Identification of Selected Resource-aware Problems Across Scientific Disciplines and Applications

Pawel Czarnul, Mariusz Matuszek

Gdansk University of Technology, 11/12 Narutowicza St., 80-233, Gdansk, Poland

Abstract

In this work we perform preliminary identification by formulations of resource-aware problems across various disciplines considered in scientific literature. Formulations considered are: integer linear programming (ILP), greedy algorithms, dynamic programming and genetic algorithms (GA). We outline scientific disciplines (associated with profiles of journals the works appear in) and practical applications. We were able to identify selected more universal resources considered in many problems, such as financial cost, time, energy, ecological value, security, apart from problem specific resources. We also identified to what degree certain resources appear in various problem formulations, as well as which problem formulations are prevalent in various disciplines.

Keywords

resource-aware problems, identification of resources, cross discipline problem analysis

1. Introduction

In computer science, resources typically considered include: execution time (performance), energy, memory/storage, ease of programming/development time. Problem formulations in these cases are typically associated with trade-offs, for example: performance vs energy [1, 2], performance vs security of a system [3], performance vs storage [4], performance/time vs memory [5, 6], performance vs ease of programming/development effort [7], as well as optimization/portability.

Problem domains considered in this analysis include, among others: allocating resources for fighting forest fires [8], emission minimization, fossil resource usage minimization, employment maximization [9], allocation of health care resources [10], reconfiguration and resource optimization in power distribution networks [11], site selection of a wind power plant [12], operation of a hospital emergency department, studying the impact staffing policies have on such key quality measures as patient length of stay (LoS), number of handoffs, staff utilization levels, and cost [13], decision-CPM network in order to obtain an overall optimum including time, cost, quality and safety in a road building project [14], resource allocation in communication [15, 16], clouds [17, 18], high performance computing systems [19, 1], management of natural resources [20], education [21] etc.

CERCIRAS WS01: 1st Workshop on Connecting Education and Research Communities for an Innovative Resource Aware Society

pczarnul@eti.pg.edu.pl (P. Czarnul); Mariusz.Matuszek@pg.edu.pl (M. Matuszek)
http://pg.edu.pl/pawel.czarnul (P. Czarnul)
0000-0002-4918-9196 (P. Czarnul); 0000-0001-7551-256X (M. Matuszek)

In terms of resources considered in this cross-discipline preliminary review, these can be divided into two groups:

problem specific resources – we consider resources specific to the given domain, e.g. water in water research, natural resources in environmental protection, computing resources in cloud computing etc.

general resources applicable to many domains and applications, specifically optimization i.e. mainly: time (determined by system/process performance) – execution time, cost – monetary, energy (used within an optimization process), ecological/environmental value (respected by a society which it concerns), security – prevention of a crime, break-in.

Outcome of this analysis allows to further outline problem formulations from the identified works and link analogous synthetic formulations and approaches used to solve the latter from the algorithmic point of view. This potentially allows to reuse approaches to take up problems already used in other disciplines and correspondingly identify base algorithms that form algorithmic foundations for resource-aware computing.

2. Resource-aware problems across disciplines by formulations

Works considered in this analysis include selection (scientific papers) out of approximately 100 results returned by the Google search engine for queries involving particular problem formulations and *resource*, *resource-aware problems*. The search had been extended by selected results obtained from the Bing search engine, queried about *resource aware computing* an *resource aware computing problems*. Classification of these is included in Tables 1,2,3,4, versus:

resources: both problem specific as well as more general ones like time, financial cost, security,

formulation: ILP, dynamic programming, greedy approach, GA as an example of evolutionary approaches,

discipline – a broader category of applications considered in the given work.

Table 1: Selected resource-aware problems from various disciplines by resources and discipline, using ILP formulation

problem description	resources	formulation	discipline	bib
allocating resources for fighting forest fires	human resources; time; financial cost	ILP	wildfire suppression, simulation	[8]
Mixed-Integer Linear Programming for Resource Constrained Project Scheduling Problem	jobs belonging to projects; time; renewable, non-renewable resources for executing jobs	ILP	general cross domain applicable	[22]

Continued on next page

Table 1 – continued from previous page

problem description	resources	formulation	discipline	bib
total electricity cost minimization, CO2 emission minimization, energy import minimization, fossil resource usage minimization, employment maximization, social acceptance maximization	energy resources (solar, wind, coal, natural gas, hydroelectric, nuclear etc.)	multi-objective mixed integer linear programming (MOMILP)	energy sector	[9]
allocation of health care resources (treatments, population, healthcare programs)	health care resources , financial cost	ILP	healthcare domain, maximization of benefit	[10]
finding the minimum power loss configuration of the network, definition of the most efficient operating condition of voltage control apparatus and reactive power resources	power distribution network resources	ILP	reconfiguration and resource optimization in power distribution networks, losses optimization	[11]
site selection of a wind power plant single and multiple-type wind turbine models for a selected site	energy	ILP	energy sector	[12]
decision-CPM network in order to obtain an overall optimum including time, cost, quality and safety in a road building project	time; cost; quality; safety	ILP	road construction domain	[14]
operation of a hospital emergency department, studying the impact staffing policies have on such key quality measures as patient length of stay (LoS), number of handoffs, staff utilization levels, and cost	staff; time; resources assigned by staff	ILP, simulation	hospital resource management	[13]

Continued on next page

Table 1 – continued from previous page

problem description	resources	formulation	discipline	bib
data assignment for parallel processing in a hybrid heterogeneous environment considering communication costs	time	ILP	high performance computing using a cluster with multicore/manycore CPUs and GPUs	[19]
cloudlet selection in the multi-cloudlet environment, selection of cloudlet(s), selection of VMs for cloudlets	computing, storage and network resources	ILP	cloud computing	[18]
Data-center power-aware management, efficient utilization of available resources	data-center resources, power, time	ILP	HPC	[23] [24]
scheduling of satellite observations	observation capabilities of satellites, mission time constraints	ILP	satellite Earth observations	[25]

Table 2: Selected resource-aware problems from various disciplines by resources and discipline, using greedy formulation

problem description	resources	formulation	discipline	bib
dynamic multi-user resource allocation in the downlink of OFDMA system, power consumption minimization	communication medium (channels); power consumption	greedy algorithm	resource allocation in communication	[15]
scheduling of flows from various applications in overload states, downlink scheduling	throughput; loss; time (delay)	greedy knapsack algorithm	resource allocation in communication	[16]
preparation of educational schedule in the higher education	school resources: human; classes; courses	greedy approach with local optimal steps	education	[21]

Continued on next page

Table 2 – continued from previous page

problem description	resources	formulation	discipline	bib
allocating resources in Virtual Sensor Networks, maximizing revenue of multiple concurrent applications' schedule	shared physical resources (processing power, bandwidth, storage); time; energy	greedy algorithm	Virtual Sensor Networks	[26]
Set Covering Problem as a template for resource management, examples of applications given for: operational research, machine learning, planning, data mining, information retrieval	problem specific resources; time (algorithm running time)	weighted greedy algorithm	resource management	[27]
Maximizing utility and revenue of hardware resources in virtual machine allocation	problem specific resources	greedy algorithm	datacenter provisioning	[28] [29]
Reducing task duplication in task scheduling on heterogeneous distributed systems	distributed computational resources	greedy algorithm	distributed computing	[30]
Task offloading and resource allocation in power network monitoring (PIoT)	computational and communication resources	greedy algorithm	power network monitoring	[31]
Flexible co-scheduling of computational and communication resources in fluid dynamics calculations	problem specific resources	greedy algorithm	physics modeling	[32]
task scheduling in a cloud computing environment, with time and energy constraints	energy consumption, time	greedy algorithm	cloud computing	[33]

Table 3: Selected resource-aware problems from various disciplines by resources and discipline, using dynamic formulation

problem description	resources	formulation	discipline	bib
agriculture and natural resources management: buffer stocks policy; farm machinery replacement; crop irrigation; fertilizer and pest management; livestock feeding and marketing; mining; pollution control; irreversible development; forestry management and fisheries management	natural resources	dynamic programming	agriculture, management of natural resources	[20]
dynamic programming for scheduling water resources; minimization of expected cost of running a hydroelectric system	water resources; cost	dynamic programming	power systems	[34]
stochastic resource allocation	problem specific resources; financial cost; time	dynamic programming	general resource allocation, decision making	[35]
stochastic resource allocation	problem specific resources; time; security (stemming from the application)	dynamic programming	military naval operations – setting resources to maximum efficiency in real-time on a ship	[36]

Continued on next page

Table 3 – continued from previous page

problem description	resources	formulation	discipline	bib
HPC compute nodes allocation	application specific resources; accelerators, storage	dynamic programming	high performance computing, dynamic allocation of resources, X10 programming language	[37]
Dynamic code loading	grid resources, power consumption	dynamic programming	dynamic reconfiguration of internet servers, agent systems	[38]
Balancing resources in robotic vision	computational power, bandwidth, responsiveness	dynamic programming	obtaining balanced utilization of available computing resources between operating tasks of humanoid robots	[39]
Edge computing, integration of low cost wearable sensors, processing of sensors' data at the cloud edge	energy, bandwidth, processing power, measurement quality	dynamic programming	healthcare, clinical-level continuous patient monitoring	[40]
Seamless image manipulation	still images	dynamic programming	image processing	[41]
Task scheduling and allocation of resources in distributed systems	distributed computing resources, incl. grids, cloud, supercomputers, cost credits	dynamic programming	distributed processing	[42] [43] [44]
Continued on next page				

Table 3 – continued from previous page

problem description	resources	formulation	discipline	bib
planning water resources management systems under uncertainty	water resources	dual interval robust stochastic dynamic programming (DIRSDP) method	water resources management	[45]
hydraulics and water resources simulating and optimizing water transfer system	water resources	dynamic programming and integrated solution of water resource and hydraulic models	agricultural consumption, environmental needs	[46]
stochastic dynamic programming for military applications	military resources; financial cost	dynamic programming	military applications, determining soldiers/ medical support location, planning policies vs opponent's behavior	[47]
data center resource dynamic scheduling for energy optimization, emission reduction	energy; time; computational resources: servers, storage, routers; physical resources: cooling equipment, lighting equipment, power supply, distribution facilities	dynamic programming	data center optimization	[48]

Table 4: Selected resource-aware problems from various disciplines by resources and discipline, using genetic formulation

problem description	resources	formulation	discipline	bib
resource provisioning and scheduling in uncertain cloud environments	financial cost; time (deadlines imposed)	genetic algorithm	cloud computing	[17]
solving resource-constrained project scheduling problem with transfer times	problem specific resources; time	genetic algorithm, transfer times for activities at various locations considered	cross discipline applicable problem formulation	[49]
solving resource constrained multi-project scheduling problem (many projects, time dependencies, constrained resources)	problem specific resources; time	genetic algorithm	cross discipline applicable problem formulation	[50]
solving resource constrained project scheduling problem (RCPSP)	problem specific resources; time	genetic algorithm, comparison of GA algorithms	cross discipline applicable problem formulation	[51] [52] [53]
		GA parameter tuning		[54]
		decomposition based GA		[55]
		quantum inspired GA		[56]
		Elitist GA		[57]
construction scheduling/resource scheduling problem	problem specific resources; time	genetic algorithm	general problem formulation, bridge construction example considered	[58]
troops-to-tasks problem (generalized RCPSP, additional constraints)	military resources, time	genetic algorithm	military field/ applications	[59, 60]

Continued on next page

Table 4 – continued from previous page

problem description	resources	formulation	discipline	bib
grid resource allocation	grid resources: computational systems, storage servers, and network servers; time	genetic algorithm	grid computing	[61]
regional drinking water supply	water resources; financial cost (pumping, purification, transport); ecological/environment value (vs potential damage, groundwater drawdown); energy	genetic algorithm	water resource research	[62]
groundwater management	water resources; financial cost; environmental value (risk of drawdown); time (pumping rate)	genetic algorithm	water resource research	[63]
surgery scheduling, maximizing the use of operating rooms	hospital resources; time (runtime of algorithm and indirectly because of resource usage)	genetic algorithm	healthcare sector	[64]
scheduling problems on flexible manufacturing systems (FMS)	resource types: machines (M), storage buffers (SB), material handling devices (HD), tool-changing devices (TD), fixtures (FX) and pallets (PL); time	genetic algorithm, also other approaches like PSO,	manufacturing system	[65]
protection of marine environment and allocation of response vessels to minimize costs of oil spill at sea	cost; time; environmental burden	genetic algorithm	environmental protection	[66]

Continued on next page

Table 4 – continued from previous page

problem description	resources	formulation	discipline	bib
Power aware resource reconfiguration	resources, power consumption	genetic algorithm	cloud computing	[67]
processing of time-constrained workflows in mobile edge computing	resources, power limitation	genetic algorithm	mobile edge computing	[68]
power-aware allocation of virtual machines in a cloud	energy, power consumption	genetic algorithm	cloud computing, virtualization	[69]
Solving resource constraints in fog computing	problem specific resources	genetic algorithm	Fog-cloud computing, Internet of Things	[70]
virtual network embedding onto underlying physical infrastructure	problem specific resources	genetic algorithm	network virtualization	[71]

Additionally, during research we have encountered works that consider various formulations. Selected examples of these are shown in Table 5, described in terms of the same features as works in the previous tables.

Table 5: Selected resource-aware problems from various disciplines by resources, mixed formulations

problem description	resources	formulation	discipline	bib
investigation of the quality and execution times of several algorithms for scheduling service based workflow applications with changeable service availability and parameters	time; (financial) cost	ILP, genetic algorithm, divide-and-conquer, heuristic GAIN approach	applicable to scientific, business and mixed workflow applications	[72]
performance and energy trade-off analysis for running parallel applications on heterogeneous multi processing systems	execution time; energy	(Halton number) sampling of configuration space for Pareto front generation	high performance computing	[1]

Continued on next page

Table 5 – continued from previous page

problem description	resources	formulation	discipline	bib
investigation of execution time vs energy consumption trade-offs for parallel applications using power capping, both using multi-core CPUs and GPUs	time; energy	(regular, linear) configuration (stemming from power limits) space exploration	high performance computing	[73, 74, 75]
tugboat allocation optimization in container terminals	vessels; tugboats; time	combined genetic algorithm and ant colony optimization	marine research	[76]
approximate dynamic programming approach to resource management in multi-cloud environments, multi-cloud resource allocation algorithm to manage requests to the cloud with maximization of a cloud broker revenue	cloud resources; time (mapping pre-purchased and online requests to resources)	approximate dynamic programming, reinforcement learning	cloud resource management	[77]

3. Conclusions – problem formulations and resources vs disciplines

Preliminary identification of resource-aware problems by querying of Google and Bing search engines allows us to identify:

1. to what degree certain resources appear in various problem formulations,
2. which problem formulations are prevalent in various disciplines.

Resources typically considered in various domains can be domain specific or more universal, such as time and financial cost. The aforementioned factors can be, based on the aforementioned analysis, summarized as follows. Resources often considered in various problem formulations are shown in Table 6.

Table 6: Resources identified in various problem formulations

resource	ILP	greedy algorithms	dynamic programming	GA
time	X	X	X	X
cost	X		X	X
energy	X	X	X	
human resources	X	X		
computing and storage	X		X	X
natural resources			X	X
resources in general problem formulations			X	X

Furthermore, applications that are prevalent in various problem formulations are listed in Table 7.

Table 7: Applications for which selected problem formulations are used

application	ILP	greedy algorithms	dynamic programming	GA
power/energy	X	X	X	
general/specific resource management	X			
HPC	X			
grid/cloud computing	X			X
resource allocation in communication		X		
education		X		
natural resources management			X	X
military applications			X	X

Additionally, we can identify common resources used in various applications/disciplines, apart from problem specific resources. The former can be identified as shown in Table 8.

Table 8: General resources identified in various applications/disciplines

resource	**power/energy**	**HPC, grid/cloud**	**healthcare**	**nat res mgmt**	**military**
time		X	X		X
cost	X		X	X	X
energy		X		X	
data quality			X		
ecological value				X	
security					X

Finalizing this research, we can say that, apart from details shown in the aforementioned tables, we can generalize links between resources and problem formulations, resources and applications as well as applications and formulations among a relatively small number of these entities, which hints that some applications/disciplines can be linked by selected problem formulations. This, however, needs further analysis and identification of concrete variables and formulation mappings between these disciplines. Additionally, we can see that formulations such as dynamic programming and GA appear in research works in general problem formulations that are abstracted from particular applications but can be potentially mapped onto several application areas.

4. Future work

Future work, extending the results presented in this paper, will involve the following:

1. involving other problem formulations such as other evolutionary approaches etc.
2. extending research in-depth by querying scientific databases, including Web of Science, Scopus and publisher's like IEEE, Springer, Elsevier etc.,
3. identifying other possible papers giving a broader-scope generalized approach to the subject,
4. finding actual links and generalizations between problem formulations that describe particular use cases. Some of the works, as noted above, refer to generalized problem

formulations, while others have introduced problem specific constraints and specifics. It is possible to build an inheritance tree of resource-aware problem formulations by prior finding core problem descriptions.

Acknowledgements

This work is partially supported by CERCIRAS COST Action CA19135 funded by COST.

References

[1] A. M. Coutinho Demetrios, D. De Sensi, A. F. Lorenzon, K. Georgiou, J. Nunez-Yanez, K. Eder, S. Xavier-de Souza, Performance and energy trade-offs for parallel applications on heterogeneous multi-processing systems, Energies 13 (2020). URL: https://www.mdpi.com/1996-1073/13/9/2409. doi:10.3390/en13092409.

[2] S. Diouani, H. Medromi, Trade-off between performance and energy management in autonomic and green data centers, in: Proceedings of the 2nd International Conference on Networking, Information Systems & Security, NISS19, Association for Computing Machinery, New York, NY, USA, 2019. URL: https://doi.org/10.1145/3320326.3320332. doi:10.1145/3320326.3320332.

[3] S. Müller, Security trade-offs in Cloud storage systems, Doctoral thesis, Technische Universität Berlin, Berlin, 2017. URL: http://dx.doi.org/10.14279/depositonce-6179. doi:10.14279/depositonce-6179.

[4] H. Jo, Y. Kim, H. Lee, Y. Lee, H. Han, S. Kang, On the trade-off between performance and storage efficiency of replication-based object storage, in: J. Chen, L. Yang (Eds.), Proceedings - 11th IEEE International Conference on Cloud Computing Technology and Science, CloudCom 2019, 19th IEEE International Conference on Computer and Information Technology, CIT 2019, 2019 International Workshop on Resource Brokering with Blockchain, RBchain 2019 and 2019 Asia-Pacific Services Computing Conference, APSCC 2019, International Conference on Cloud Computing Technology and Science, Institute of Electrical and Electronics Engineers (IEEE), United States, 2019, pp. 301–304. doi:10.1109/CloudCom.2019.00051, 11th IEEE International Conference on Cloud Computing Technology and Science, CloudCom 2019, 19th IEEE International Conference on Computer and Information Technology, CIT 2019, 2019 International Workshop on Resource Brokering with Blockchain, RBchain 2019 and 2019 Asia-Pacific Services Computing Conference, APSCC 2019 ; Conference date: 11-12-2019 Through 13-12-2019.

[5] J. M. Bermudo Mera, A. Karmakar, I. Verbauwhede, Time-memory trade-off in toom-cook multiplication: an application to module-lattice based cryptography, IACR Transactions on Cryptographic Hardware and Embedded Systems 2020 (2020) 222–244. URL: https://tches.iacr.org/index.php/TCHES/article/view/8550. doi:10.13154/tches.v2020.i2.222-244.

[6] G. Avoine, P. Junod, P. Oechslin, Characterization and improvement of time-memory trade-off based on perfect tables, ACM Trans. Inf. Syst. Secur. 11 (2008). URL: https://doi.org/10.1145/1380564.1380565. doi:10.1145/1380564.1380565.

[7] K. Karimi, The feasibility of using opencl instead of openmp for parallel cpu programming, 2015. arXiv:1503.06532.
[8] J. Rodríguez-Veiga, M. J. Ginzo-Villamayor, B. Casas-Méndez, An integer linear programming model to select and temporally allocate resources for fighting forest fires, Forests 9 (2018). URL: https://www.mdpi.com/1999-4907/9/10/583. doi:10.3390/f9100583.
[9] E. Özcan, S. Erol, A multi-objective mixed integer linear programming model for energy resource allocation problem: The case of turkey, Gazi University Journal of Science 27 (2014) 1157 – 1168.
[10] D. Epstein, Z. Chalabi, K. Claxton, M. Sculpher, Mathematical programming for the optimal allocation of health care resources, 2005.
[11] A. Borghetti, Mixed Integer Linear Programming Models for Network Reconfiguration and Resource Optimization in Power Distribution Networks, John Wiley & Sons, Ltd, ????, pp. 43–88. doi:https://doi.org/10.1002/9781119116080.ch2.
[12] E. S. Ari, C. Gencer, Proposal of a novel mixed integer linear programming model for site selection of a wind power plant based on power maximization with use of mixed type wind turbines, Energy & Environment 31 (2020) 825–841. URL: https://doi.org/10.1177/0958305X19882394. doi:10.1177/0958305X19882394. arXiv:https://doi.org/10.1177/0958305X19882394.
[13] S. Y. Shin, Y. Brun, H. Balasubramanian, P. L. Henneman, L. J. Osterweil, Discrete-event simulation and integer linear programming for constraint-aware resource scheduling, IEEE Transactions on Systems, Man, and Cybernetics: Systems 48 (2018) 1578–1593. doi:10.1109/TSMC.2017.2681623.
[14] J. R. San Cristóbal Mateo, An integer linear programming model including time, cost, quality, and safety, IEEE Access 7 (2019) 168307–168315. doi:10.1109/ACCESS.2019.2953185.
[15] S. Najeh, H. Besbes, A. Bouallegue, Greedy algorithm for dynamic resource allocation in downlink of ofdma system, in: 2005 2nd International Symposium on Wireless Communication Systems, 2005, pp. 475–479. doi:10.1109/ISWCS.2005.1547746.
[16] N. Ferdosian, M. Othman, B. M. Ali, K. Y. Lun, Greedy–knapsack algorithm for optimal downlink resource allocation in lte networks, Wireless Networks 22 (2015) 1427–1440. URL: http://dx.doi.org/10.1007/s11276-015-1042-9. doi:10.1007/s11276-015-1042-9.
[17] M. C. Calzarossa, L. Massari, G. Nebbione, M. L. Della Vedova, D. Tessera, Tuning genetic algorithms for resource provisioning and scheduling in uncertain cloud environments: Challenges and findings, in: 2019 27th Euromicro International Conference on Parallel, Distributed and Network-Based Processing (PDP), 2019, pp. 174–180. doi:10.1109/EMPDP.2019.8671564.
[18] L. Liu, Q. Fan, Resource allocation optimization based on mixed integer linear programming in the multi-cloudlet environment, IEEE Access 6 (2018) 24533–24542. doi:10.1109/ACCESS.2018.2830639.
[19] T. Boiński, P. Czarnul, Optimization of Data Assignment for Parallel Processing in a Hybrid Heterogeneous Environment Using Integer Linear Programming, The Computer Journal (2021). doi:10.1093/comjnl/bxaa187.
[20] J. O. Kennedy, Dynamic programming applications to agriculture and natural resources (1986). URL: https://www.osti.gov/biblio/7151445.

[21] A. A. Popov, O. N. Lopateeva, A. K. Ovsyankin, M. M. Satsuk, Application of greedy algorithms for the formation of the educational schedule in the higher education, Journal of Physics: Conference Series 1691 (2020) 012066. URL: https://doi.org/10.1088/1742-6596/1691/1/012066. doi:10.1088/1742-6596/1691/1/012066.
[22] J. A. S. Araujo, Mixed-Integer Linear Programming Based Approaches for the Resource Constrained Project Scheduling Problem, Ph.D. thesis, Universidade Federal de Ouro Preto, 2019.
[23] J. L. B. García, R. G. Mestre, J. T. Viñals, An integer linear programming representation for data-center power-aware management, 2010.
[24] S. Shin, Y. Brun, H. Balasubramanian, P. Henneman, L. Osterweil, Discrete-event simulation and integer linear programming for constraint-aware resource scheduling, IEEE Transactions on Systems, Man, and Cybernetics: Systems PP (2017) 1–16. doi:10.1109/TSMC.2017.2681623.
[25] X. Chen, G. Reinelt, G. Dai, A. Spitz, A mixed integer linear programming model for multi-satellite scheduling, 2018. arXiv:1811.12114.
[26] S. Bousnina, M. Cesana, J. Ortín, C. Delgado, J. R. Gállego, M. Canales, A greedy approach for resource allocation in virtual sensor networks, in: 2017 Wireless Days, 2017, pp. 15–20. doi:10.1109/WD.2017.7918108.
[27] H. Singh, Performance Evaluation of Weighted Greedy Algorithm in Resource Management, Master's thesis, University of Windsor, Windsor, Ontario, Canada, 2018. Https://scholar.uwindsor.ca/etd/7397.
[28] S. Rampersaud, D. Grosu, A sharing-aware greedy algorithm for virtual machine maximization, in: 2014 IEEE 13th International Symposium on Network Computing and Applications, NCA 2014, Cambridge, MA, USA, 21-23 August, 2014, 2014, pp. 113–120. URL: https://doi.org/10.1109/NCA.2014.24. doi:10.1109/NCA.2014.24.
[29] S. Rampersaud, D. Grosu, An approximation algorithm for sharing-aware virtual machine revenue maximization, IEEE Trans. Serv. Comput. 14 (2021) 1–15. URL: https://doi.org/10.1109/TSC.2017.2786728. doi:10.1109/TSC.2017.2786728.
[30] A resource-aware scheduling algorithm with reduced task duplication on heterogeneous computing systems, J Supercomput 68 (2014) 1347––1377.
[31] H. Liao, Z. Zhou, X. Zhao, Y. Wang, Learning-based queue-aware task offloading and resource allocation for space–air–ground-integrated power iot, IEEE Internet of Things Journal 8 (2021) 5250–5263. doi:10.1109/JIOT.2021.3058236.
[32] A. Yin, Y. Guo, D. Tang, Resource-aware fluid scheduling with time constraints for clustered many-core architectures, Journal of Physics: Conference Series 1971 (2021) 012090. URL: https://doi.org/10.1088/1742-6596/1971/1/012090. doi:10.1088/1742-6596/1971/1/012090.
[33] P. Venuthurumilli, S. Mandapati, An energy and deadline aware scheduling using greedy algorithm for cloud computing, Ingénierie des systèmes d information 24 (2019) 583–590. doi:10.18280/isi.240604.
[34] A. Castellano, C. Martínez, P. Monzón, J. A. Bazerque, A. Ferragut, F. Paganini, Quadratic approximate dynamic programming for scheduling water resources: a case study, 2020. arXiv:2010.02122.
[35] A. Forootani, R. Iervolino, M. Tipaldi, J. Neilson, Approximate dynamic programming for

stochastic resource allocation problems, IEEE/CAA Journal of Automatica Sinica 7 (2020) 975–990. doi:10.1109/JAS.2020.1003231.

[36] P. Plamondon, B. Chaib-draa, A. R. Benaskeur, A real-time dynamic programming decomposition approach to resource allocation, in: 2007 Information, Decision and Control, 2007, pp. 308–313. doi:10.1109/IDC.2007.374568.

[37] M. Braun, S. Buchwald, M. Mohr, A. Zwinkau, Dynamic X10: Resource-Aware Programming for Higher Efficiency, Technical Report 8, Karlsruhe Institute of Technology, 2014. URL: http://digbib.ubka.uni-karlsruhe.de/volltexte/1000041061, x10 '14.

[38] L. Moreau, C. Queinnec, Resource aware programming, ACM Trans. Program. Lang. Syst. 27 (2005) 441–476.

[39] J. Paul, W. Stechele, M. Kröhnert, T. Asfour, Resource-aware programming for robotic vision, CoRR abs/1405.2908 (2014). URL: http://arxiv.org/abs/1405.2908. arXiv:1405.2908.

[40] D. Amiri, A. Anzanpour, I. Azimi, M. Levorato, P. Liljeberg, N. Dutt, A. M. Rahmani, Context-aware sensing via dynamic programming for edge-assisted wearable systems 1 (2020). doi:10.1145/3351286.

[41] S. Avidan, A. Shamir, Seam carving for content-aware image resizing, in: ACM Trans. Graph, SIGGRAPH, 2007, p. 10.

[42] R. Gianni M., H. Soon-Wook, Cost-aware dynamic resource allocation in distributed computing infrastructures, International Journal of Contents 2 (2011). URL: http://dx.doi.org/10.5392/IJoC.2011.7.2.001. doi:10.5392/IJoC.2011.7.2.001.

[43] G. Ricciardi, S.-W. Hwang, Cost-aware dynamic resource allocation in distributed computing infrastructures, International Journal of Contents 7 (2011) 1–5. doi:10.5392/IJoC.2011.7.2.001.

[44] J. G. D. S. M. Poladian, Vahe; Sousa, Dynamic configuration of resource-aware services. carnegie mellon university. journal contribution (2018). doi:10.1184/R1/6622013.v1.

[45] Z. Liu, Y. Zhou, G. Huang, B. Luo, Risk aversion based inexact stochastic dynamic programming approach for water resources management planning under uncertainty, Sustainability 11 (2019). URL: https://www.mdpi.com/2071-1050/11/24/6926. doi:10.3390/su11246926.

[46] R. Mansouri, H. T. Pudeh, H. A. Yonesi, A. H. Haghiabi, Dynamic programming model for hydraulics and water resources simulating and optimizing water transfer system (a case study in Iran), Journal of Water Supply: Research and Technology-Aqua 66 (2017) 684–700. URL: https://doi.org/10.2166/aqua.2017.110. doi:10.2166/aqua.2017.110. arXiv:https://iwaponline.com/aqua/article-pdf/66/8/684/223306/jws0660684.pdf.

[47] R. Johansson, C. Mårtenson, R. Suzić, P. Svenson, Stochastic dynamic programming for resource allocation, Technical Report, FOI – Swedish Defence Research Agency FOI-R–1666–SE, Command and Control Systems, 2005. FOI-R–1666–SE.

[48] X. Li, L. Nie, S. Chen, Approximate dynamic programming based data center resource dynamic scheduling for energy optimization, in: 2014 IEEE International Conference onÂ Internet of Things(iThings), and IEEEÂ Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing(CPSCom), IEEE Computer Society, Los Alamitos, CA, USA, 2014, pp. 494–501. URL: https://doi.ieeecomputersociety.org/10.1109/iThings.2014.87. doi:10.1109/iThings.2014.87.

[49] R. L. Kadri, F. F. Boctor, An efficient genetic algorithm to solve the resource-constrained project scheduling problem with transfer times: The single mode case, European Journal of Operational Research 265 (2018) 454–462. URL: https://www.sciencedirect.com/science/article/pii/S0377221717306549. doi:https://doi.org/10.1016/j.ejor.2017.07.027.

[50] J. Gonçalves, J. Mendes, M. Resende, A genetic algorithm for the resource constrained multi-project scheduling problem, European Journal of Operational Research 189 (2008) 1171–1190. URL: https://www.sciencedirect.com/science/article/pii/S0377221707005929. doi:https://doi.org/10.1016/j.ejor.2006.06.074.

[51] F. Gargiulo, D. Quagliarella, Genetic algorithms for the resource constrained project scheduling problem, in: 2012 IEEE 13th International Symposium on Computational Intelligence and Informatics (CINTI), 2012, pp. 39–47. doi:10.1109/CINTI.2012.6496807.

[52] J. Alcaraz, C. Maroto, A Robust Genetic Algorithm for Resource Allocation in Project Scheduling, Annals of Operations Research 102 (2001) 83–109. URL: https://ideas.repec.org/a/spr/annopr/v102y2001i1p83-10910.1023-a1010949931021.html. doi:10.1023/A:1010949931021.

[53] J. Liu, Y. Liu, Y. Shi, J. Li, Solving resource-constrained project scheduling problem via genetic algorithm, Journal of Computing in Civil Engineering 34 (2020) 04019055. doi:10.1061/(ASCE)CP.1943-5487.0000874.

[54] X. Tiana, S. Yuanb, Genetic algorithm parameters tuning for resource-constrained project scheduling problem, in: AIP Conference Proceedings, volume 1955, 2018. Https://doi.org/10.1063/1.5033723.

[55] D. Debels, M. Vanhoucke, A decomposition-based genetic algorithm for the resource-constrained project-scheduling problem, Operations Research 55 (2007) 457–469. URL: https://doi.org/10.1287/opre.1060.0358. doi:10.1287/opre.1060.0358. arXiv:https://doi.org/10.1287/opre.1060.0358.

[56] H. M. H. Saad, R. K. Chakrabortty, S. Elsayed, M. J. Ryan, Quantum-inspired genetic algorithm for resource-constrained project-scheduling, IEEE Access 9 (2021) 38488–38502. doi:10.1109/ACCESS.2021.3062790.

[57] J. Lee, Efficient elitist genetic algorithm for resource-constrained project scheduling, Korea Journal of Construction Engineering and Management 8 (2007) 235–245.

[58] Y. C. Toklu, Application of genetic algorithms to construction scheduling with or without resource constraints, Canadian Journal of Civil Engineering 29 (2002) 421–429. URL: https://doi.org/10.1139/l02-034. doi:10.1139/l02-034. arXiv:https://doi.org/10.1139/l02-034.

[59] M. F. Fauske, Using a genetic algorithm to solve the troops-to-tasks problem in military operations planning, The Journal of Defense Modeling and Simulation 14 (2017) 439–446. URL: https://doi.org/10.1177/1548512917711310. doi:10.1177/1548512917711310. arXiv:https://doi.org/10.1177/1548512917711310.

[60] M. F. Fauske, Optimizing the troops-to-tasks problem in military operations planning, Military Operations Research 20 (2015) 49–57. URL: http://www.jstor.org/stable/24838652.

[61] A. E. Ezugwu, N. A. Okoroafor, S. M. Buhari, M. E. Frincu, S. B. Junaidu, Grid resource allocation with genetic algorithm using population based on multisets:, Journal of Intelligent Systems 26 (2017) 169–184. URL: https://doi.org/10.1515/jisys-2015-0089.

doi:doi:10.1515/jisys-2015-0089.

[62] K. Vink, P. Schot, Multiple-objective optimization of drinking water production strategies using a genetic algorithm, Water Resources Research 38 (2002) 20–1–20–15. URL: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2000WR000034. doi:https://doi.org/10.1029/2000WR000034. arXiv:https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2000WR000034.

[63] R. M. Khalaf, W. H. Hassan, Multi-objective groundwater management using genetic algorithms in kerbala desert area, iraq, IOP Conference Series: Materials Science and Engineering 1067 (2021) 012013. URL: https://doi.org/10.1088/1757-899x/1067/1/012013. doi:10.1088/1757-899x/1067/1/012013.

[64] G. Rivera, L. Cisneros, P. Sánchez-Solís, N. Rangel-Valdez, J. Rodas-Osollo, Genetic algorithm for scheduling optimization considering heterogeneous containers: A real-world case study, Axioms 9 (2020). URL: https://www.mdpi.com/2075-1680/9/1/27. doi:10.3390/axioms9010027.

[65] M. G. Filho, C. F. Barco, R. F. T. Neto, Using genetic algorithms to solve scheduling problems on flexible manufacturing systems (fms): a literature survey, classification and analysis, Flexible Services and Manufacturing Journal 26 (2014) 408–431.

[66] K. Łazuga, L. Gucma, Genetic algorithm method for solving the optimal allocation of response resources problem on the example of polish zone of the baltic sea, Journal of KONBiN 38 (2016) 291–310. URL: https://doi.org/10.1515/jok-2016-0028. doi:doi:10.1515/jok-2016-0028.

[67] L. Deng, Y. Li, L. Yao, Y. Jin, J. Gu, Power-aware resource reconfiguration using genetic algorithm in cloud computing, Mob. Inf. Syst. 2016 (2016) 4859862:1–4859862:9. URL: https://doi.org/10.1155/2016/4859862. doi:10.1155/2016/4859862.

[68] S. X. Q. H. Kai Peng, Bohai Zhao, Energy- and resource-aware computation offloading for complex tasks in edge environment (2020). doi:10.1155/2020/9548262.

[69] N. N. H. T. N. T. N. Quang-Hung N., Nien P.D., A genetic algorithm for power-aware virtual machine allocation in private cloud (2013).

[70] F. Hoseiny, S. Azizi, M. Shojafar, F. Ahmadiazar, R. Tafazolli, Pga: A priority-aware genetic algorithm for task scheduling in heterogeneous fog-cloud computing, in: IEEE INFOCOM 2021 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), 2021, pp. 1–6. doi:10.1109/INFOCOMWKSHPS51825.2021.9484436.

[71] Z. Zhou, X. Chang, Y. Yang, L. Li, Resource-aware virtual network parallel embedding based on genetic algorithm, 2016 17th International Conference on Parallel and Distributed Computing, Applications and Technologies (PDCAT) (2016) 81–86.

[72] P. Czarnul, Comparison of selected algorithms for scheduling workflow applications with dynamically changing service availability, J. Zhejiang Univ. Sci. C 15 (2014) 401–422. URL: https://doi.org/10.1631/jzus.C1300270. doi:10.1631/jzus.C1300270.

[73] A. Krzywaniak, P. Czarnul, J. Proficz, Extended investigation of performance-energy trade-offs under power capping in hpc environments, in: 2019 International Conference on High Performance Computing Simulation (HPCS), 2019, pp. 440–447. doi:10.1109/HPCS48598.2019.9188149.

[74] A. Krzywaniak, P. Czarnul, Performance/energy aware optimization of parallel applications

on gpus under power capping, in: R. Wyrzykowski, E. Deelman, J. Dongarra, K. Karczewski (Eds.), Parallel Processing and Applied Mathematics, Springer International Publishing, Cham, 2020, pp. 123–133.

[75] A. Krzywaniak, J. Proficz, P. Czarnul, Analyzing energy/performance trade-offs with power capping for parallel applications on modern multi and many core processors, in: M. Ganzha, L. A. Maciaszek, M. Paprzycki (Eds.), Proceedings of the 2018 Federated Conference on Computer Science and Information Systems, FedCSIS 2018, Poznań, Poland, September 9-12, 2018, volume 15 of *Annals of Computer Science and Information Systems*, 2018, pp. 339–346. URL: https://doi.org/10.15439/2018F177. doi:10.15439/2018F177.

[76] S. Wang, B. Meng, Resource allocation and scheduling problem based on genetic algorithm and ant colony optimization, in: Z.-H. Zhou, H. Li, Q. Yang (Eds.), Advances in Knowledge Discovery and Data Mining, Springer Berlin Heidelberg, Berlin, Heidelberg, 2007, pp. 879–886.

[77] A. Pietrabissa, F. D. Priscoli, A. D. Giorgio, A. Giuseppi, M. Panfili, V. Suraci, An approximate dynamic programming approach to resource management in multi-cloud scenarios, International Journal of Control 90 (2017) 492–503. URL: https://doi.org/10.1080/00207179.2016.1185802. doi:10.1080/00207179.2016.1185802. arXiv:https://doi.org/10.1080/00207179.2016.1185802.