parameters applied to evaluate the predictive VM migration schemes

References

1. Masdari, M., Jalali, M.: A survey and taxonomy of DoS attacks in cloud computing. Secur. Commun. Netw. 9, 3724–3751 (2016)
2. Masdari, M., Nabavi, S.S., Ahmadi, V.: An overview of virtual machine placement schemes in cloud computing. J. Netw. Comput. Appl. 66, 106–127 (2016)
3. Masdari, M., ValiKardan, S., Shahi, Z., Azar, S.I.: Towards workflow scheduling in cloud computing: a comprehensive analysis. J. Netw. Comput. Appl. 66, 64–82 (2016)
4. Masdari, M., Salehi, F., Jalali, M., Bidaki, M.: A survey of PSO based scheduling algorithms in cloud computing. J. Netw. Syst. Manag. 25, 122–158 (2017)
5. Rong, H., Zhang, H., Xiao, S., Li, C., Hu, C.: Optimizing energy consumption for data centers. Renew. Sustain. Energy Rev. 58, 674–691 (2016)
6. Jin, H., Deng, L., Wu, S., Shi, X., Chen, H., Pan, X.: MECOM: Live migration of virtual machines by adaptively compressing memory pages. Future Gener. Comput. Syst. 38, 23–35 (2014)
7. Mishra, M., Das, A., Kulkarni, P., Sahoo, A.: Dynamic resource management using virtual machine migrations. IEEE Commun. Mag. 50, 34–40 (2012)

8. Liu, H., Jin, H., Liao, X., Yu, C., Xu, C.: Live virtual machine migration via asynchronous replication and state Synchronization. *IEEE Trans. Parallel Distrib. Syst.* 22, 1986–1999 (2011)
9. Wang, X., Chen, X., Yuen, C., Wu, W., Zhang, M., Zhan, C.: Delay-cost tradeoff for virtual machine migration in cloud data centers. *J. Netw. Comput. Appl.* 78, 62–72 (2017)
10. Ahmad, R.W., Gani, A., Hamid, S.H.A., Shiraz, M., Yousafzai, A., Xia, F.: A survey on virtual machine migration and server consolidation frameworks for cloud data centers. *J. Netw. Comput. Appl.* 52, 11–25 (2015)
11. Zhang, J., Ren, F., Lin, C.: Delay guaranteed live migration of virtual machines. In: *IEEE INFOCOM 2014-IEEE Conference on Computer Communications*, pp. 574–582, (2014)
12. Wang, H., Li, Y., Zhang, Y., Jin, D.: Virtual machine migration planning in software-defined networks. *IEEE Trans. Cloud Comput.* 7(4), 1168–1182 (2017)
13. Amiri, M., Mohammad-Khanli, L.: Survey on prediction models of applications for resources provisioning in cloud. *J. Netw. Comput. Appl.* 82, 93–113 (2017)
14. Ahmad, R.W., Gani, A., Hamid, S.H.A., Shiraz, M., Xia, F., Madani, S.A.: Virtual machine migration in cloud data centers: a review, taxonomy, and open research issues. *J. Supercomput.* 71, 2473–2515 (2015)
15. Zhang, F., Liu, G., Fu, X., Yahyapour, R.: A survey on virtual machine migration: challenges, techniques, and open issues. *IEEE Commun. Surv. Tutor.* 20, 1206–1243 (2018)
16. Zhang, J., Ren, F., Shu, R., Huang, T., Liu, Y.: Guaranteeing delay of live virtual machine migration by determining and provisioning appropriate bandwidth. *IEEE Trans. Comput.* 65, 1–1 (2016)
17. Tseng, F.-H., Chen, X., Chou, L.-D., Chao, H.-C., Chen, S.: Support vector machine approach for virtual machine migration in cloud data center. *Multimed. Tools Appl.* 74, 3419–3440 (2015)
18. Liu, J., Li, Y., Jin, D., Su, L., Zeng, L.: Traffic aware cross-site virtual machine migration in future mobile cloud computing. *Mobile Netw. Appl.* 20, 62–71 (2015)
19. Desai, M. R., Patel, H. B.: Efficient virtual machine migration in cloud computing. In: *Communication Systems and Network Technologies (CSNT), 2015 Fifth International Conference on*, pp. 1015–1019, (2015)
20. De Maio, V., Prodan, R., Benedict, S., Kecskemeti, G.: Modelling energy consumption of network transfers and virtual machine migration. *Future Gener. Comput. Syst.* 56, 388–406 (2016)
21. Wang, B., Qi, Z., Ma, R., Guan, H., Vasilakos, A.V.: A survey on data center networking for cloud computing. *Comput Netw* 91, 528–547 (2015)
22. Qi, H., Shiraz, M., Liu, J.-Y., Gani, A., Rahman, Z.A., Altameem, T.A.: Data center network architecture in cloud computing: review, taxonomy, and open research issues. *J. Zhejiang Univ. Sci. C* 15, 776–793 (2014)
23. Yang, C.-T., Liu, J.-C., Huang, K.-L., Jiang, F.-C.: A method for managing green power of a virtual machine cluster in cloud. *Future Gener. Comput. Syst.* 37, 26–36 (2014)
24. YamunaDevi, L., Aruna, P., Devi, D. S., Priya, N.: Security in virtual machine live migration for KVM. In *2011 International Conference on Process Automation, Control and Computing*, pp. 1–6, (2011)
25. Zhang, W., Han, S., He, H., Chen, H.: Network-aware virtual machine migration in an overcommitted cloud. *Future Gener. Comput. Syst.* 76, 428–442 (2017)
26. Noshay, M., Ibrahim, A., Ali, H.A.: Optimization of live virtual machine migration in cloud computing: a survey and future directions. *J. Netw. Comput. Appl.* 110, 1–10 (2018)
27. Masdari, M., Zangakani, M.: Green cloud computing using proactive virtual machine placement: challenges and issues. *J. Grid Comput.* 37, 1–33 (2019)
28. Khosravi, A., Nadjaran Toosi, A., Buyya, R.: Online virtual machine migration for renewable energy usage maximization in geographically distributed cloud data centers. *Concurr. Comput.* 29, e4125 (2017)

29. Sva`rd, P., Hudzia, B., Walsh, S., Tordsson, J., Elmroth, E.: The noble art of live VM migration-principles and performance of pre copy, post copy and hybrid migration of demanding workloads. Technical report, 2014. Tech Report UMINF 14.10. Submitted, (2014)
30. Paulraj, G. J. L., Francis, S. A. J., Peter, J. D., Jebadurai, I. J.: Route aware virtual machine migration in cloud datacenter. In: 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT), pp. 363–367, (2018)
31. Guo, F., Zhang, D., Liu, Z., Qi, K.: VM3: Virtual Machine Multicast Migration Based on Comprehensive Load Forecasting. Springer, Cham (2015)
32. Liu, Y., Gong, B., Xing, C., Jian, Y.: A virtual machine migration strategy based on time series workload prediction using cloud model. Math. Probl. Eng., Article ID 973069, (2014)
33. Hu, B., Lei, Z., Lei, Y., Xu, D., Li, J.: A time-series based precopy approach for live migration of virtual machines. In: 2011 IEEE 17th International Conference on Parallel and Distributed Systems, pp. 947–952, (2011)
34. Zhang, W., Lam, K. T., Wang, C. L.: Adaptive live VM migration over a WAN: modeling and implementation. In: 2014 IEEE 7th International Conference on Cloud Computing, pp. 368–375, (2014)
35. Lin, C.-C., Jian, Z.-D., Wu, S.-T.: Live migration performance modelling for virtual machines with resizable memory. In: Lee, R. (ed.) Computer and Information Science, pp. 87–100. Springer International Publishing, Cham (2015)
36. Kherbache, V., Madelaine, E ´., Hermenier, F.: Scheduling live migrations for fast, adaptable and energy-efficient relocation operations. In: 2015 IEEE/ACM 8th International Conference on Utility and Cloud Computing (UCC), pp. 205–216, (2015)
37. Zakarya, M.: An extended energy-aware cost recovery approach for virtual machine migration. IEEE Syst. J 13, 1–12 (2018)
38. Zheng, J., Ng, T.S.E., Sripanidkulchai, K., Liu, Z.: Comma: coordinating the migration of multi-tier applications. ACM SIGPLAN Not. 13, 153–164 (2014)
39. Forsman, M., Glad, A., Lundberg, L., Ilie, D.: Algorithms for automated live migration of virtual machines. J. Syst. Softw. 101, 110–126 (2015)
40. Yin, L., Luo, J., Zhang, S., Yang, Z.: Virtual machine migration scheme based on score matrix in data centers. In: 2017 IEEE International Symposium on Parallel and Distributed Processing with Applications and 2017 IEEE International Conference on Ubiquitous Computing and Communications (ISPA/IUCC), pp. 737–743, (2017)
41. Faruk, D.O ´.: A hybrid neural network and ARIMA model for water quality time series prediction. Eng. Appl. Artif. Intell. 23, 586–594 (2010)
42. Lee, C.-M., Ko, C.-N.: Short-term load forecasting using lifting scheme and ARIMA models. Expert Syst. Appl. 38, 5902–5911 (2011)
43. Patel, M., Chaudhary, S., Garg, S.: Machine learning based statistical prediction model for improving performance of live virtual machine migration. J. Eng. (2016). <https://doi.org/10.1155/2016/3061674>
44. Patel, M., Chaudhary, S., Garg, S.: Improved pre-copy algorithm using statistical prediction and compression model for efficient live memory migration. Int. J. High Perform. Comput. Netw. 11, 55–65 (2018)
45. Fang, W., Lu, Z., Wu, J., Cao, Z.: RPPS: a novel resource prediction and provisioning scheme in cloud data center. In: 2012 IEEE Ninth International Conference on Services Computing, pp. 609–616, (2012)
46. Patel, M., Chaudhary, S., Garg, S.: Performance modeling and optimization of live migration of virtual machines in cloud infrastructure. In: Chaudhary, S., Somani, G., Buyya, R. (eds.) Research Advances in Cloud Computing, pp. 327–350. Springer, New York (2017)
47. Paulraj, G. J. L., Francis, S. J., Jebadurai, I. J. R.: A novel combined forecasting technique for efficient virtual machine migration in cloud environment. In: Annual Convention of the Computer Society of India, pp. 181–190, (2016)
48. Han, Y., Chan, J., Leckie, C.: Analysing virtual machine usage in cloud computing. In: 2013 IEEE Ninth World Congress on Services, pp. 370–377, (2013)
49. Choudhary, A., Govil, M. C., Singh, G., Awasthi, L. K., Pilli, E. S., Kumar, N.: Improved virtual machine migration approaches in cloud environment. In: 2016 IEEE International Conference on Cloud Computing in Emerging Markets (CEEM), pp. 17–24, (2016)

50. Shaw, S.B., Singh, A.K.: Use of proactive and reactive hotspot detection technique to reduce the number of virtual machine migration and energy consumption in cloud data center. *Comput. Electr. Eng.* 47, 241–254 (2015)
51. Jiang, J., Zhao, X., Wu, Y., Zheng, W.: I/O-conscious and prediction-enabled virtual machines scheduling. In: 2016 IEEE International Conference on Computer and Information Technology (CIT), pp. 760–767, (2016)
52. Wang, R., Le, W., Zhang, X.: Design and implementation of an efficient load-balancing method for virtual machine cluster based on cloud service. *Comput. Electr. Eng.* 34, 321–324 (2011)
53. Zheng, J., Ng, T.S.E., Sripanidkulchai, K., Liu, Z.: Pacer: a progress management system for live virtual machine migration in cloud computing. *IEEE Trans. Netw. Serv. Manag.* 10, 369–382 (2013)
54. Babu, K.R.R., Samuel, P.: Interference aware prediction mechanism for auto scaling in cloud. *Comput. Electr. Eng.* 69, 351–363 (2018)
55. Wang, Z., Sun, D., Xue, G., Qian, S., Li, G., Li, M.: Ada-things: an adaptive virtual machine monitoring and migration strategy for internet of things applications. *J. Parallel Distrib. Comput.* 132, 164–176 (2018)
56. Rybina, K., Schill, A.: Estimating energy consumption during live migration of virtual machines. In: 2016 IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom), pp. 1–5, (2016)
57. Farahnakian, F., Liljeberg, P., Plosila, J.: LiRCUP: linear regression based CPU usage prediction algorithm for live migration of virtual machines in data centers. In: 2013 39th Cluster Computing Euromicro Conference on Software Engineering and Advanced Applications, pp. 357–364, (2013)
58. Shaw, S. B., Kumar, C., Singh, A. K.: Use of time-series based forecasting technique for balancing load and reducing consumption of energy in a cloud data center. In: 2017 International Conference on Intelligent Computing and Control (I2C2), pp. 1–6, (2017)
59. Cao, R., Tang, Z., Li, K., Li, K.: HMGOWM: a hybrid decision mechanism for automating migration of virtual machines. *IEEE Trans. Serv. Comput.* 51, 1–1 (2018)
60. Reguri, V. R., Kogata, S., Moh, M.: Energy efficient trafficaware virtual machine migration in green cloud data centers. In: 2016 IEEE 2nd International Conference on Big Data Security on Cloud (BigDataSecurity), IEEE International Conference on High Performance and Smart Computing (HPSC), and IEEE International Conference on Intelligent Data and Security (IDS), pp. 268–273, (2016)
61. Shukla, R., Gupta, R.K., Kashyap, R.: A multiphase pre-copy strategy for the virtual machine migration in cloud. In: Satapathy, S.C., Bhateja, V., Mohanty, J.R., Udgata, S.K. (eds.) *Smart Intelligent Computing and Applications*, pp. 437–446. Springer, New York (2019)
62. Liu, H., Xu, C.-Z., Jin, H., Gong, J., Liao, X.: Performance and energy modeling for live migration of virtual machines. In: *Proceedings of the 20th International Symposium on High Performance Distributed Computing*, pp. 171–182, (2011)
63. Beloglazov, A., Buyya, R.: Optimal online deterministic algorithms and adaptive heuristics for energy and performance efficient dynamic consolidation of virtual machines in cloud data centers. *Concurr. Comput.* 24, 1397–1420 (2012)
64. Sohrabi, S., Moser, I.: The effects of hotspot detection and virtual machine migration policies on energy consumption and service levels in the cloud. *Proc. Comput. Sci.* 51, 2794–2798 (2015)
65. Chen, J., Qin, Y., Ye, Y., Tang, Z.: A live migration algorithm for virtual machine in a cloud computing environment. In: 2015 IEEE 12th International Conference on Ubiquitous Intelligence and Computing and 2015 IEEE 12th International Conference on Autonomic and Trusted Computing and 2015 IEEE 15th International Conference on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom), pp. 1319–1326, (2015)
66. Liu, H., He, B.: VMbuddies: coordinating live migration of multitier applications in cloud Environments. *IEEE Trans. Parallel Distrib. Syst.* 26, 1192–1205 (2015)
67. Nguyen, T. H., Francesco, M. D., Yla-Jaaski, A.: Virtual machine consolidation with multiple usage prediction for energy-efficient cloud data centers. *IEEE Transactions on Services Computing*. pp. 1–1, 2018.
68. Rybina, G., Dargie, W., Umashankar, S., Schill, A.: Modelling the Live Migration Time of Virtual Machines, pp. 575–593. Springer, Cham (2015)

69. Strunk, A.: A lightweight model for estimating energy cost of live migration of virtual machines. In: 2013 IEEE Sixth International Conference on Cloud Computing, pp. 510–517, (2013)
70. Al-Anzi, F., AbuZeina, D.: A survey of Markov chain models in linguistics applications, *Comput. Sci. Inform. Technol.* (2016)
71. Sun, X., Ansari, N., Fan, Q.: Green energy aware avatar migration strategy in green cloudlet networks. *arXiv preprint arXiv:1509.03603*, (2015)
72. Melhem, S. B., Agarwal, A., Goel, N., Zaman, M.: A Markov based prediction model for host load detection in live VM migration. In: 2017 IEEE 5th International Conference on Future Internet of Things and Cloud (FiCloud), pp. 32–38, (2017)
73. Ruan, Y., Cao, Z., Cui, Z.: Pre-filter-copy: efficient and self adaptive live migration of virtual machines. *IEEE Syst. J.* 10, 1459–1469 (2016)
74. Lei, Z., Sun, E., Chen, S., Wu, J., Shen, W.: A novel hybrid-copy algorithm for live migration of virtual machine. *Future Internet* 9, 37 (2017)
75. Zhang, J., Zhu, C., Chen, S., Liu, X., Du, H.: Virtual machine migrating based on Markow chain. In: 2016 International Conference on Audio, Language and Image Processing (ICALIP), pp. 1–6, (2016)
76. Chen, C., Cao, J.: Prediction-Based Optimization of Live Virtual Machine Migration, pp. 347–356. Springer, Berlin (2014)
77. Melhem, S.B., Agarwal, A., Goel, N., Zaman, M.: Markov prediction model for host load detection and VM placement in live migration. *IEEE Access* 6, 7190–7205 (2018)
78. Wu, T.-Y., Guizani, N., Huang, J.-S.: Live migration improvements by related dirty memory prediction in cloud computing. *J. Netw. Comput. Appl.* 90, 83–89 (2017)
79. Cerroni, W.: Network performance of multiple virtual machine live migration in cloud federations. *J. Internet Serv. Appl.* 6, 6 (2015)
80. Xia, C., Lan, Y., Xiao, L.: Scheduling Resource of IaaS Clouds for Energy Saving Based on Predicting the Overloading Status of Physical Machines, pp. 211–221. Springer, Berlin (2015)
81. Sun, G., Liao, D., Anand, V., Zhao, D., Yu, H.: A new technique for efficient live migration of multiple virtual machines. *Future Gener. Comput. Syst.* 55, 74–86 (2016)
82. Grygorenko, D., Farokhi, S., Brandic, I.: Cost-Aware VM Placement Across Distributed DCs Using Bayesian Networks, pp. 32–48. Springer, Cham (2016)
83. Karthikeyan, K., Sunder, R., Shankar, K., Lakshmanaprabu, S.K., Vijayakumar, V., Elhoseny, M., Manogaran, G.: Energy consumption analysis of Virtual Machine migration in cloud using hybrid swarm optimization (ABC–BA). *J. Supercomput.* 12, 1–17 (2018)
84. Li, J., Shuang, K., Su, S., Huang, Q., Xu, P., Cheng, X., Wang, J.: Reducing operational costs through consolidation with resource prediction in the cloud. In: Proceedings of the 2012 12th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (CCGRID 2012), pp. 793–798, (2012)
85. Altomare, A., Cesario, E., Talia, D.: Energy-aware migration of virtual machines driven by predictive data mining models. In: 2015 23rd Euromicro International Conference on Parallel, Distributed, and Network-Based Processing, pp. 549–553, (2015)
86. Arif, M., Kiani, A.K., Qadir, J.: Machine learning based optimized live virtual machine migration over WAN links. *Telecommun. Syst.* 64, 245–257 (2017)
87. Hong, H., Boyan, C.: The Scheduling Strategy of Virtual Machine Migration Based on the Gray Forecasting Model, pp. 84–91. Springer, Cham (2016)
88. Jia, J., Chen, N., Zhang, S.: Forecasting availability of virtual machine based on grey-exponential curve combination model. In: International Conference on Security, Privacy and Anonymity in Computation, Communication and Storage, pp. 297–310, (2016)
89. Farahnakian, F., Pahikkala, T., Liljeberg, P., Plosila, J.: Energy aware consolidation algorithm based on K-nearest neighbor regression for cloud data centers. In: 2013 IEEE/ACM 6th International Conference on Utility and Cloud Computing, pp. 256–259, (2013)
90. Farahnakian, F., Pahikkala, T., Liljeberg, P., Plosila, J., Tenhunen, H.: Utilization prediction aware VM consolidation approach for green cloud computing. In: 2015 IEEE 8th International Conference on Cloud Computing, pp. 381–388, (2015)
91. Duggan, M., Shaw, R., Duggan, J., Howley, E., Barrett, E.: A multitime-steps-ahead prediction approach for scheduling live migration in cloud data centers. *Software* 49, 617–639 (2018)

92. Garg, S.K., Toosi, A.N., Gopalaiyengar, S.K., Buyya, R.: SLA-based virtual machine management for heterogeneous workloads in a cloud datacenter. *J. Netw. Comput. Appl.* 45, 108–120 (2014) *Cluster Computing*
93. Mason, K., Duggan, M., Barrett, E., Duggan, J., Howley, E.: Predicting host CPU utilization in the cloud using evolutionary neural networks. *Future Generat. Comput. Syst.* 86, 162–173 (2018)
94. Duggan, M., Mason, K., Duggan, J., Howley, E., Barrett, E.: Predicting host CPU utilization in cloud computing using recurrent neural networks. In: 2017 12th International Conference for Internet Technology and Secured Transactions (ICITST), pp. 67–72, (2017)
95. Radhakrishnan, A., Kavitha, V.: Energy conservation in cloud data centers by minimizing virtual machines migration through artificial neural network. *Computing* 98, 1185–1202 (2016)
96. Re, M., Valentini, G.: *Ensemble Methods: A Review*. Chapman & Hall, London (2011)
97. Paulraj, G.J.L., Francis, S.A.J., Peter, J.D., Jebadurai, I.J.: A combined forecast-based virtual machine migration in cloud data centers. *Comput. Electr. Eng.* 69, 287–300 (2018)
98. Lu, T., Stuart, M., Tang, K., He X.: Clique migration: affinity grouping of virtual machines for inter-cloud live migration. In: 2014 9th IEEE International Conference on Networking, Architecture, and Storage, pp. 216–225, (2014)