Azerbaijan Journal of High Performance Computing, Vol 4, Issue 2, 2021, pp. 198-205
https://doi.org/10.32010/26166127.2021.4.2.198.205

AzJHPC
Azerbaijan Journal of High Performance Computing

*Correspondence:
Nigar Ismayilova,
Azerbaijan State Oil and Industry University, Baku, Azerbaijan, nigar.ismayilova@asoiu.edu.az

Challenges of Using the Fuzzy Approach in Exascale Computing Systems

Nigar Ismayilova

Azerbaijan State Oil and Industry University, Baku, Azerbaijan, nigar.ismayilova@asoiu.edu.az

Abstract

In this paper were studied opportunities of using fuzzy sets theory for constructing an appropriate load balancing model in Exascale distributed systems. The occurrence of dynamic and interactive events in multicore computing systems leads to uncertainty. As the fuzzy logic-based solutions allow the management of uncertain environments, there are several approaches and useful challenges for the development of load balancing models in Exascale computing systems.

Keywords: Fuzzy load balancing, Dynamic computing systems, Heterogenous distributed systems, Dynamic and Interactive events

1. Introduction

Nowadays, the progress in science and industry, while the fast development of computational re-sources, requires the thoroughgoing operation system to manage the Exascale computing systems with the dynamic nature of processes and resources (Stone et al., 2010). The main problem related to the operation in Exascale systems corresponds to the dynamic and interactive nature of the exe-cuted process and computational resources (Saleh et al., 2018). Dynamic changing of the process requirements and resource attributes during the runtime makes it complicated to manage the computing systems, consequently successful operation of load balancing, resource discovery, and process migration.

It is essential to design and develop an automated load balancing method to manage the execution of dynamic and interactive scientific problems defined recently (Mirtaheri & Grandinetti, 2017). Dynamic changing of the loads on the computing machines and restrictions of the information about process requirements after dynamic and interactive event occurrence makes it necessary to propose the algorithms for automatization of the load balancing process using artificial intelligence algorithms with high-level intelligence. As a solution, many researchers proposed to use search-based, variable-based and logic-based techniques for reliable load balancing algorithms (Bakhishoff et al., 2020; Mao et al., 2014; Setia et al., 2009). This paper highlighted approaches using fuzzy sets theory as the primary logic-based model for dynamic load balancing, which war-ranties the solution with high-level intelligence and stability. In the third section, different ap-proaches for dynamic load balancing were analyzed using the fuzzy logic approach.

Another main problem of Exascale computing systems is related to the failures of the resource dis-covery process after dynamic and interactive event occurrence

(Adibi & Khaneghah, 2021). The het-erogeneity and dynamic nature of computational resources in high-performance computing sys-tems require more intellectual approaches to perfectly manage the resource discovery process and reduce the required time. For this purpose, researchers investigated different approaches using da-ta analysis, evolutionary algorithms, linear algebra, and different methodologies (Adibi & Khaneghah, 2020; Ma et al., 2011; Vaithiya et al., 2013). Section 4 analyzes the possibilities of ap-plying the fuzzy logic-based solution to resource discovery in heterogeneous systems.

The complexity of the current scientific and industrial programs and their dynamic interactive na-ture requires new solutions for their realization in Exascale computing systems (Khaneghah et al., 2018). The most exciting approaches for the solution of this problem, i.e., to find the appropriate process migration method, are based on the usage of the evolutionary algorithms and finding the way for migration by evaluation of the individuals from the search space (Hui & Yong, 2014; Shravya et al., 2017). The uncertainty and vagueness in the process and computational environment make it possible to find solutions by applying the fuzzy logic approach described in the fifth section.

2. Related Work

Increasing the number of IoT users and the necessity of executing high-intensive applications make it necessary to develop progressive methods for managing heterogeneous and dynamic computing systems (Haibeh et al., 2022). The main challenge in applying heterogeneous computing systems is automating the executing process and reducing human involvement (Di Girolamo et al., 2022).

Much work has been devoted to the optimal task scheduling problem stable for the dynamic and interactive events. For determination of the best assignment between processes and resources in the heterogeneous systems where existing problems for definition of the precise process require-ments and resource attributes, it is necessary to apply self-learning algorithms that will be able to observe the system during some period and start to make decisions during the dynamic and inter-active event occurrence. Many researchers have used different methodologies of supervised learn-ing, unsupervised learning, clustering, and soft computing to realize the load balancing process in distributed computing systems (Lin et al., 2019; Negi et al., 2021; Oikawa et al., 2020). Using the bipartite graphs approach also solve the problem related to the control of multi-energy systems which requires execution of the multiple simulation task blocks and processes and task scheduling problem during the complete life cycle of the system (Tang et al., 2022).

Proposed approaches try to solve the problem related to the heterogeneity of the computing envi-ronment and the dynamicity of the executed processes and resources. Although there are benefi-cial results by applying the methodologies mentioned above, we can still define many problems for successfully implementing the dynamic processes in distributed computing systems. For this pur-pose, this paper analyzed different efforts to apply the fuzzy logic-based approaches to solve the problems of heterogeneous and dynamic environments and discussed possibilities of improving these methods by increasing their intelligence level using logic-based artificial intelligence tech-nologies.

3. Load Balancing

As in heterogeneous computing systems, load balancing meets difficult to make decisions in case of uncertain information, and inconsistency fuzzy logic-based approach can lead to the valua-ble results. Different researchers applied fuzzy inference systems for optimization of the load bal-ancing in dynamic and heterogeneous computing systems; they evaluated the response time of the load balancing using different defuzzification methods, different types of membership functions, different fuzzy inference models, etc. (Ali & Bagchi, 2018; Barazandeh et al., 2009; Rantonen et al., 2010). Some researchers applied hybrid methods such as adaptive neuro-fuzzy inference system, which combines the learning ability of neural networks and explainable activity of fuzzy inference system. A combination of advantages of these two techniques of soft computing allows us to make better decisions for load balancing using fewer data and knowledge (Chourasia & Silakari, 2021; Han et al., 2005; Suresh et al., 2014).

Perfect matching between resources and computing machines for minimizing the response time and maximizing the resource usage in distributed computing systems can be solved by graph modeling. It is possible to define resources and processes set as two different sets of bipartite graphs and to apply different algorithms for perfect matching. To apply the matching algorithms, it is necessary to define weights of the edges between graph nodes, for weight calculation can be used similarities between the resource attribute and process requirement vectors. In heterogene-ous systems, when the nature of the executed processes and involved resources is dynamic, it is not very easy to calculate these weights and apply maximum matching algorithms. Some works investigated ways to manage the load balancing using fuzzy graphs (Ahn & Youn, 2005; Dun et al., 2020).

4. Resource Discovery

One of the most used solutions for resource discovery in distributed computing systems based on using the clustering techniques, fuzzy clustering methods are beneficial for solving this problem in heterogeneous systems such as fog computing (Bharti et al., 2018; Kalaiselvi & Selvi, 2020). De-cision-making to determine the appropriate computing nodes using uncertain information can also be solved using fuzzy logic-based decision-making systems (Cai et al., 2010; Gharajeh, 2021).

For determination of the appropriate resources among the computing nodes with dynamic na-ture in heterogeneous computing systems have been successfully used methods of soft computing such as fuzzy inference systems, neural networks, evolutionary algorithms, especially for resource discovery in grid environment (Chen et al., 2004; Ma et al., 2011; Neri et al., 2007).

Although the application of the approaches mentioned above for dynamic resource discovery in distributed computing systems makes improvements in reducing the response time, there are still some drawbacks related to the finding of the optimal solutions for the problem. Different models developed based on the fuzzy sets theory have an availability to improve resource discovery during uncertain information and inconsistency. For example, the improvement of the approaches using fuzzy clustering methodologies can be upgraded by applying fuzzy ranking algorithms (Tiwari et al., 2020).

5. Process Migration

Increasing usage of mobile devices, the progress of the Internet of Things, and the necessity for improving edge computing systems enforce the development of new methodologies for optimizing the process migration phase of distributed computing systems. The ability to eliminate the uncer-tain and inconsistent situation of the fuzzy logic-based approach makes it possible to use them to determine the most appropriate method for process migration in heterogeneous distributed sys-tems (Ramezani et al., 2016; Wu et al., 2014).

Fuzzy logic-based models allow us to evaluate priorities and make decisions for the optimal process migration model to find the most appropriate migration method and path in the heteroge-neous systems with dynamic processes and computing nodes (Kulkarni et al., 2017; Singla et al., 2015). Another exciting approach is made using fuzzy transfer learning to determine the most in-formative process requirements for the determination of the optimal process migration model and path (Wu et al., 2020).

6. Conclusion

Exascale computing systems are characterized by the dynamic nature of the executed processes related to the current need for scientific computing, and the heterogeneity of the computational nodes requires applying more progressive methods with a high intelligence level. Fuzzy sets theory, with its ability to control during uncertain information and inconsistency, additionally possibility of its combination with the different methodologies of the soft computing and development of the hybrid intellectual systems provides a good possibility for optimization of the load balancing, re-source discovery, and process migration problems in dynamic computing systems. Although many efforts have been made to optimize the computing process in multi-core systems with the dynamic processes using the fuzzy logic-based approach, there are still many possibilities to apply this branch of soft computing to optimize the exascale computing systems. Usage of the fuzzy graphs for task scheduling, fuzzy Bayesian inference networks, or fuzzy decision-making models can im-prove the control of all computing steps in multi-core systems with a dynamic and interactive nature.

References

Adibi, E., & Khaneghah, E. M. (2020). ExaRD: introducing a framework for empowerment of resource discovery to support distributed exascale computing systems with high consistency. *Cluster Computing-the Journal of Networks Software Tools and Applications, 23*(4), 3349-3369. https://doi.org/10.1007/s10586-020-03091-5

Adibi, E., & Khaneghah, E. M. (2021). A mathematical model to describe resource discovery failure in distributed exascale computing systems. *Peer-to-Peer Networking and Applications, 14*(3), 1021-1043. https://doi.org/10.1007/s12083-020-01067-1

Ahn, H. C., & Youn, H. Y. (2005). A fuzzy grouping-based load balancing for distributed object computing systems. *Computational Science and Its Applications - Iccsa 2005*, Vol 4, Proceedings, 3483, 916-925.

Ali, M., & Bagchi, S. (2018). Hybrid Architecture for Autonomous Load Balancing in Distributed Systems based on Smooth Fuzzy Function. *Intelligent Automation and Soft Computing, 24*(4), 851-868.

Bakhishoff, U., Khaneghah, E. M., Aliev, A. R., & Showkatabadi, A. R. (2020). DTHMM ExaLB: discrete-time hidden Markov model for load balancing in distributed exascale computing environment. *Cogent Engineering, 7*(1), 22, Article 1743404. https://doi.org/10.1080/23311916.2020.1743404

Barazandeh, I., Mortazavi, S. S., & Rahmani, A. M. (2009). Intelligent Fuzzy based Biasing Load Balancing Algorithm in Distributed Systems. *2009 Ieee 9th Malaysia International Conference on Communications (Micc),* 713-718. https://doi.org/10.1109/micc.2009.5431403

Bharti, M., Kumar, R., & Saxena, S. (2018). Clustering-based resource discovery on Internet-of-Things. *International Journal of Communication Systems, 31*(5), 23, Article e3501. https://doi.org/10.1002/dac.3501

Cai, M., Zhang, W. Y., Chen, G., Zhang, K., & Li, S. T. (2010). SWMRD: a Semantic Web-based manufacturing resource discovery system for cross-enterprise collaboration. *International Journal of Production Research, 48*(12), 3445-3460. https://doi.org/10.1080/00207540902814330

Chen, H. P., Jiang, J. W., Mang, B. W., & ieee. (2004, Aug 26-29). Design of an artificial-neural-network-based application-oriented grid resource discovery service. International Conference on Machine Learning and Cybernetics, Shanghai, PEOPLES R CHINA.

Chourasia, U., & Silakari, S. (2021). Adaptive Neuro-Fuzzy Interference and PNN Memory Based Grey Wolf Optimization Algorithm for Optimal Load Balancing. *Wireless Personal Communications, 119*(4), 3293-3318. https://doi.org/10.1007/s11277-021-08400-8

Di Girolamo, A., Legger, F., Paparrigopoulos, P., Schovancova, J., Beermann, T., Boehler, M., . . . Tuckus, N. (2022). Preparing Distributed Computing Operations for the HL-LHC Era With Operational Intelligence. *Frontiers in Big Data, 4,* 10, Article 753409. https://doi.org/10.3389/fdata.2021.753409

Dun, M., Li, Y. C., You, X., Sun, Q. X., Luan, Z. R., & Yang, H. L. (2020, Oct 02-04). Accelerating De Novo Assembler WTDBG2 on Commodity *Servers.Lecture Notes in Computer Science*. 20th International Conference on Algorithms and Architectures for Parallel Processing (ICA3PP), New York, NY.

Gharajeh, M. S. (2021). A knowledge and intelligent-based strategy for resource discovery on IaaS cloud systems. *International Journal of Grid and Utility Computing, 12*(2), 205-221.

Haibeh, L. A., Yagoub, M. C. E., & Jarray, A. (2022). A Survey on Mobile Edge Computing Infrastructure: Design, Resource Management, and Optimization Approaches [Article]. *Ieee Access, 10*, 27591-27610. https://doi.org/10.1109/access.2022.3152787

Han, I., Kim, W., & Kim, H. (2005). An optimal load balancing method for the web-server cluster based on the ANFIS model. *Ieice Transactions on Information and Systems, E88D*(3), 652-653. https://doi.org/10.1093/ietisy/e88-d.3.652

Hui, Z., & Yong, L. (2014). Virtual machine migrating algorithm based on genetic algorithm in cloud data center. *Applied Science, Materials Science and Information Technologies in Industry,* 513-517, 2031-2034. https://doi.org/10.4028/www.scientific.net/AMM.513-517.2031

Kalaiselvi, S., & Selvi, C. S. K. (2020). Hybrid Cloud Resource Provisioning (HCRP) Algorithm for Optimal Resource Allocation Using MKFCM and Bat Algorithm. *Wireless Personal Communications, 111*(2), 1171-1185. https://doi.org/10.1007/s11277-019-06907-9

Khaneghah, E. M., ShowkatAbad, A. R., Ghahroodi, R. N., & Assoc Comp, M. (2018). Challenges of Process Migration to Support Distributed Exascale Computing Environment. *Proceedings of 2018 7th International Conference on Software and Computer Applications (Icsca 2018), 20-24.* https://doi.org/10.1145/3185089.3185098

Kulkarni, R. A., Patil, S. B., Balaji, N., & Ieee. (2017). Fuzzy based task prioritization and VM Migration of Deadline Constrained tasks in Cloud Systems. *Proceedings of the International Conference on Inventive Computing and Informatics (Icici 2017),* 400-404.

Lin, Q. L., Gong, Z. B., Wang, Q. L., & Li, J. L. (2019). TELNET: A Reinforcement Learning Based Load Balancing Approach for Datacenter Networks. *Machine Learning for Networking, 11407,* 44-55. https://doi.org/10.1007/978-3-030-19945-6_4

Ma, Y., Liang, Y. Y., & Jiang, X. P. (2011). The Strategy Research on Dynamic Discovery of Grid Resource. Advanced Research on Mechanical Engineering, Industry and Manufacturing Engineering, Pts 1 and 2, 63-64, 41-+. https://doi.org/10.4028/www.scientific.net/AMM.63-64.41

Ma, Y., Liang, Y. Y., & Jiang, X. P. (2011). The Strategy Research on Dynamic Discovery of Grid Resource. *Advanced Research on Mechanical Engineering, Industry and Manufacturing Engineering, Pts 1 and 2, 63-64,* 41-+. https://doi.org/10.4028/www.scientific.net/AMM.63-64.41

Mao, H. Y., Yuan, L., & Qi, Z. W. (2014). A Load Balancing and Overload Controlling Architecture in Clouding Computing. *2014 Ieee 17th International Conference on Computational Science and Engineering (CSE),* 1589-1594. https://doi.org/10.1109/cse.2014.293

Mirtaheri, S. L., & Grandinetti, L. (2017). Dynamic load balancing in distributed exascale computing systems. *Cluster Computing-the Journal of Networks Software Tools and Applications, 20*(4), 3677-3689. https://doi.org/10.1007/s10586-017-0902-8

Negi, S., Rauthan, M. M. S., Vaisla, K. S., & Panwar, N. (2021). CMODLB: an efficient load balancing approach in cloud computing environment. *Journal of Supercomputing, 77*(8), 8787-8839. https://doi.org/10.1007/s11227-020-03601-7

Neri, F., Kotilainen, N., & Vapa, M. (2007). An adaptive global-local memetic algorithm to discover resources in P2P networks. *Applications of Evolutionary Computing, Proceedings,* 4448, 61-+.

Oikawa, A., Freitas, V., Castro, M., Pilla, L. L., & Soc, I. C. (2020, Mar 11-13). Adaptive Load Balancing based on Machine Learning for Iterative Parallel Applications.Euromicro Conference on Parallel, Distributed and Network-Based Processing. *28th Euromicro International Conference on Parallel, Distributed and Network-Based Processing (PDP),* Electr Network.

Ramezani, F., Naderpour, M., Lu, J., & Ieee. (2016, Jul 24-29). A Multi-objective Optimization Model for Virtual Machine Mapping in Cloud Data Centres.IEEE International Fuzzy Systems Conference Proceedings. *IEEE International Conference on*

Fuzzy Systems (FUZZ-IEEE) held as part of IEEE World Congress on Computational Intelligence (IEEE WCCI), Vancouver, CANADA.

Rantonen, M., Frantti, T., & Leiviska, K. (2010). Fuzzy expert system for load balancing in symmetric multiprocessor systems. *Expert Systems with Applications, 37*(12), 8711-8720. https://doi.org/10.1016/j.eswa.2010.06.049

Saleh, S. R., Khaneghah, E. M., Shadnoush, N., & Aliev, A. R. (2018). A mathematical framework for managing interactive communication distortions in exascale organizations. *Cogent Business & Management, 5*(1), 22, Article 1545356. https://doi.org/10.1080/23311975.2018.1545356

Setia, A., Swarup, V. M., Kumar, S., Singh, L., & Ieee. (2009). A Novel Adaptive Fuzzy Load Balancer for Heterogeneous LAM/MPI Clusters Applied to Evolutionary Learning in Neuro-Fuzzy Systems. *2009 Ieee International Conference on Fuzzy Systems,* Vols 1-3, 68-+. https://doi.org/10.1109/fuzzy.2009.5277322

Shravya, K. S., Deepak, A., & Chandrasekaran, K. (2017). Using Genetic Algorithm for Process Migration in Multicore Kernels. *Proceedings of International Conference on Communication and Networks,* 508, 439-448. https://doi.org/10.1007/978-981-10-2750-5_46

Singla, C., Kaushal, S., & Ieee. (2015). Cloud Path Selection using Fuzzy Analytic Hierarchy Process for Offloading in Mobile Cloud Computing. *2015 2nd International Conference on Recent Advances in Engineering & Computational Sciences (Races),* 5.

Stone, J. E., Gohara, D., & Shi, G. C. (2010). OpenCL: A PARALLEL PROGRAMMING STANDARD FOR HETEROGENEOUS COMPUTING SYSTEMS. *Computing in Science & Engineering, 12*(3), 66-72. https://doi.org/10.1109/mcse.2010.69

Suresh, M., Kumar, B. S., Karthik, S., & Ieee. (2014). A LOAD BALANCING MODEL IN PUBLIC CLOUD USING ANFIS AND GSO. *2014 International Conference on Intelligent Computing Applications (Icica 2014),* 85-89. https://doi.org/10.1109/icica.2014.27

Tang, X. Y., Ding, Y., Lei, J. Y., Yang, H., & Song, Y. K. (2022). Dynamic load balancing method based on optimal complete matching of weighted bipartite graph for simulation tasks in multi-energy system digital twin applications. *Energy Reports, 8,* 1423-1431. https://doi.org/10.1016/j.egyr.2021.11.145

Tiwari, A., Lohani, Q. M. D., Muhuri, P. K., & Ieee. (2020, Jul 19-24). Interval-valued Intuitionistic Fuzzy TOPSIS method for Supplier Selection Problem.IEEE International Conference on Fuzzy Systems. *IEEE International Conference on Fuzzy Systems* (FUZZ-IEEE), Electr Network.

Vaithiya, S. S., Bhanu, S. M. S., & Ieee. (2013). Ontology-based Resource Discovery Mechanism for Mobile Grid Environment. *2013 Second International Conference on Advanced Computing, Networking and Security (Adcons 2013),* 154-159. https://doi.org/10.1109/adcons.2013.21

Wu, J., Wang, Z. Y., & Gao, S. S. (2014, Jun 25-27). Assessing the Cloud Migration Readiness A Fuzzy AHP Approach Based on BTR Framework.International Conference on Service Systems and Service Management. *11th International Conference on Service Systems and Service Management (ICSSSM),* Beijing Jiaotong Univ, Int Ctr Informat Res, Beijing, PEOPLES R CHINA.

Wu, X., Wang, H. H., Tan, W., Wei, D. S., & Shi, M. Y. (2020). Dynamic allocation strategy of VM resources with fuzzy transfer learning method. *Peer-to-Peer Networking and Applications, 13*(6), 2201-2213. https://doi.org/10.1007/s12083-020-00885-7

Submitted: 15.07.2021
Accepted: 15.11.2021