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Research on Problem Formulations in Resource-aware Problems Across Scientific Domains and Applications

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Abstract. In this paper we conducted thorough analysis of research papers focused on resource aware problems and using one of the following formulations: integer linear programming (ILP), greedy algorithms (GrA), dynamic programming (DP), evolutionary algorithms (EA) and machine learning (ML). Basing on such general problem formulations we identified actual research tasks considered in many different domains. Furthermore, we analyzed each of these problems in terms of: resources being considered/subject to optimization, specific optimization algorithms, if applicable, and domains. Finally, based on over 170[1] research papers, we assessed which particular resources like: time, cost, energy, human, computer, natural resources, data/information are used in which problems formulations, which formulations and resources are used and considered in which application/domains. It can serve as reference for algorithms in particular domains or, conversely, looking for unexplored approaches in specific contexts.

Keywords: resource aware problems, resource, domain, integer linear programming, greedy approach, dynamic programming, evolutionary algorithm, machine learning.

1. Introduction and Motivation

Research in various domains is inevitably linked with specific resources as well as optimization problems. Such optimization problems are typically expressed as multi-objective optimization that involves metrics referring to the given domain, in particular resources in a given domain. We can distinguish physical resources such as computers, interconnects, cooling systems, human resources in a cloud computing center as well as more general resources such as time, energy, budget etc. We shall note that in optimization problems certain metrics are often linked to particular physical, problem specific resources e.g.: performance or power consumption of a computer node. These, in turn, can be reflected in metrics describing such a resource, i.e., execution time and energy used within a particular period. These can then be used in a multi-objective optimization. We shall note that optimization often involves trade-offs, e.g., performance vs energy [36,45], performance vs security [120], performance vs storage [79], performance vs memory [18,13], performance vs ease of programming/development effort [84].

[1] the total number of over 190 citations includes also references to related work.

While researching the topic of resource aware optimization we observed that in the literature there are several review papers considering specific resources within a particular domain. These include, for example:

– renewable energy [8,122]
– human resources management [69,23,59],
– computer systems, e.g., cloud computing [68,4],
– telecommunication [152],
– education [180],
– natural resources management [138,22],
– tourism [118,55,151],
– manufacturing [132],
– health [73,158],
– transport [115],
– space [117],
– disaster management [20,3].

We also identified some research papers on multidisciplinary (design) optimization, e.g., [37]. On the hand, to the best of our knowledge, there is no research on applicability of specific optimization problem formulations across various domains, with consideration of resources and metrics.

In this paper, we aim at conducting cross-domain analysis of research works that involve resource aware problems, in terms of resources / metrics considered, problem formulations and domains they target.

This paper is a very significantly extended version of workshop paper [39] that extends it in the following aspects:

1. Considering a new set of research works fetched from a reliable scientific database – Scopus. While the former paper considered approximately 70 works, we have now considered more than 190 research papers.
2. Involving other problem formulations such as a more general evolutionary algorithm concept (versus genetic algorithms considered before) as well as the popular and important machine learning.
3. Final classification of the research versus a larger number of resources: 8 vs 7 as well as applications/domains: 15 vs 8, for a more thorough analysis.

The outline of the paper is as follows. Section 2 details the methodology we used for selection of research papers used as input for subsequent analysis. Section 3 contains analysis of identified resource aware problems across domains with identification of resources, metrics and problem formulations. Section 4 includes comprehensive analysis of the previous problem descriptions with cross linking resources and problem formulations, applications/domains and problem formulations as well as resources and domains. Finally, Section 5 contains summary and outline of possible future work.

2. Methodology for Selection of Source Scientific Works

In this paper we build on and significantly extend the results originally obtained in paper [39]. In that work, analysis was based on selected scientific papers found by the standard Google search engine returned for querying for combinations of a given problem formulation and phrases: *resource*, *resource-aware problems*. The original problem formulations included: integer linear programming, dynamic programming, greedy approach as well as genetic algorithm. Furthermore, this input data set has been extended with selected results returned by the Bing search engine, queried about *resource aware computing* and *resource aware computing problems*.

In this paper, we significantly extended our previous input data set by adding scientific papers returned by the Scopus database. We used an extended query which specified: integer linear programming (ILP), dynamic programming (DP), greedy approach, evolutionary algorithm (EA) (that encompasses the previously considered class of genetic algorithms) as well as the widely popular nowadays machine learning (ML). Specifically, for each of these formulations, we ran a query as follows: <problem formulation> AND <"resource" OR "resource aware problems"> and sorted the results by relevance. Scopus provides details on how relevance is computed[2] which considers: Number of hits, how significant the word is, position in the document and occurrence in title, keywords etc., proximity of terms and completeness in terms of the words from the query. Finally, out of each of these queries we analyzed top 50 works in terms of problems in specific domains, using the given problem formulation. This has increased the number of sources considered very considerably. Additionally, several new applications/domains have been distinguished, along with new general type resources identified in the works.

3. Resource-aware Problems Across Domains with Resources and Problem Formulations

3.1. Resources, Formulations and Applications/Domains

Within this paper we use the term resource in a broad context that encompasses two classes of assets, that can refer to both physical and non-physical forms:

1. problem specific resources – entities and assets that show up in the context of an optimization problem in a given domain. For instance, in the case of resource allocation in cloud computing, such resources would include: computational nodes with CPUs, GPUs, storage, network, applications.
2. general resources – entities and assets that are of interest in optimization problems in potentially various domains that can exist either in a physical or in a non-physical form. Examples of these include: time, monetary/other cost, energy used, etc. As indicated before, these can in fact be metrics describing the use of particular physical resources e.g. response/execution time of an application run in a computer system at the given cost with a certain amount of energy used within the execution time frame.

In order to classify problems considered in possibly various domains, we have decided to distinguish selected, frequently used problem formulations/approaches used for stating problems formally which can be subsequently solved using specific algorithms. The formulations we distinguish are as follows: integer linear programming (ILP); dynamic programming (DP); greedy approach (GrA); evolutionary algorithms (EA), including genetic

[2] https://service.elsevier.com/app/answers/detail/a_id/14182/supporthub/scopus/

algorithms (GA) considered previously in paper [39] as well as the very popular machine learning (ML).

Furthermore, we aim at assignment of specific optimization problems considered in research works to particular domains, i.e., cloud systems, grid systems, IoT, medical, education, manufacturing etc.

3.2. Classification of Problems in Terms of Resources, Formulations and Domains

Classification of the research works, selected using the methodology outlined in Section 2, was performed separately by problem formulation. Then, we recorded all found problem domains in the given formulation in the respective tables. For each considered paper, we identified a given specific optimization problem and classified it in terms of: resources / metrics used, formulation[3] adopted (possibly more detailed description when applicable) and assignment to a particular domain. Classification of these is included in Tables 1,2,3,4, 5 for ILP, GrA, DP, EA and ML respectively.

Table 1. Selected resource-aware problems by resources / metrics and domain, using ILP formulation

problem description	resources / metrics	formulation	domain	bib
allocating resources for fighting forest fires	human resources; time; financial cost	ILP	wildfire suppression; wildfire simulation	[145]
Mixed-Integer Linear Programming for Resource Constrained Project Scheduling Problem	jobs; projects; time; resources for executing jobs	ILP	general cross domain applicable	[9]
minimization of: electricity cost, CO2 emission, energy import, fossil resource usage, maximization of: employment, social acceptance	solar energy; wind energy; coal energy; natural gas energy; hydroelectric energy; nuclear energy	MOMILP	energy sector	[193]
allocation of health care resources (treatments, population, healthcare programs)	health care resources; financial cost	ILP	healthcare domain; maximization of benefit	[48]
finding the minimum power loss configuration of the network	power distribution network resources	ILP	resource optimization in power distribution networks	[24]
site selection of a wind power plant	energy; power plant	ILP	energy sector	[10]

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[3] for explanation of less frequently appearing abbreviations see Appendix A

Table 1 – continued from previous page

problem description	resources / metrics	formulation	domain	bib
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	[150]
scheduling resources in systems that integrate humans with hardware and software components	staff; time; cost; resources assigned by staff	ILP	hospital resource management; simulation	[155]
data assignment optimization in a hybrid heterogeneous environment	computer resources; time	ILP	high performance computing	[21]
cloudlet selection in the multi-cloudlet environment, selection of cloudlet(s), selection of VMs for cloudlets	computing; storage; network	ILP	cloud computing	[102]
Data-center power-aware management, efficient utilization of available resources	data-center resources; power; time	ILP	high performance computing	[58] [154]
scheduling of satellite observations	observation capabilities of satellites; mission time constraints	ILP	satellite Earth observations	[34]
hospital capacity assessment	hospital resources; number of patients; treatment time	MILP	healthcare	[30]
agricultural water management under uncertainty	water resources; ecological water requirements; uncertainty levels	MILP	agriculture; water allocation	[184]
preventive maintenance scheduling	cost; reliability; resources;	MILP	generic preventive maintenance	[111]
mobile workforce scheduling	traveling cost; action cost; teams; task	MILP	mobile workforce scheduling	[192]
Volt/var optimization of unbalanced power distribution networks	transformers; reactive power resources; embedded generators	MILP	power distribution networks	[25]
selection of an appropriate agent in a military confrontation	properties of combat agents; properties of combat forces	MILP	military operations	[15]

Continued on next page

Table 1 – continued from previous page

problem description	resources / metrics	formulation	domain	bib
allocation and sequencing of elective operations on hospital operating rooms	operations; human resources; time; schedule	MILP	healthcare	[107]
continuous berth allocation	quayside resources; vessels; time;	ILP	ship terminal management	[181]
bus scheduling	bus seats demand; bus seats supply;	MILP	public transport scheduling	[116]
optimization of building energy use	electricity sources; electricity cost; grid power import/export schedule	MILP	smart grid; smart home	[71]
carrier optimization in wireless localization networks	network resources; power allocation; spectrum allocation	MILP	wireless networks	[183]
optimization of humanitarian aid resource distribution time	distance; vehicle density; travel time; aid resources demand	MILP	disaster response	[2]
telescope network scheduling	astronomers; reservations; preferences	ILP	astronomy	[93]
planning and operations of renewable energy-based distributed power systems	energy cost; energy supply availability; energy sources; optimal energy source sizes	ILP	smart grid; renewable energy	[41]
optimization of multi-period investment planning in street lighting systems	energy savings; budget constraints; state of the system; available technologies	MILP	streetlight systems; investment planning	[144]
optimal selection and sizing of a smart building system	thermal storages; electrical storages; heating and cooling systems; renewable energy sources; policies; cost	MILP	low-energy building design	[11]
dynamic optimal nurse scheduling	nurses; tasks; constraints; locations; preferences; work regulations	ILP	healthcare	[72]

Table 2. Selected resource-aware problems by resources / metrics and domain, using greedy formulation

problem description	resources / metrics	formulation	domain	bib
dynamic multi-user resource allocation in the downlink of OFDMA system, power consumption minimization	communication channels; power consumption	GrA	resource allocation; telecomm.	[121]
scheduling of flows from various applications in overload states, downlink scheduling	throughput; loss; time (delay)	GrkA	resource allocation; telecomm.	[53]
preparation of educational schedule in the higher education	human resources; classes; courses; time; cost	GrA	education	[133]
allocating resources in Virtual Sensor Networks, maximizing revenue of multiple concurrent applications' schedule	processing power; bandwidth; storage; time; energy	GrA	Virtual Sensor Networks	[27]
Set Covering Problem as a template for resource management	generic resources; time	wGrA	resource management	[156]
Maximizing utility and revenue of hardware resources in virtual machine allocation	processing power; memory; storage	GrA	datacenter provisioning	[136] [137]
Reducing task duplication in task scheduling on heterogeneous distributed systems	computational resources	GrA	distributed computing	[1]
Task offloading and resource allocation in power network monitoring (PIoT)	computational resources; communication resources	GrA	power network monitoring	[98]
Resource-aware fluid scheduling	computational resources; communication resources; fluids	GrA	physics modeling	[182]
task scheduling in a cloud computing environment, with time and energy constraints	energy consumption; time	GrA	cloud computing	[165]
radio resource allocation and interference management	link performance; cell throughput	GrA	telecomm.	[161]

Continued on next page

Table 2 – continued from previous page

problem description	resources	formulation	domain	bib
allocation of resources for data traffic in 5G networks	network resources; quality of service; resource scheduling	GrA	telecomm.	[47]
allocation of resources for online teaching	course resources; network; bandwidth; delay	GrA	online education	[173]
dynamic battlefield resource scheduling	campaign resources	GrA	military	[160]
combinatorial auctions in efficient cloud resource allocation	cloud resources; resource pricing	aGrA	cloud computing	[35]
computing resource scheduling in the computing-aware network	computing resources; QoS attributes; network; tasks	dGrA	edge computing; IoT; internet-of-vehicles	[95]
allocation or constrained resources to multi-activity projects	human resources; equipment; materials;	GrA	manufacturing industry	[100]
HW/SW partitioning in SoC design	task criticality; time savings; task frequency; task area	GrA	System-on-Chip design	[167]
relief resource allocation to areas of disaster	equity constraint; relief resource demand; relief resources	GrA	relief operations	[61]

Table 3. Selected resource-aware problems by resources / metrics and domain, using dynamic programming formulation

problem description	resources / metrics	formulation	domain	bib
agriculture and natural resources management	natural resources	DP	agriculture; natural resources	[86]
scheduling water resources; minimization of cost of running a hydroelectric system	water resources; cost	DP	power systems	[32]
stochastic resource allocation	generic resources; financial cost; time	DP	general resource allocation	[56]
stochastic resource allocation	ships; weapons; time; security	DP	military real-time naval operations	[130]

Continued on next page

Table 3 – continued from previous page

problem description	resources / metrics	formulation	domain	bib
HPC compute nodes allocation	application specific resources; accelerators; storage	DP	HPC	[29]
dynamic code loading	grid resources; power consumption	DP	dynamic reconfiguration of servers	[119]
Balancing resources in robotic vision	computational power; bandwidth; responsiveness	DP	balanced utilization of computing resources	[125]
integration of low cost wearable sensors, processing of sensors' data at the cloud edge	energy; bandwidth; processing power; measurement quality	DP	healthcare; clinical-level continuous patient monitoring	[6]
Seamless image manipulation	still images	DP	image processing	[12]
task scheduling and resource allocation in distributed systems	computing resources; cost	DP	distributed processing	[63] [142] [131]
planning water resources management systems under uncertainty	water resources	DIRSDP	water resources management	[105]
hydraulics and water resources simulating, optimizing water transfer system	water resources	DP	agriculture; water consumption	[110]
stochastic dynamic programming for military applications	military resources; financial cost	DP	determining soldiers/ medical support location	[80]
data center resource dynamic scheduling for energy optimization, emission reduction	energy; time; computational resources; physical resources	DP	data center optimization	[97]
finding the optimal bidding strategy for a firm	resources available to the firm	infinite horizon semi-Markov DP	public tenders in oligopolistic market	[70]
bandwidth allocation in OFDM systems with rate constraint to minimize transmission power	bandwidth; user profiles	aDP	telecomm.	[75]

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Table 3 – continued from previous page

problem description	resources / metrics	formulation	domain	bib
sensor resource management	time to acquire target; target priorities; sensor field of view	sDP	surveilance (civil and military)	[171]
optimization of energy purchase and production	energy sources	DP	energy market	[109]
dynamic fleet management	vehicles; vehicle states; customer demands	aDP	vehicle fleet management	[64]
optimization of resource allocation in a factory	production line resources; profit	DP	industry	[172]
price management, maximizing revenue	customer; resource (requests)	aDP & sDP	price management systems	[57]
optimization of water treatment and allocation	water resource; resource state	DP	environmental resources allocation	[187]
resource allocation in R&D projects	project; activities; cost;	DP	cost optimization in R&D projects	[87]
resource allocation to cloud storage	storage; efficiency; load	aDP	cloud computing	[141]
operation of a water reservoir system	water reservoirs; reservoir state; operation policy	DP	water resource planning	[17]
resource-constrained project scheduling	resources; resource availability	aDP with Markov decision process	applicable to many fields	[175]
resource allocation in industrial maintenance	human resources; equipment; time	DP	heavy industry	[62]
finding optimal preventive maintenance budget in power distribution network with reliability constraints	maintenance resources; reliability constraints	DP	power distribution networks	[14]
resource allocation in sliced 5G radio access networks	rate; latency; reliability; separation	DP with hierarchical auction	telecomm.	[153]
assembly line balancing	resource constraints; task precedence relations	DP	manufacturing	[135]
optimization of regional industrial structure development	labor; capital; energy; natural resources; technological progress	grey DP	economy	[126]

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Table 3 – continued from previous page

problem description	resources / metrics	formulation	domain	bib
reducing stochastic errors in accelerometers and gyroscopic sensors	computational resources	DP	metrology	[113]

Table 4. Selected resource-aware problems by resources / metrics and domain, using evolutionary algorithms

problem description	resources / metrics	formulation	domain	bib
resource provisioning and scheduling in uncertain cloud environments	financial cost; time; deadlines imposed	GA	cloud computing	[31]
resource-constrained project scheduling with transfer times	generic resources; transfer time	GA	cross domain applicable problem formulation	[82]
resource constrained multi-project scheduling	generic resources; time	GA	cross domain applicable problem formulation	[66]
resource constrained project scheduling - comparison of GAs	generic resources; time	multiple GA	cross domain applicable problem formulation	[60] [5] [101]
		GA parameter tuning		[162]
		decomposition based GA		[43]
		quantum inspired GA		[149]
		Elitist GA		[94]
construction scheduling	generic resources; bridge; time	GA	general problem formulation; bridge construction	[163]
troops-to-tasks problem	military resources; time	GA	military field applications	[52,51]
grid resource allocation	grid resources; time	GA	grid computing	[49]
regional drinking water supply	water resources; financial cost; ecological value; energy	GA	water resource research	[166]
groundwater management	water resources; financial cost; environmental value; time	GA	water resource research	[88]
surgery scheduling	hospital resources; time	GA	healthcare sector	[143]

Continued on next page

Table 4 – continued from previous page

problem description	resources / metrics	formulation	domain	bib
scheduling problems on flexible manufacturing systems (FMS)	machines; storage buffers; material; tool-changing devices; fixtures; pallets; time	GA+PSO	manufacturing system	[54]
protection of marine environment and allocation of response vessels to minimize costs of oil spill at sea	cost; time; environmental burden	GA	environmental protection	[194]
Power aware resource reconfiguration	resources; power consumption	GA	cloud computing	[44]
processing of time-constrained workflows in mobile edge computing	resources; power limitations	GA	mobile edge computing	[83]
power-aware allocation of virtual machines in a cloud	energy; power consumption	GA	cloud computing; virtualization	[134]
Solving resource constraints in fog computing	fog computing resources	GA	Fog-cloud computing; Internet of Things	[74]
virtual network embedding onto underlying physical infrastructure	physical infrastructure; network topology	GA	network virtualization	[190]
scheduling in grid resource management	grid resources; cost; time	EA + learning	grid computing	[159]
design of combinational logic circuits	circuit; gate; cost; time	EA	electronics	[185]
dynamic multicast routing with network coding	network topology; cost; time	EA	telecomm.	[176]
multi-agent coalition formation	agents; tasks; cost; time	IMOEA	multi-agent processing	[177]
employment level planning for assigned construction project lead time	human resources; project; time	GA+HEA	project management	[146]
optimization of subcarrier allocation and transmit power	network; time	EA	telecomm.	[99]
multi-period dynamic emergency resource scheduling	roads; time	MOEA/D-mdERS	post-disaster emergency resource scheduling	[189]
resource planning and scheduling of payload	space resources	PEA	space (satellite)	[96]

Continued on next page

Table 4 – continued from previous page

problem description	resources / metrics	formulation	domain	bib
order quantities in a multi-item inventory with constraints on storage space and capital	storage; cost	two-phase EA	retail	[81]

Table 5. Selected resource-aware problems by resources / metrics and domain, using machine learning formulation

problem description	resources / metrics	formulation	domain	bib
resource allocation, optimization of the downlink communication [76], resource allocation for 5G [140], medium access control in 6G [89]	network resources	sML, RL	wireless systems; telecomm.	[76] [140] [89]
fog computing resource management review	cost; energy; throughput; time; task	NN, RL, DT, etc.	fog computing	[50]
resource planning system for grocery retail delivery services	groceries; customer; driver; cost	ML	grocery retail	[178]
highlighting geologic sweet spots for multiple US onshore basins	natural resources	ML	geology	[28]
ML for tourism information system, optimization of economy of scenic spots	cost; tourism resources	GBDT, Lambdamart	tourism; economy	[191]
using ML for hydrological modeling, flood forecasting, drought prediction, water resource management	water resources; cost; time	ANNs, RMTs, DL, RNNs, LSTM	water resources management	[128]
compression of quantum data	information	ML	quantum computing	[127]
identification of groundwater potential zones	water resources	EBM, GAMI-net	water resource research	[40]
pronominal coreference resolution using machine learning	text corpus	KNN, LR, XGBoost	languge research	[16]
machine learning-based handoff management in 5G networks	energy; network topology; resource allocation	ML	wireless networks; telecomm.	[139]

Continued on next page

Table 5 – continued from previous page

problem description	resources / metrics	formulation	domain	bib
interpretable machine learning methods and their applications in the field of information resource management	information resources	RMs, DTs, attention mechanisms, PDP, ICE, PFI, LIME, SHAP	public opinion research; social network user behavior; healthcare; scientometric research	[106]
soil moisture prediction through machine learning	natural resources	ML	environmental; water resources management	[85]
ML based employee engagement, appraisal, organizational culture prediction [147], recruitment procedures[77]	human resources	DTs, LR[147], sML[77]	human resource systems management	[147] [77]
mineral resource estimation, exploration	natural resources	SVM, SVR, and ANN used for MRE, mostly RF, neuro-fuzzy, SVM, and ANN ML	management of natural resources	[108] [46] [26]
multi-core resource management	computer resources	RL, ANNs	computer resource management	[112]
water quality prediction	water resources; time	DNNs	water research	[157] [104]
workload prediction in serverless environments	computer resources; cost	LSTM, ARIMA, VAR	serverless computing	[123]
sharing digital education training resources[179], personalized learning[168]	information; training resources; students	SVMs, DT, NNs	education	[179] [168]
increasing the resource efficiency of screw-fastening process	screws; cost	DT, SVM, ANNs	manufacturing	[114]
predicting confirmed cases and trend, classification and diagnosis, medical management	medical resources	ML	medical	[7]

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Table 5 – continued from previous page

problem description	resources / metrics	formulation	domain	bib
resource provisions, scheduling, allocation, energy efficiency, resource[164] management[67] resource scheduling[103]	cloud resources; time; cost; energy	regression, NNs, DTs, RL, SVM	cloud resource management	[164] [67] [103]
resource-efficient computation offloading in IoT devices	computer resources; time	ML + backward induction	IoT; edge computing; cloud computing	[19]
project resource allocation	project resources; cost; time	SVM	project management	[148]
water availability prediction	natural resources; natural phenomena	NNs, LSTM, SVM, etc.	water research	[104]
intrusion detection system for IoT	computer resources; time; memory	logistic regression, passive-aggressive classifiers; perception	IoT	[42]
vehicular network resource allocation strategy	vehicles; network; cost; time	DL, RL, regression	vehicular distributed system	[124]

Additionally, during research we have encountered works that consider various and mixed formulations. Selected examples of these are shown in Table 6, described in terms of the same features as works in the previous tables.

Table 6. Selected resource-aware problems by resources / metrics, mixed formulations

problem description	resources / metrics	formulation	domain	bib
scheduling service based workflow applications with changeable service availability	time; cost	ILP, GA, GAIN, divide-and-conquer	scientific workflows; business workflows; mixed workflows	[38]
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	HPC	[36]

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Table 6 – continued from previous page

problem description	resources / metrics	formulation	domain	bib
performance-energy optimization for parallel applications using power capping, for CPUs and GPUs	time; energy	linear configuration space exploration	HPC	[91,90,92]
tugboat allocation optimization in container terminals	vessels; tugboats; time	combined GA + ant colony optimization	marine research	[169]
approximate DP for resource management in multi-cloud environments	cloud resources; time; revenue	approximate DP, RL	cloud resource management	[129]
allocation method of wind resources under the background of carbon neutralization	natural resources; energy; cost	EA, LP	wind energy; natural resource management	[188]
comb jamming resource allocation algorithm	data/information	greedy + EA	telecomm.	[174]
optimal financial investment of limited resources in enterprise	risk; benefit; time; financial resources	DP and GA	investment management; financial	[65]
virtual network function (VNF) scheduling and deployment	resource cost; delay-satisfied request ratio	ILP + greedy	software-defined networks; telecomm.	[186]
optimal multi-resource allocation in big data mining model training	resources; tasks; parallelism; resource constraints	greedy + GA	big data model training	[170]

We shall note that performing the extended search for the articles from the Scopus database, we generally identified different articles than those in the original paper [39]. There was almost no overlap between current and previous search results. On the other hand, though, the set of domains of identified problems in the two searches mostly matched.

4. Summary of Problem Formulations, Resources and Domains

Based on the classification of the research works shown in the previous section, we can now perform comprehensive analysis concerning:

1. which resources are used in particular problem formulations referring to practical applications,
2. which problem formulations are typically used in particular applications and domains,

3. which resources typically occur in the context of a given application and domain which in fact denotes which of these are considered in the process of an optimization problem in a given domain.

Such analysis allows us to draw conclusions regarding whether:

1. a particular problem formulation is used in the majority of domains,
2. there are formulations that are specific for particular applications/domains,
3. there is a resource that is used only with a specific problem formulation.

It should be noted that this analysis was performed for the source data used within this paper and outlined in Tables 1 through 6. This does mean that the following results reflect the source data analyzed in the paper rather than the whole set of existing research works.

We shall note during preparation of the following summary results we considered the most frequently occurring resources, without problem-specific ones, as well as applications. Integration of the results from the aforementioned tables required relevant generalization of terms used by respective authors in specific problem formulations. Furthermore, in the following Tables 7 and 8, we counted occurrences of terms corresponding to resources and domains per article i.e. possibly several energy-related terms in an article shown before would be counted as one reference to energy. In Table 9 we placed counts of relevant tuples of a resource and a domain and there can be several such tuples resulting from one article.

Resources considered with various problem formulations are shown in Table 7.

Table 7. Resources identified in various problem formulations, notation: I/M – I denotes the number of occurrences in individual formulations, M – denotes the number of occurrences in mixed formulations

resource	**ILP**	**GrA**	**DP**	**EA**	**ML**	**sum**
time	11/2	7/3	5/2	22/2	8/1	63
monetary resources	10/3	1/2	6/1	9/2	9/	43
energy	13/1	3/	5/	4/1	3/	30
human resources	10/	2/	2/	1/	4/	19
computer, network, storage	8/	17/	11/1	6/	8/1	52
natural resources	5/1	/	8/	2/1	7/	24

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Table 7 – continued from previous page

resource	ILP	GrA	DP	EA	ML	sum
resources in general problem formulations	6/	6/	6/	8/	/	26
data/information	/	/1	1/	/1	4/	7
sum	70	42	48	59	45	264

Applications that are considered in various problem formulations are presented in Table 8.

Table 8. Applications for which selected problem formulations are used, notation: I/M – I denotes the number of occurrences in individual formulations, M – denotes the number of occurrences in mixed formulations

application	ILP	GrA	DP	EA	ML	sum
power/energy	6/	1/	3/	/	/	10
general resource management	4/1	3/	4/	10/1	/	23
computer resource management	3/1	8/1	6/1	10/2	9/1	42
communication	1/1	5/2	2/	3/1	4/	19
education	/	2/	/	/	1/	3
natural resources management	3/1	/	8/	3/1	8/	24
military applications	1/	1/	3/	1/	/	6
retail	/	/	2/	1/	2/	5
tourism	1/	/	1/	/	1/	3
manufacturing	/	1/	4/	2/	1/	8
medical/health	5/	/	4/	1/	3/	13

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Table 8 – continued from previous page

application	ILP	GrA	DP	EA	ML	sum
human resources management	2/	1/	/	/	1/	4
transport	3/	/	1/	1/1	/	6
space	2/	/	/	1/	/	3
disaster management	1/	1/	/	1/	/	3
sum	36	26	39	40	31	172

Additionally, we identify how resources are considered within selected applications/domains. Such assessment, based on the reviewed papers, is included in Table 9.

Table 9. Resources identified in selected applications/domains

resource	power/energy	general res mgmt	computer res mgmt	communication	education	nat res mgmt	military	retail	tourism	manufacturing	medical/health	human res mgmt	transport	space	disaster management	sum
time	/	10/1	16/3	6/1	2/	4/	2/	1/	/	5/	4/	2/	4/1	1/	3/	66
monetary resources	4/	4/1	8/1	2/1	1/	5/1	1/	2/	1/	3/	2/	3/	3/	1/	3/	47
energy	9/	/	12/2	6/	/	4/1	/	/	/	/	1/	/	1/	/	/	36
human resources	/	1/	/	1/	2/	/	2/	2/	1/	2/	6/	4/	2/	1/	4/	28
computer, network, storage	7/	/	32/1	14/	2/	/	1/	/	/	/	2/	/	1/	/	/	60
natural resources	11/	/	/	/	/	22/	/	/	/	/	/	/	/	/	/	33
resources in general problem formulations	/	14/	2/	1/	/	1/	/	/	/	1/	2/	/	2/	/	/	23

Continued on next page

Table 9 – continued from previous page

resource	power/energy	general res mgmt	computer res mgmt	communication	education	nat res mgmt	military	retail	tourism	manufacturing	medical/health	human res mgmt	transport	space	disaster management	sum
data/information	/	2/	/	1/	3/	/	/	/	/	/	/	1/	/	/	/	7
sum	31	33	77	33	10	38	6	5	2	11	17	10	14	3	10	300

Based on this analysis we can draw the following conclusions:

1. All the problem formulations are similarly frequent across applications (total), as can be seen from Table 8. The same can be seen across the resources used, as shown in Table 7.
2. Not surprisingly, as shown in Tables 7 and 9, time and cost are the most frequently addressed non-physical resources, followed by energy. Out of the physical resources, computer, network and storage devices are most frequently considered. Across applications/domains, computer system management, natural resource management, general universally applicable resource management problems, and communication are the most frequently considered ones.
3. ML targets all but general resources and appears in most of the specific contexts, as it is linked to particular applications. This also emphasizes its popularity nowadays.
4. While data/information as a resource is present during optimization using GrA+EA, DP and ML, it is not as frequently considered as the other resources like time, energy, cost.
5. From Table 8 we can see that within the set of papers analyzed, papers on tourism tend to use ILP, DP and ML approaches rather than GrA and EA. Retail domain seems to omit ILP and GrA formulations. While we know that ML can be used for disaster management e.g. in [33,78], this has not been visible in our set of papers, suggesting it is an area worthy of further exploration. The same would apply to military and space domains.
6. From Table 9 we can see that time and cost are practically considered in all identified fields, there is room for further energy-aware research in many fields, including: education, retail, tourism, manufacturing and transport. While, in some of these, energy aspects can be considered within costs, energy considerations, especially concerning environmental impact, are becoming more and more important and are likely to require more direct exposure. Other interesting cross resource domain combinations that could be further explored, in our opinion, include: more focus on human resources in the computer resources management, as well as more focus on consideration of natural resources in contexts other than those specifically focused on natural resource management, as visible in Table 9. Finally, data/information per se is

not deeply present as a resource in other domain-specific areas, other than in works specifically focused on general resource management models and algorithms, education, communication and social contexts.

5. Summary and Future Work

We were able to identify resources and metrics used in various problem formulations as well as problem formulations typically used in a given application/domain. Additionally, we mapped particular resources to applications/domains which allows to draw conclusions about their perceived importance.

Resource identification in Table 9 shows that time and monetary resources are always considered as important, while energy is explicitly considered in 1/3rd of domains and natural resources are given even less direct consideration. It would be interesting to conduct a similar literature survey in, e.g., five years and check, whether increased awareness of energy cost and of demand pressure on natural resources will be reflected in the repeated survey findings. Furthermore, the search for source research works could be extended to include other scientific (indexing) databases, including: ACM DL, IEEE Xplore, Web of Science etc.

Ongoing research in this field has a potential for new formulations. Such occurrences could trigger a new research to amend our findings.

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A. Abbreviations

aDP – approximate Dynamic Programming;
aGrA – adaptive Greedy Algorithm;
ANN – Artificial Neural Network;
ARIMA – Auto Regressive Integrated Moving Average;
dGrA – dynamic Greedy Algorithm;
DIRSDP – Dual Interval Robust Stochastic Dynamic Programming;
DNN – Deep Neural Network;
DT – Decision Trees;
EBM – Explainable Boosting Machine;
GBDT – Gradient Boosting Decision Trees;
GrkA – Greedy knapsack Algorithm;
HEA – Hybrid Evolutionary Algorithm;
ICE – Individual Conditional Expectation;
IMOEA – Improved Multi-Objective Evolutionary Algorithm;
KNN – k-nearest neighbors;
LIME – Local Interpretable Model-agnostic Explanations;
LP – Linear Programming;
LR – Logistic Regression;
LSTM – Long Short-Term Memory;

MILP – Mixed Integer Linear Programming;
MOEA/D-mdERS – Multi-Objective Evolutionary Algorithm for Dynamic multi-period dynamic Emergency Resource Scheduling;
MOMILP – Multi Objective MILP;
MRE – Most Relevant Explanation;
NN – Neural Network;
PDP – Partial Dependence Plot;
PEA – Plasmodium Evolutionary Algorithm;
PFI – Permutation Feature Importance;
PSO – Particle Swarm Optimization;
RF – Random Forest;
RL – Reinforcement Learning;
RMT – Regression and Model Trees;
RNN – Recurrent Neural Network;
sDP – stochastic Dynamic Programming;
SHAP – SHapley Additive exPlanations;
sML – supervised Machine Learning;
SVM – Support Vector Machine;
SVR – Super Vector Regression;
VAR – Vector Auto Regression;
wGrA – weighted Greedy Algorithm.

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