Reducing Energy Usage in Drive Storage Clusters through Intelligent Allocation of Incoming Commands

E. Smart^{a,*}, D. Brown^a, K. Toumi Borges^b, N. Granger-Brown^b

^a*Institute of Industrial Research, 36-40 Middle Street, University of Portsmouth, Portsmouth, Hampshire, PO5 4BP, United Kingdom.*

^b*Seagate Technology, Langstone Road, Havant, Hampshire, PO9 1SA, United Kingdom*

Abstract

Although significant research has been undertaken to reduce high level energy consumption in a data centre, there has been very little focus on reducing storage drive energy consumption via the intelligent allocation of workload commands at the file system level. This paper presents a method for optimising drive energy consumption within a custom built storage cluster containing multiple drives, using multi-objective goal attainment optimization. Significantly, the model developed was based on actual power consumption values (from current/voltage sensors on the drives themselves), which is rare in this field.

The results showed that command energy savings of up to 87% (17% overall energy) could be made by optimising the allocation of incoming commands for execution to drives within a storage cluster for different workloads. More significantly, the transparency of the method meant that it showed exactly

*Corresponding author. Tel: +44 (0) 23 9284 4448, Fax: +44 (0) 23 9284 5192

Email addresses: edward.smart@port.ac.uk (E. Smart),
david.j.brown@port.ac.uk (D. Brown), kais.toumi@seagate.com (K. Toumi Borges),
nick.grangerbrown@seagate.com (N. Granger-Brown)

how such savings could be made and on which drives. It also highlighted that whilst it is well known that solid state drives use less energy than traditional hard disk drives, the difference is not consistent for different sizes of data transfers. It is far larger for small data transfers (less than or equal to 4 kB) and our algorithm utilised this.

Significantly, it highlights how much larger energy savings can be made through using the optimisation results to show which drives can be safely put into a low power state without affecting storage cluster performance.

Keywords: Decision support systems, disk drives, data storage systems, pareto optimization, optimal scheduling

1. Introduction

Data centres are a key part of the world's economic infrastructure and vary in size from server farms that support the likes of Google and Facebook to the server rooms that support small-to-medium corporations. This heavy reliance on data has made data centres one of the biggest consumers of electricity (estimated at 91 billion kilowatt hours in America alone in 2013)¹. However, according to the same report, as much as 50% of this is wasted. As such, energy efficiency in data centres is a key topic for the research community.

The topic of energy reduction within a data centre is well researched with significant activity in the following areas; power usage within a disk drive, reducing disk drive power states within a storage cluster and intelligent data assignment. However, nearly all of this research focusses on high level data flow within sets of storage clusters.

15 Our research focuses on the problem from a new angle and analyses en-
16 ergy management at a much lower level. It looks at modifying the way in
17 which read/write commands are managed within a storage system in order
18 to minimise the energy used in this process. The algorithm proposed is in-
19 tended to operate at a level between the operating system and the storage
20 devices and would be embedded within the kernel. The algorithm would then
21 take commands that come from the upper layers and redirect them to the
22 most appropriate drives. To conceptually illustrate the algorithm in action,
23 suppose that the file storage system is blank. If a given application wants to
24 store data that would be rarely retrieved (read), the algorithm would redi-
25 rect that data to drives with the least write energy costs. However, if the
26 data was to be retrieved (read) often, it would be stored (written) on those
27 drives with the lowest read energy costs (even if they had higher write energy
28 costs than other drives). This would occur until all of the storage devices
29 were full, thus creating a storage system with an overall low optimal energy
30 consumption profile.

31 The following areas are out of scope of this piece of research; algorithm
32 implementation, where it should sit within the storage system and also what
33 happens to data once it has been initially written (e.g. should it be replicated
34 onto other drives).

35 We propose the use of the multi-objective goal attainment algorithm to
36 optimally assign individual commands to drives in order to achieve minimal
37 command energy usage at the storage cluster level. In storage clusters, it is
38 not unreasonable to see multiple copies of regularly accessed files stored on
39 different drives (e.g. popular YouTube videos). This means that any energy

management algorithm could access a file by reading different sections of it from different drives. To the best of the author’s knowledge, there are no other methods that operate so deep within the file system at such a low level. For this reason, it was not meaningful to compare the proposed method with others in the literature review (see section 2).

A custom built storage cluster was fitted with two types of drive: solid state drive (SSD) and hard disk drive (HDD). Their energy usage was computed directly using current and voltage sensors to ensure accurate values. This is a significant advantage over previous research (e.g. Chou et al.²) as usually storage clusters are simulated numerically, which can lead to inaccuracies if drive background activity is not taken into consideration.

The paper is organised as follows. Section 2 contains the literature review. Section 3 describes the multi-objective goal attainment method. Section 4 explains the experimental setup. Section 5 describes the method. Section 6 details the results and section 7 lists the conclusions.

2. Literature Review

In this paper, we assess the available literature for energy saving methods, hardware and software based, for disk storage clusters as well as for optimisation methods.

2.1. Storage Cluster Energy Saving

The main methods used to perform energy saving focus on general dynamic power techniques and general performance enhancing techniques that additionally improve power usage.

63 Modern drives have multiple power states such as 'active' (data trans-
64 fer ready), 'idle' (waiting for data transfer) and 'standby' (some electronics
65 turned off and disk platters stopped)³. For more details on drive power
66 states, see section 4.4. Significant power savings can be made by putting
67 HDDs into standby mode but if a drive receives a new I/O request, it takes
68 time and energy to spin up, which often has too much of an impact on per-
69 formance in certain applications. The duty cycle rating is defined as the
70 number of spin ups and spin downs a disk can withstand before the failure
71 risk on spin up exceeds 50%. For server based drives, this figure is much less
72 than for laptop drives so energy saving measures should not spin up or spin
73 down a drive indiscriminately⁴.

74 A basic approach is to use Traditional Power Management (TPM) meth-
75 ods, which are usually threshold based⁵. In such methods, drive power states
76 are changed after a given threshold time τ , which can be static or dynamic.
77 This can be effective if the pattern of I/O requests is known but for the more
78 common unknown circumstance, it can be shown that by using competitive
79 analysis to set τ to the break-even time, this policy uses at most twice the
80 power of the most optimal offline policy.

81 Another proposed method is to use variable speed disk drives⁶. Rather
82 than having 2 discrete states (idle and standby), this approach lets drives
83 spin at different speeds so that at least a few will be at full speed to service
84 requests. It has been shown that this is a good way to manage the balance
85 between performance and energy usage.

86 A more common approach is to use Dynamic Power Management (DPM)
87 techniques, which seek to maximise energy savings by distributing I/O re-

88 requests over time and across all the disks in the array⁷. It achieves energy
89 savings by first controlling the frequency of I/O requests to each disk so that
90 the mean idle time is large whilst maximising the idle-time variance across
91 all the disks and through time. Techniques include power aware caching and
92 buffering in memory⁸, across disks⁹, workload consolidation through data
93 replication¹⁰, popular data concentration¹¹ and diverting disk accesses by
94 utilising data redundancy¹².

95 Previous work has been undertaken to analyse the performance of drives
96 and storage clusters. Härder et al.¹³ looked at the performance and power
97 consumption of SSDs in a storage cluster and found significant differences
98 in consumption. However, it is difficult to assess this as power consumption
99 was not measured directly from the drives themselves and it was not stated
100 whether the drives were performing maintenance actions at the time.

101 Attempts at energy reduction in storage systems are usually made at a
102 higher system level. For example, improved methods of heat dissipation via
103 different types of coolants or through different systems architecture. Our
104 approach seeks to focus on the properties of the different drive types and the
105 types of commands they are able to process more efficiently (with respect to
106 energy) so that workload commands can be assigned optimally.

107 *2.2. Optimisation Methods*

108 To the best of the authors knowledge, there have been no attempts to ap-
109 ply optimisation methods to assign commands to drives. The basic problem
110 is to assign n commands to m drives where n is much larger than m and both
111 are natural numbers. This could be tackled by means of a semi-assignment
112 algorithm. Drwal¹⁴ used this method to assign streams of requests to servers

113 in order to minimise the worst case processing times although he offers no
 114 details as to how his algorithm improves the total time. Vasudevan¹⁵ uses
 115 a semi-assignment algorithm to optimally assign applications to virtual ma-
 116 chines in a data centre with respect to energy usage, CPU utilisation and
 117 application completion time which shows good results. For problems where
 118 there are more than one parameter to optimise, multi-objective goal attain-
 119 ment optimization has been suggested. This algorithm tries to satisfy a given
 120 set of well defined goals subject to multiple constraints. Jones¹⁶ used the goal
 121 attainment algorithm to show how multiple goals regarding supply and de-
 122 mand could be satisfied. Oddoye¹⁷ has applied goal attainment optimization
 123 in the health care sector and shown how it can optimally cut waiting times
 124 for patients whilst effectively assigning doctors, nurses and consultants to
 125 keep queues to a minimum. Ghoseiri¹⁸ uses goal attainment to solve the
 126 vehicle routing problem and was successful in optimising multiple goals in a
 127 reasonable amount of computational time. Multi-objective goal attainment
 128 optimization will be used in this paper to solve this “command-to-drive”
 129 assignment problem.

130 Hybrid genetic algorithms¹⁹ and evolutionary algorithms²⁰ have also been
 131 used to optimally schedule computing resources over a network where energy
 132 was one of the optimisation objectives. However, a weakness is that it did
 133 not verify the algorithm on real data.

134 **3. Multi-Objective Goal Attainment Optimization**

135 The main problem is to allocate n commands onto m drives for $n \gg m$ in
 136 order to achieve the goals of minimal energy usage, fast execution time and

low storage cost. Let $\mathbf{x} = \{x_{ij}\}$ be the primary decision variable defined by:

$$x_{ij} = \begin{cases} 1 & \text{if command } i \text{ is allocated to drive } j \\ 0 & \text{otherwise, } i = 1, \dots, n; \quad j = 1, \dots, m. \end{cases}$$

Energy usage is modelled by considering the energy needed to execute command i on drive j . Let $\mathbf{e} = \{e_{ij}\}$ denote the energy decision variable:

$$e_{ij} = \text{energy usage if command } i \text{ is assigned to drive } j \quad (1)$$

$$\text{for } i = 1, \dots, n; \quad j = 1, \dots, m. \quad (2)$$

The time to execute command i on drive j is modelled using the decision variable $\mathbf{t} = \{t_{ij}\}$ where:

$$t_{ij} = \text{execution time if command } i \text{ is assigned to drive } j \quad (3)$$

$$\text{for } i = 1, \dots, n; \quad j = 1, \dots, m. \quad (4)$$

The storage cost is defined as the percentage of free disk space needed to execute command i on drive j . This cost will therefore be smaller on large capacity bulk hard drives but larger on small capacity drives. It is modelled by the decision variable $\mathbf{s} = \{s_{ij}\}$ where:

$$s_{ij} = \text{storage cost if command } i \text{ is assigned to drive } j \quad (5)$$

$$\text{for } i = 1, \dots, n; \quad j = 1, \dots, m. \quad (6)$$

The multi-objective goal attainment model proposed considers energy usage $\mathbf{e}$, execution time $\mathbf{t}$ and storage cost $\mathbf{s}$ and has the form:

$$\begin{aligned}
\min G = & w_e \sum_{i=1}^n \frac{p_i^e}{E_i^{goal}} + w_t \sum_{i=1}^n \frac{p_i^t}{T_i^{goal}} + w_s \sum_{j=1}^m \frac{p_j^s}{S_j^{goal}}, \\
\text{subject to } & \sum_{i=1}^n e_{ij}x_{ij} + n_i^e - p_i^e = E_{goal}, \text{ for } j = 1, \dots, m; \\
& \sum_{i=1}^n t_{ij}x_{ij} + n_i^t - p_i^t = T_{goal}, \text{ for } j = 1, \dots, m; \\
& \sum_{i=1}^n s_{ij}x_{ij} + n_i^s - p_i^s = S_{goal}, \text{ for } j = 1, \dots, m; \quad (7) \\
& \sum_{i=1}^n t_{ij}x_{ij} \leq T_{max}, \text{ for } j = 1, \dots, n; \\
& \sum_{i=1}^n s_{ij}x_{ij} \leq S_{max}, \text{ for } j = 1, \dots, m; \\
& \sum_{j=1}^n x_{ij} = 1, \text{ for } i = 1, \dots, n;
\end{aligned}$$

148 The following conditions also hold

$$x_{ij} = 0 \text{ or } 1 \quad i = 1, \dots, n; \quad j = 1, \dots, m \quad (8)$$

$$n_i^e, p_i^e \geq 0; n_i^t, p_i^t \geq 0 \quad i = 1, \dots, n; \quad (9)$$

$$n_j^s, p_j^s \geq 0; n_i^t, p_i^t \geq 0 \quad j = 1, \dots, m; \quad (10)$$

149 In this formulation E_{goal} , T_{goal} and S_{goal} denote the goals for energy usage,
150 execution time and storage cost respectively. For each of these goals n_i^e, p_i^e ,
151 n_i^t, p_i^t and n_j^s, p_j^s denote the positive and negative deviations from the energy,
152 time and storage goals respectively. The constraints T_{max} and S_{max} are im-
153 posed so that the total time and storage costs respectively for a given set of
154 commands do not exceed these thresholds. This is to ensure that commands
155 are executed within a given time period and that the commands are not all

156 issued to solid state drives. The parameters w_e, w_t, w_s are used to weight
 157 the importance of each of the goals for energy, time and storage respectively.
 158 The final constraint of equation 7 ensures that each command is assigned to
 159 exactly one drive.

160 4. Experimental Details

161 Two different experimental setups were required to gather all the nec-
 162 essary data for this paper. Firstly, a data logger system was designed to
 163 capture current and voltage data from individual drives. This setup was
 164 necessary to identify the characteristics of each model of drive.

165 Secondly, another data logger system was created to capture voltage and
 166 current data from a much larger drive storage cluster containing multiple
 167 drives. This was created in order to test the effectiveness of the proposed
 168 method on a real data storage system.

169 4.1. Data Logger System for Individual Drives

170 The data logger system for an individual drive (see figure 1) consists of:

- 171 • One unit of the drive to be tested.
- 172 • Two Adafruit INA219 voltage and current sensor boards to measure
 173 current and voltage from the drive's +5V and +12V supply lines.
- 174 • One Arduino Leonardo controller board for controlling the sensors, col-
 175 lecting samples and sending the data to the computer.
- 176 • One desktop computer to run the software to supervise the controller,
 177 store the samples and generate the required workloads for the drive.

Figure 1: Data logger system for an individual drive

178 4.2. Data Logger System for a Drive Cluster

179 The data logger for the drive cluster (see figure 2) consists of:

- 180 • Thirty-six drives consisting of five different drive types.
- 181 • Seventy-two Adafruit INA219 sensor boards (one for each of the two
- 182 power lines into each of the thirty six drives).
- 183 • Twelve Arduino Leonardo controller boards.
- 184 • One desktop computer to monitor the controllers, store the sensor data
- 185 and to provide power for sensors and controllers.
- 186 • One high-performance drive cluster populated with the thirty six drives.
- 187 • One Hewlett-Packard ProLiant DL360 Generation 5 server to generate
- 188 workloads.

189 Additionally the sensors were linked to the controllers via I2C buses, the
 190 controllers were linked to the computer via USB and the storage cluster was
 191 linked to the server via a SAS cable.

Figure 2: Data logger system for a cluster of drives

192 For these experiments, the Arduino IDE programming environment was
 193 used to develop the code to control the controller boards. To generate the
 194 workloads, the latest version of Iometer was used (version 1.1.0). To analyse
 195 the resulting workload and sensor data, Matlab 2014a was used.

196 Table 1 shows the drives used in the storage cluster, their quantity, their
 197 position, their type and their specifications. The drives selected include those
 198 types commonly found in a storage cluster. For example, type 5 (high speed
 199 SSD), type 1 (fast HDD), types 2 and 3 (medium HDD) and type 4 (slow,
 200 bulk storage HDD). The Drive Position column shows where each drive was
 201 positioned in the drawer and this number is used to identify drives in the

Table 1: Details of Drive Types Used

Drive Posi- tion	Type Num- ber	Drive Type	Units	Details
7-12, 20	1	HDD	7	SAS, 73.4 GB, 2.5, 15 krpm
22-24	2	HDD	3	SAS, 450 GB, 2.5, 10 krpm
1-6, 21	3	HDD	7	SAS, 900 GB, 2.5, 10 krpm
25-36	4	HDD	12	SAS, 3000 GB, 2.5, 7.2 krpm
13-19	5	SSD	7	SAS, 200 GB, 2.5, SLC

202 results section.

203 4.3. Experimental Setup

204 In order to prepare the model, it was necessary to understand the char-
 205 acteristics in terms of energy and time of each of the five drive types. Two
 206 different command sets (workloads) were created in order to test the model's
 207 performance. Throughout this paper, they will be referred to as the 'Stan-
 208 dard' command set and the 'File Server' command set.

209 4.3.1. Description of Commands

210 In this section, the types of command used will be described and ex-
 211 plained. The term 'Data Transfer Size' (e.g. 4096B) refers to the amount of
 212 data than is being either read from a drive or written onto a drive.

213 The term 'Read Access' refers to the percentage of data that is being
214 read from the drive. A value of 100% means all of the data is being read. A
215 value of 50% means that half of the data is being read from the drive and
216 the other half is being written. A value of 0% means that no data is being
217 read so all the data is being written onto the drive.

218 Files can be stored on a drive either sequentially or in multiple sectors in
219 different areas of the drive. Unsurprisingly, it is preferable to store data in
220 contiguous locations than random locations as it uses less energy and takes
221 less time to complete. This is because if a file is stored in random locations,
222 the head (in a HDD) must move more times to access all parts of the file. The
223 term 'Random Access' refers to the percentage of data that is read/written
224 at random. A value of 100% means that all data is being read/written from
225 random locations. A value of 50% means that half of the data is being
226 read/written from random locations and the other half is being read/written
227 from sequential locations. A value of 0% means all data is being read/written
228 from sequential locations.

229 4.3.2. 'Standard' Command Set

230 Twenty-four commands were selected to form the 'Standard' command
231 set and details of these commands can be found in table 2. Each of these
232 commands was repeatedly executed on each drive model for 60 seconds over 3
233 separate tests. The average energy and time taken to execute each command
234 was computed and details can be found in figures 3 and 4 respectively.

Table 2: Specifications of standard commands to be executed

Profile Num- ber	Data Trans- fer Size [B]	Read Access [%]	Ac- cess [%]	Random Access [%]
1	512	100	100	
2	512	50	100	
3	512	0	100	
4	512	100	0	
5	512	50	0	
6	512	0	0	
7	4096	100	100	
8	4096	50	100	
9	4096	0	100	
10	4096	100	0	
11	4096	50	0	
12	4096	0	0	
13	65536	100	100	
14	65536	50	100	
15	65536	0	100	
16	65536	100	0	
17	65536	50	0	
18	65536	0	0	
19	1048576	100	100	
20	1048576	50	100	
21	1048576	0	100	
22	1048576	100	0	
23	1048576	50	0	
24	1048576	0	0	

Figure 3: Typical Command Energy Consumption of Each of the Drive Types for the Standard Command Set

Figure 4: Typical Command Time Execution of Each of the Drive Types for the Standard Command Set

235 4.3.3. File Server Command Set

236 A set of commands typically found in file server applications (see table 3)
 237 was also constructed. This was based on a typical file server access pattern
 238 as defined by Intel²¹. Three workloads were executed comprising of 100

239 commands in the proportions given in table 3 on each of the drive types for
240 60 seconds. The average energy used and time taken to execute one command
241 were computed and can be seen in figures 5 and 6.

242 This data was used to populate an energy usage and execution time
243 lookup table that forms the basis for the model. Figure 3 shows the aver-
244 age energy usage for all twenty-four commands executed on the five different
245 drive types. The average execution times are shown in figure 4. In order
246 to present the data, the scale on the y-axis was made logarithmic so it was
247 possible to compare the solid state type 5 drive with the other 4 hard disks.
248 Figures 5 and 6 show the execution energies and times for the File Server
249 commands respectively. The energy and time graphs clearly show that the
250 solid state drive offers superior energy consumption and execution times. To
251 ensure a balanced comparison, a 'storage cost' is introduced (for the defini-
252 tion, see section 3). This variable will be small for the large capacity drives
253 such as the type 4 but larger for the type 1 and type 5 drives. A weight-
254 ing towards this variable will ensure that not all commands are repeatedly
255 assigned to the solid state drive. This will make the model more realistic.

256 4.4. *Idle Data Collection*

257 The vast majority of energy usage during drive operation occurs in simply
258 providing power to the electronics (+5 volt line on SSD and HDD) and in
259 keeping the platters spinning and the arm moving (+12 volt line HDD only).
260 The drives themselves have their own in-built intelligence, which acts to check
261 the integrity of data written. On traditional hard disks, a Background Media
262 Scan (BMS) can take place to check for errors by reading previously writ-
263 ten data. This activity usually takes place during idle periods, depending on

Figure 5: Typical Command Energy Consumption of Each of the Drive Types for the File Server Commands

Figure 6: Typical Command Time Execution of Each of the Drive Types for the File Server Commands

264 how much data has been written. On certain hard disk types, data is checked
 265 immediately after writing. This activity is known as Idle Read After Write
 266 (IRAW). Solid state drives perform an activity known as Wear-levelling Main-
 267 tenance (WLR) to ensure erase/write cycles are evenly distributed across all

Table 3: Specifications of File Server commands to be executed

Percentage of [%]	Total Transfer Size [kB]	Read Access [%]	Random Access [%]
10	0.5	80	100
5	1	80	100
5	2	80	100
60	4	80	100
2	8	80	100
4	16	80	100
4	32	80	100
10	64	80	100

268 locations. These maintenance activities caused difficulty when attempting to
 269 accurately measure the energy required for a given set of commands or for
 270 a given power mode (active or idle). As such, data collected regarding idle
 271 state and command energies was collected after these maintenance activities
 272 were completed. Not all power states could be observed (or even detected)
 273 during a 24 hour idle period that the drives were subjected to but the ob-
 274 served power states are listed. For the purposes of the model, it was assumed
 275 that if a drive is not executing commands, it is in the IDLE A power state
 276 (HDD) or the IDLE state (SSD). Table 4 provides details of the average
 277 power on the +5V and +12V supply lines for each observed drive state. Not
 278 all states (according to manufacturer guides) were observed and it was not
 279 possible to 'force' a drive into all specific states during this research. The
 280 single drive data logger was used to gather this information.

281 For the HDD's, the IDLE A state occurs when the disks are spinning

282 at full speed. Some electronics are turned off but the heads are loaded so
283 commands can be received and processed immediately. The IDLE B state
284 occurs when the disks are spinning at full speed but the heads are unloaded.
285 In the IDLE C state, the disks are spinning at a reduced speed and the heads
286 are again unloaded. In the STANDBY state, the disks do not spin and the
287 heads are unloaded but commands can still be received (though the drive
288 will take a while to get up to speed). The SLEEP state is a slightly lower
289 power level than STANDBY.

290 The idle data analysis shows that significant energy savings can be made
291 over time if it is possible to put drives into lower power states without com-
292 promising the performance of the storage cluster. For example, if a Type 4
293 disk spends 2 hours in IDLE B instead of IDLE A state, the energy saved is
294 approximately 11,124 Joules (20%).

295 **5. Proposed Method**

296 Through preliminary experiments, it was found that a time interval of
297 10 milliseconds was a suitable interval between consecutive optimisations for
298 the File Server commands as well as the Standard commands for the drive
299 cluster system. If the time interval was too low, then there would be too many
300 commands to be assigned and not enough drives to make the assignment.

301 In the proposed model, the drives were modelled with a command queue
302 and without. For this model, if a drive has a command queue, it is able to
303 continue to be assigned commands until the queue is full. If it doesn't have
304 a command queue, it must wait until it has executed its current command
305 before it can be assigned another command.

Table 4: Details of Detected Drive States

Type Number	Drive Type	Power (+5V line) [W]	Power (+12V line) [W]	Total Power	Idle State
1	HDD	5.004	2.183	7.187	Active
1	HDD	3.437	2.201	5.638	IDLE A
2	HDD	3.640	2.943	6.583	Active
2	HDD	1.739	2.948	4.687	IDLE A
3	HDD	3.010	2.080	5.089	BMS
3	HDD	1.983	2.302	4.284	IDLE A
3	HDD	1.361	1.678	3.038	IDLE B
4	HDD	2.795	5.762	8.557	BMS
4	HDD	1.743	5.868	7.611	IDLE A
4	HDD	1.349	4.717	6.066	IDLE B
5	SSD	3.212	1.725	4.937	IDLE

306 As the proposed method is new (to the best of the author’s knowledge),
 307 there are no other algorithms or methods that operate so deep within storage
 308 clusters at the file system level in this manner. The other methods listed in
 309 section 2 focus on a higher level, whereby a drive can be put into a different
 310 energy saving state depending on its level of activity. For this reason, the
 311 multi-objective goal attainment algorithm was compared against a purely
 312 random assignment of commands to drives at each round of optimisation. If
 313 drive d_i is executing command c_j , it cannot execute another until time t_{ij}
 314 has passed, where t_{ij} is the time taken to execute command c_j on disk d_i .
 315 For example, if a command takes 31 milliseconds to execute on a given drive
 316 and this command is assigned during optimisation round p , then this drive
 317 is unavailable until optimisation round $p + 4$. The experiment was carried

318 out as follows:

- 319 • With all 36 drives available for assignment, perform the first round of
320 optimisation.
- 321 • Assign commands to drives using the optimisation results.
- 322 • Identify all $36 - n$ free drives where n is the number of busy drives and
323 perform the next round of optimisation.
- 324 • Continue until all rounds of optimisation are complete.

325 5.1. Goal Attainment Algorithm Parameters

326 The setting up of these experiments required a fine balance between
327 achieving a feasible solution and the assignment that offered the lowest en-
328 ergy consumption. In section 3, there are parameters T_{max} and S_{max} to set.
329 Parameter T_{max} is a hard limit on the total amount of time it takes for any
330 HDD/SDD to execute commands assigned to it. For these experiments, T_{max}
331 was set at 36 milli-seconds. If the value was set too small, the optimisation
332 problem was infeasible whereas if it was set too large, the algorithm would
333 find sub-optimal solutions. Parameter S_{max} is a limit on the maximum stor-
334 age cost per drive and is set at 1.000001. The decimal component refers
335 to the maximum proportion of free drive space that data from an executed
336 (write) command may occupy (i.e. 0.0001%). This ensures that for example
337 large write commands are issued to drives with the biggest amounts of free
338 space.

339 The weights are set in the proportion of 100:100:1 for energy, time and
340 storage respectively as energy and time are deemed more important than stor-
341 age. The goals are set as 0.0005:0.0005:0 for energy (joules), time (seconds)

342 and storage (proportion of free space) respectively. Preliminary experimen-
343 tation showed it was best to set goals that were slightly unobtainable rather
344 than dynamically using the minimum possible values for a given command
345 set.

346 5.2. *Standard Commands Experiment*

347 The model was run to simulate 60 seconds of drive cluster activity, which
348 meant that $60/0.01 = 6,000$ rounds of optimisation would be carried out for
349 the Standard commands. A set of random commands was collected from
350 the Standard command set (see table 2). For each of the 6,000 rounds of
351 optimisation, 10 commands were chosen at random from the selection of 24.
352 Duplicates were allowed. This meant in total that 60,000 random commands
353 were optimised. Five different random command datasets were created in
354 order to validate the performance of the model. This was to ensure that
355 the performance of the algorithm was consistent and un-biased. The average
356 energy consumption from these command datasets was reported and was
357 found to be remarkably consistent with a standard deviation of less than
358 0.03 %.

359 5.3. *File Server Commands Experiment*

360 The model was again run to simulate 60 seconds of file server activity as
361 defined by Intel²¹, which meant that $60/0.01 = 6,000$ rounds of optimisation
362 would be carried out for the File Server commands. Table 3 shows that
363 there were 8 unique commands. In order to dynamically model a typical file
364 server, a set of 100 commands was created, which consisted of the 8 unique
365 commands in the proportions given in the first column of this table. For each

366 of the 6,000 rounds of optimisation, 10 commands were chosen at random
 367 from this selection of 100. Duplicates were allowed. This meant in total that
 368 60,000 random commands were optimised. Five different random command
 369 datasets were created in order to validate the performance of the model. The
 370 average energy consumption from these command datasets was reported and
 371 was found to be remarkably consistent with a standard deviation of less than
 372 0.03 %. Again, this was to ensure that the performance of the algorithm was
 373 consistent and un-biased.

374 **6. Results**

375 In this section, the energy results for both the Standard commands and
 376 the File Server commands are presented and analysed in depth. A brief
 377 summary is presented in table 5. The method shows clear energy savings
 378 for both workloads, particularly for the File Server, regardless of whether
 379 the drives have a queue or not, over a purely random assignment. Note
 380 that 'command' energy refers to the energy used by the drive to specifically
 381 execute the commands. Total energy is defined as command energy plus idle
 382 energy.

383 *6.1. File Server Command Set Results*

384 *6.1.1. Without Queue*

385 Using all 36 drives in the IDLE A state for 60 seconds required a total idle
 386 energy consumption of 12,565 Joules. By assigning commands randomly, the
 387 total energy consumption was 15,713 Joules (3,148 Joules of command en-
 388 ergy). However, by optimally assigning commands using the goal attainment

Table 5: Overall Results Summary

Workload Set	Queue	Ave. mand Saving [%]	Com- Energy [%]	Ave. Energy [%]	Overall Saving
File Server	Yes	84.88		16.37	
File Server	No	86.25		17.41	
Standard Com- mands	Yes	15.97		1.05	
Standard Com- mands	No	13.27		1.31	

method, the total energy consumption was only 12,978 Joules (433 Joules of command energy). This resulted in a huge energy saving of around 86% for command energy and 17% in total (see Figure 7). The smooth gradient of the optimised line in figure 7 shows that the energy savings were made continuously throughout each round of optimisation, whatever random set of commands were chosen.

Figure 8 compares the number of commands that were assigned to each of the 36 drives using the optimised and the random assignment and unsurprisingly, the majority of commands have been assigned to drive types 5 (low energy solid state), type 1 (fastest HDD) and type 3 (next lowest energy HDD).

Figure 9 shows a comparison between the command energy consumption for each drive type using the optimised and random assignments. As expected, there are large energy savings (nearly 1,000 Joules) to be made by

Figure 7: Command Energy Consumption of the Drives using an Optimised or Random Assignment

not assigning commands to drive types 2 and 4. Interestingly it shows that drive type 5 is using more energy in the optimised assignment but this is because it has received many more commands to execute.

Figure 10 shows an illustrated example of the distribution of the different types of commands assigned to drive types 1, 3 and 5 using the optimised method. It shows that commands with very small data transfer sizes (≤ 4 kB) are mostly executed by type 5 drives whereas for File Server commands with larger data transfer rates (≥ 4 kB), type 1 drives are preferred. In this experiment, the type 5 drives received the maximum possible allocation of commands (1 command per drive per iteration) so it shows that if the type 5 drives are not available then the type 1 disks are the next best, followed by type 3.

Table 6 shows the percentages of commands that have been assigned to each drive type unit. The random assignment column will not have roughly

Figure 8: Number of Commands Assigned to Each of the Drives using an Optimised or Random Assignment

Figure 9: Command Energy Consumption for Each Drive Type using an Optimised or Random Assignment

417 equal proportions of commands assigned to each unit as some drives can
 418 execute commands faster than others so they will be available for assignment
 419 more often. It shows clearly how drive type 5 was favoured for its low energy
 420 properties.

Figure 10: Distribution of Optimised Command Assignments to Drive Types 1, 3 and 5

6.1.2. With Queue

Using all 36 drives in the IDLE A state for 60 seconds required a total energy consumption of 12,565 Joules. By assigning commands randomly, the total energy consumption was 15,567 Joules (3,002 Joules of command energy). However, by optimally assigning commands using the goal attainment method, the total energy consumption was only 13,019 Joules (454 Joules of command energy). This resulted in a huge energy saving of around 85% for command energy and 16% in total. The figures for the results in this section will not be included here as they are almost identical to those in the 'Without Queue' subsection.

The key differences between the optimisations without a queue and with a queue can be seen in table 7. When the drives are modelled with a queue, the random assignment doesn't favour the type 5 drives as much because the other drive types are available for longer periods (as the queue allows more commands to be assigned even if the current ones haven't yet been

Table 6: Proportion of Commands Assigned per Drive Type Unit

Drive Type Number	Optimised Assign- ment [%]	Random Assignment [%]	As- sign- ment [%]	Percentage Difference [%]
1	4.27	2.80		152.50
2	0.00	2.40		-100.00
3	0.01	2.80		-99.64
4	0.00	2.18		-100.00
5	10.00	3.92		255.10

Table 7: Proportion of Commands Assigned per Drive Type Unit for the File Server Commands With Queue

Drive Type Number	Optimised Assign- ment [%]	Random Assignment [%]	As- sign- ment [%]	Percentage Difference [%]
1	4.19	3.07		36.48
2	0.00	2.58		-100.00
3	0.09	3.04		-97.04
4	0.00	2.36		-100.00
5	10.00	3.02		331.13

executed). This is why the random assignment uses more energy because the higher energy disks are more available. However, there is little difference between the optimisation results with or without a queue.

6.2. 'Standard' Command Set Results

6.2.1. Without Queue

Optimising the Standard command set posed a different set of challenges as there was a larger variation in the properties of the different commands

Figure 11: Command Energy Consumption of the Drives using an Optimised or Random Assignment

443 compared to the File Server set. For example, writing a 1MB file on an SSD
 444 or a HDD will be slower and will use more energy than executing a 512B
 445 read command.

446 The idle energy used by this model was 12,565 Joules. Using the optimised
 447 method, the average total energy consumption was 13,506 Joules (941 Joules
 448 of command energy) across the five random command sets with a standard
 449 deviation of 4 Joules. Using the random assignment method, the average
 450 total energy consumption was 13,650 Joules (1,085 Joules of command en-
 451 ergy) across the five random command sets with a standard deviation of 3
 452 Joules. This was a saving of around 13% in terms of command energy and
 453 around 1% in total. Again, figure 11 shows that the energy savings through
 454 optimisation were made throughout.

455 Figure 12 shows how many commands were assigned to each of the 36
 456 drives using the random and optimised methods. Type 5 drives (SSD) have

Figure 13: Distribution of Commands to Drives using an Optimised or Random Assignment

472 The main energy savings are made by assigning fewer commands to drive
 473 types 2 and 4. Drive type 5 uses more energy in the optimised assignment
 474 because it is receiving many more commands.

475 Figure 14 shows exactly which commands were assigned to drive types 4
 476 and 5. Although the type 5 drives (SSD) offer superior energy performance
 477 over nearly all commands, the superiority is biggest for the 512B commands
 478 (command numbers 1-6) so they are mainly assigned to this drive type. The
 479 frequency and type of commands is too great to just assign everything to
 480 type 5 drives and so the type 4 drives are also used, mainly on commands
 481 with higher data transfer rates (64 kB and 1 MB, commands 13-24). This
 482 provides clear insight into exactly how the model made its assignments.

483 Table 8 shows the percentages of commands assigned to each drive type
 484 unit. The random assignment has not assigned an equal proportion of com-
 485 mands to each drive type unit because there is no queue and so as some

Figure 14: Distribution of Optimised Command Assignments to Drive Types 4 and 5

486 drives execute commands faster than others, the random assignment will be
 487 uneven. As expected, drive types 3 and 5 receive more commands at the
 488 expense of drive types 2 and 4.

489 6.2.2. With Queue

490 The presence of a drive command queue makes no difference to the
 491 amount of idle energy consumed over a fixed period so for this model, the
 492 amount of idle energy used was 12,565 Joules. Using the optimised method,
 493 the average total energy consumption was 13,507 Joules (942 Joules of com-
 494 mand energy) over the 5 random command datasets with a standard devi-
 495 ation of 1 Joule. Using the random assignment method, the average total
 496 energy consumption was 13,686 Joules (1,121 Joules of command energy)
 497 across the five random command sets with a standard deviation of 3 Joules.
 498 This was a command energy saving of 16% and a total energy saving of 1%.
 499 It is interesting to note that for the Standard command set, the presence of
 500 the queue makes barely any difference on the optimised energy consumption.

Table 8: Proportion of Commands Assigned per Drive Type Unit

Drive Type Number	Optimised Assign- ment [%]	Random Assignment [%]	As- sign- ment [%]	Percentage Difference [%]
1	2.68	2.74		-2.22
2	1.93	2.71		-28.78
3	3.45	2.84		21.48
4	1.84	2.59		-28.96
5	4.19	3.10		35.16

Table 9: Proportion of Commands Assigned per Drive Type Unit

Drive Type Number	Optimised Assign- ment [%]	Random Assignment [%]	As- sign- ment [%]	Percentage Difference [%]
1	2.68	2.78		-3.60
2	1.95	2.72		-28.31
3	3.49	2.80		24.64
4	1.82	2.78		-34.53
5	4.16	2.78		49.64

501 However, by having a queue, it means the drives are more available to receive
502 commands than without so there is more opportunity for random commands
503 to be assigned to high energy drives (e.g. type 4), resulting in higher energy
504 use.

505 As with the File Server results, the charts for the model with a queue are
506 very similar to the charts for the model without a queue. The main differences
507 are shown in table 9. The optimised percentage per unit assignments are
508 almost identical with or without a queue (tables 8 and 9) but in the presence

509 of a drive queue, where drives are available for assignment more often, the
510 random assignment is roughly equal the same across all drive types, which is
511 why the random assignment uses more energy when the model is run with a
512 queue.

513 *6.3. Algorithm Performance Impact Implications*

514 The research presented in this paper illustrates a proof of concept; namely
515 that it is possible to make energy savings deep within the kernel via the
516 optimal allocation of commands. A future working algorithm that is based
517 on the discoveries made in this research will have an energy and time cost and
518 as such, it is not proposed to run such an algorithm real time. This is because
519 it would need to make decisions within nano-seconds in order to ensure overall
520 file system performance is not impaired. Were it to be implemented, it would
521 likely operate offline at fixed periods. Possible fast meta-heuristic algorithms
522 include tabu search (²²) and ant colony optimisation (²³).

523 The key discovery is that the research shows where energy savings can be
524 made and further work is needed to convert these insights into a practical
525 application.

526 **7. Conclusion**

527 The results show clearly that the model is effective in achieving a reduc-
528 tion in energy consumption regardless of whether the drives have command
529 queue or not. The energy savings are far larger for the File Server command
530 set but this is because commands from this set can be executed far quicker
531 and so the less energy efficient drives (types 2 and 4) are barely used as the
532 other drives have enough capacity to process them.

533 Although the Standard command set is not particularly representative of
534 a real world workload, it was selected as it contains a wide range of different
535 command types that can illustrate more clearly how the model performs.
536 Whilst it is well known that type 5 drives (SSD) use less energy than tradi-
537 tional mechanical hard disks, the paper shows that the gap is biggest for the
538 512B commands so the model mainly assigned these commands to the type
539 5 drives.

540 More significantly, it shows how further energy savings can be made by
541 putting drives into lower power states. By showing which types of command
542 should be assigned to a given drive type, it shows that depending on the
543 current workload, some drives can be safely put into lower power states. To
544 illustrate the energy saving potential of this action, consider the File Server
545 'with queue' experiment. The total command energy saving over the random
546 assignment was 2,548 Joules. If all twelve of the type 4 drives were put into
547 IDLE B mode (instead of IDLE A) for 60 seconds (see table 4), an extra
548 1,112 Joules would be saved.

549 Currently, the proposed approach shows a proof of concept and insights
550 into how an intelligent file allocation system might work. It is true that in a
551 future system, the overheads due to this proposed optimisation would need to
552 be balanced against energy savings. The key contribution of this paper is the
553 insight into which commands are best suited to a given drive, rather than
554 how to create a working algorithm. Future research will investigate what
555 impact the proposed method has in terms of overheads but also whether it is
556 best to have a real time system, or whether it is best to periodically perform
557 this optimisation.

558 **Acknowledgment**

559 The authors would like to thank and acknowledge financial support from
560 Innovate UK (formerly known as the Technology Strategy Board) under grant
561 number 131195.

562 **Appendix A. Data Sets Used**

563 The data for the experiments detailed in this paper is presented in the ap-
564 pendix. Time and energy data is presented for both the Standard command
565 set and the File Server command set. Storage costs are not directly presented
566 as they depend on the used capacity of each drive, which is a random number
567 between seven tenths and eight tenths of the total drive capacity. Note that
568 in the appendix, all energy values are in Joules and all time values are in
569 seconds. Values are given to four decimal places.

570 *Appendix A.1. Storage Cost Generation*

571 The storage costs for the Standard commands data set and the File Server
572 data set are dependant on how much free space is available on each disk
573 before the optimisation takes place. A full table will not be provided as it
574 is more efficient to describe the computations that took place. For a given
575 drive, it is supposed that the drive is between 70% and 80% full and the
576 actual percentage value is determined via the MATLAB function 'rand'. The
577 amount of data WRITTEN to the drive for a given command is converted
578 to Gb and this is then divided by the amount of free space in Gb on the
579 drive. Given the size of the commands and the fact that drives have such
580 large amounts of space, the number computed is thus very small and so to

581 improve model performance and to reduce rounding errors, one is added to
582 each value. The storage costs will change during model operation as when
583 commands are written to the drives, the amount of free space available will
584 decrease.

585 *Appendix A.2. Standard Commands Data Set*

586 Table A.10 and table A.11 contain the energy and time values for the
587 Standard commands data set. That is, for each of the 24 commands and the
588 5 drive types used.

589 *Appendix A.3. File Server Data Set*

590 As stated, there are 100 commands in total and they are made up of the
591 8 different transfer sizes listed in tables A.12 and A.13. For reasons of space,
592 the energy and time values for every command was not listed. The above
593 tables provide a sample energy and time value for the different data transfer
594 values and each drive. There is a slight variability so energy and time values
595 for other command examples not listed will be slightly different.

Table A.10: Measured Energy Values for each Drive Type on the Standard Command Data Set

Profile Number	Drive 1	Drive 2	Drive 3	Drive 4	Drive 5
1	0.0095	0.0238	0.0177	0.0379	0.0000
2	0.0120	0.0262	0.0179	0.0451	0.0008
3	0.0133	0.0248	0.0186	0.0410	0.0001
4	0.0095	0.0003	0.0003	0.0001	0.0000
5	0.0010	0.0025	0.0039	0.0051	0.0001
6	0.0011	0.0037	0.0073	0.0069	0.0001
7	0.0097	0.0236	0.0178	0.0389	0.0000
8	0.0118	0.0251	0.0183	0.0460	0.0001
9	0.0132	0.0244	0.0187	0.0407	0.0001
10	0.0001	0.0002	0.0002	0.0001	0.0000
11	0.0008	0.0021	0.0039	0.0032	0.0001
12	0.0011	0.0033	0.0072	0.0034	0.0001
13	0.0102	0.0234	0.0193	0.0395	0.0004
14	0.0124	0.0265	0.0199	0.0457	0.0011
15	0.0135	0.0255	0.0203	0.0397	0.0015
16	0.0010	0.0011	0.0009	0.0010	0.0004
17	0.0028	0.0041	0.0053	0.0040	0.0010
18	0.0023	0.0041	0.0079	0.0014	0.0007
19	0.0471	0.0729	0.0648	0.1159	0.0249
20	0.0383	0.0566	0.0473	0.1078	0.0251
21	0.0306	0.0383	0.0319	0.0678	0.0248
22	0.0152	0.0178	0.0127	0.0168	0.0059
23	0.0247	0.0248	0.0211	0.0295	0.0140
24	0.0208	0.0177	0.0188	0.0172	0.0101

Table A.11: Measured Time Values for each Drive Type on the 24 Commands Data Set

Profile Number	Drive 1	Drive 2	Drive 3	Drive 4	Drive 5
1	0.0069	0.0083	0.0081	0.0093	0.0003
2	0.0079	0.0092	0.0082	0.0109	0.0003
3	0.0080	0.0090	0.0085	0.0102	0.0004
4	0.0002	0.0002	0.0003	0.0001	0.0002
5	0.0035	0.0045	0.0033	0.0030	0.0003
6	0.0044	0.0064	0.0064	0.0042	0.0004
7	0.0072	0.0085	0.0081	0.0094	0.0003
8	0.0078	0.0089	0.0084	0.0110	0.0003
9	0.0079	0.0093	0.0086	0.0103	0.0004
10	0.0002	0.0002	0.0001	0.0001	0.0002
11	0.0025	0.0036	0.0033	0.0020	0.0003
12	0.0044	0.0062	0.0064	0.0021	0.0004
13	0.0077	0.0094	0.0085	0.0099	0.0006
14	0.0091	0.0103	0.0096	0.0114	0.0008
15	0.0097	0.0105	0.0099	0.0106	0.0007
16	0.0007	0.0005	0.0004	0.0004	0.0003
17	0.0045	0.0049	0.0041	0.0020	0.0006
18	0.0050	0.0068	0.0067	0.0006	0.0006
19	0.0350	0.0343	0.0251	0.0355	0.0074
20	0.0267	0.0266	0.0200	0.0325	0.0065
21	0.0196	0.0188	0.0154	0.0224	0.0056
22	0.0104	0.0075	0.0055	0.0063	0.0024
23	0.0174	0.0146	0.0109	0.0119	0.0038
24	0.0148	0.0137	0.0118	0.0063	0.0036

Table A.12: Measured Energy Values for each Drive Type on the File Server Data Set

Data Transfer Size [kB]	Drive 1	Drive 2	Drive 3	Drive 4	Drive 5
0.5	0.0155	0.0196	0.0184	0.0554	0.0000
1	0.0138	0.0210	0.0181	0.0526	0.0001
2	0.0141	0.0207	0.0179	0.0525	0.0001
4	0.0122	0.0203	0.0176	0.0528	0.0000
8	0.0111	0.0200	0.0176	0.0519	0.0002
16	0.0110	0.0210	0.0181	0.0514	0.0001
32	0.0111	0.0206	0.0184	0.0507	0.0001
64	0.0107	0.0199	0.0180	0.0527	0.0001

Table A.13: Measured Time Values for each Drive Type on the File Server Data Set

Data Transfer Size [kB]	Drive 1	Drive 2	Drive 3	Drive 4	Drive 5
0.5	0.0065	0.0093	0.0083	0.0141	0.0003
1	0.0062	0.0105	0.0089	0.0133	0.0001
2	0.0064	0.0104	0.0084	0.0134	0.0002
4	0.0074	0.0101	0.0081	0.0132	0.0003
8	0.0077	0.0099	0.0081	0.0131	0.0004
16	0.0078	0.0106	0.0082	0.0129	0.0002
32	0.0078	0.0103	0.0085	0.0127	0.0003
64	0.0073	0.0097	0.0084	0.0136	0.0003

References

1. Data centre efficiency assessment. 2014. URL <http://on.nrdc.org/10cXHmD>.
2. Chou J, Kim J, Rotem D. Energy-aware scheduling in disk storage systems. In: *Distributed Computing Systems (ICDCS), 2011 31st International Conference on*. IEEE; 2011:423–433.
3. Benini L, Micheli Gd. System-level power optimization: techniques and tools. *ACM Transactions on Design Automation of Electronic Systems (TODAES)* 2000;5(2):115–192.
4. Bisson T, Brandt SA, Long DD. A hybrid disk-aware spin-down algorithm with i/o subsystem support. In: *Performance, computing, and communications conference, 2007. IPCCC 2007. IEEE International*. IEEE; 2007:236–245.
5. Irani S, Singh G, Shukla SK, Gupta RK. An overview of the competitive and adversarial approaches to designing dynamic power management strategies. *Very Large Scale Integration (VLSI) Systems, IEEE Transactions on* 2005;13(12):1349–1361.
6. Gurusurthi S, Sivasubramaniam A, Kandemir M, Franke H. Reducing disk power consumption in servers with drpm. *Computer* 2003;36(12):59–66.
7. Carrera EV, Pinheiro E, Bianchini R. Conserving disk energy in network servers. In: *Proceedings of the 17th annual international conference on Supercomputing*. ACM; 2003:86–97.

- 619 8. Papathanasiou AE, Scott ML. Energy efficient prefetching and caching.
620 In: *Proceedings of the 2004 USENIX Annual Technical Conference*.
621 2004:255–268.
- 622 9. Narayanan D, Donnelly A, Rowstron A. Write off-loading: Practical
623 power management for enterprise storage. *ACM Transactions on Storage*
624 (*TOS*) 2008;4(3):10.
- 625 10. Verma A, Koller R, Useche L, Rangaswami R. Srcmap: Energy propor-
626 tional storage using dynamic consolidation. In: *FAST*; vol. 10. 2010:267–
627 280.
- 628 11. Wildani A, Miller EL. Semantic data placement for power management
629 in archival storage. In: *Petascale Data Storage Workshop (PDSW), 2010*
630 *5th*. IEEE; 2010:1–5.
- 631 12. Leverich J, Kozyrakis C. On the energy (in) efficiency of hadoop clusters.
632 *ACM SIGOPS Operating Systems Review* 2010;44(1):61–65.
- 633 13. Härder T, Hudlet V, Ou Y, Schall D. Energy efficiency is not enough,
634 energy proportionality is needed! In: *Database Systems for Adanced*
635 *Applications*. Springer; 2011:226–239.
- 636 14. Drwal M. Algorithm for quadratic semi-assignment problem with par-
637 tition size coefficients. *Optimization Letters* 2014;8(3):1183–1190.
- 638 15. Vasudevan M, Tian YC, Tang M, Kozan E. Profiling: an application
639 assignment approach for green data centers. In: *40th Annual Confer-*
640 *ence of the IEEE Industrial Electronics Society (IECON 2014)*. IEEE;
641 2014:5400–5406.

- 642 16. Jones D, Jimenez M. Incorporating additional meta-objectives into the
643 extended lexicographic goal programming framework. *European Journal*
644 *of Operational Research* 2013;227(2):343–349.
- 645 17. Oddoie J, Jones D, Tamiz M, Schmidt P. Combining simulation and
646 goal programming for healthcare planning in a medical assessment
647 unit. *European Journal of Operational Research* 2009;193(1):250 – 261.
648 doi:\bibinfo{doi}{http://dx.doi.org/10.1016/j.ejor.2007.10.029}. URL
649 <http://bit.ly/1WFODty>.
- 650 18. Ghoseiri K, Ghannadpour SF. Multi-objective vehicle routing prob-
651 lem with time windows using goal programming and genetic algorithm.
652 *Applied Soft Computing* 2010;10(4):1096 – 1107. doi:\bibinfo{doi}
653 {http://dx.doi.org/10.1016/j.asoc.2010.04.001}. Optimisation Methods
654 & Applications in Decision-Making Processes; URL [http://bit.](http://bit.ly/1JMLLBK)
655 [ly/1JMLLBK](http://bit.ly/1JMLLBK).
- 656 19. Tao F, Feng Y, Zhang L, Liao T. Clps-ga: A case library and
657 pareto solution-based hybrid genetic algorithm for energy-aware cloud
658 service scheduling. *Applied Soft Computing* 2014;19(0):264 – 279.
659 doi:\bibinfo{doi}{http://dx.doi.org/10.1016/j.asoc.2014.01.036}. URL
660 <http://bit.ly/1Lr8ACu>.
- 661 20. Guzek M, Pecero JE, Dorronsoro B, Bouvry P. Multi-objective
662 evolutionary algorithms for energy-aware scheduling on distributed
663 computing systems. *Applied Soft Computing* 2014;24(0):432 – 446.
664 doi:\bibinfo{doi}{http://dx.doi.org/10.1016/j.asoc.2014.07.010}. URL
665 <http://bit.ly/1JMLP17>.

- 666 21. Operating systems and benchmarks - part 5. 2000. Accessed 5th Septem-
667 ber 2016; URL <http://bit.ly/2cH35mx>.
- 668 22. Ho SC. An iterated tabu search heuristic for the single source capac-
669 itated facility location problem. *Applied Soft Computing* 2015;27:169–
670 178.
- 671 23. Akpınar S, Bayhan GM, Baykasoglu A. Hybridizing ant colony opti-
672 mization via genetic algorithm for mixed-model assembly line balancing
673 problem with sequence dependent setup times between tasks. *Applied*
674 *Soft Computing* 2013;13(1):574–589.