A unification of the prevalent views on exploitation, exploration, intensification and diversification

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Abstract: Terms such as *exploitation*, *exploration*, *intensification* and *diversification* are routinely employed in the metaheuristic literature to explain empirical runtime performance. Six prevalent views on *exploitation* and *exploration* are identified in the literature, each expressing a different aspect of these notions. The consistency and meaningfulness of these views are substantiated by their deducibility from the proposed novel definitions of *exploitation* and *exploration*, based on the hypothetical construct of a *probable fitness landscape*. This unifies, and thereby clarifies, the terminology and understanding of metaheuristics.

Keywords: exploitation; exploration; intensification; diversification; fitness landscape; definitions; metaheuristic; literature; meta-model.

Reference to this paper should be made as follows: Fagan, F. and van Vuuren, J.H. (2013) 'A unification of the prevalent views on exploitation, exploration, intensification and diversification', *Int. J. Metaheuristics*, Vol. 2, No. 3, pp.294–327.

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1 Introduction

Metaheuristic algorithms are extremely effective optimisation techniques, which have been applied in a number of fields (Kelly and Osman, 1996; Osman and Laporte, 1996; Griffis et al., 2012). Typically a metaheuristic approximately optimises a problem by iteratively improving candidate solutions (Luong et al., 2013), which converge to a (near) optimal value.

Although they are practically proficient, metaheuristics are notoriously hard to analyse. Papadimitriou and Steiglitz (1982) affirmed this claim as follows: “Although very little has been rigorously established about the performance of such algorithms, they often seem to do remarkably well on certain problems”. Due to the stochastic nature of metaheuristics (Blum and Roli, 2003; Yang, 2011), it is difficult to put practically useful theoretical bounds on performance runtime; hence they are often studied empirically instead of theoretically. Empirical simulations of problem instances may be used to demonstrate the performance of algorithms in particular problem classes (Jagerskupper, 2003). For example, recently a new empirical methodology has been used to show that certain metaheuristics have superior performance in the problem class of binary real-world problems (García-Martinez et al., 2012). Although empirical results indicate expected runtime performance, they do not guarantee performance nor do they yield explicit explanations for performance. As Cohen (1995) puts it [according to Watson (2010)]: “It is good to demonstrate performance, but it is even better to explain performance”.

To complement empirical analysis, qualitative descriptions may be used to explain the performance of an algorithm. The most common terminology used in these explanations includes: *exploitation*, *exploration*, *intensification* and *diversification*. These terms are used extensively in the literature, appearing in the vast majority of articles in the leading journals on metaheuristics (see Section 2). Hence, these terms are of great importance in the field of metaheuristics.

However, there are no universally agreed upon definitions for these terms (Eiben and Schippers, 1998; Naudts and Schippers, 1999). Specific definitions may be given in each context of use, but these must be shown to be meaningful and consistent with the rest of the literature in order to be generally effective. If the terminology is meaningless or inconsistently applied then it loses its communicative power and thereby undermines its use in research publications.

In this paper we identify six prevalent views of exploitation and exploration in the literature and argue that they are meaningful and reasonably consistent. This is a direct consequence of them being derivable from novel definitions of exploitation and exploration proposed in this paper. In turn, these definitions are based on a hypothetical construct, the *probable fitness landscape* (PFL), which is also presented. A limitation is that the definitions only apply when the PFL is applicable, that is for continuous fitness functions.

The paper is structured as follows: In Section 2 the current use of the terms *exploitation*, *exploration*, *intensification* and *diversification* is reviewed. The PFL is introduced in Section 3 and is used to formally define the notions of exploitation and exploration, from which the prevalent views on exploitation and exploration are deduced, in Section 4. Finally, the paper concludes with some ideas for future work in Section 5.

2 Literature review

In ‘Review of metaheuristics and generalised evolutionary walk algorithm’, Yang (2011, p.3) states that “the main components of any metaheuristic algorithms are: intensification and diversification, or exploitation and exploration". These terms are certainly extensively used in the literature. The *Journal of Heuristics*, *IEEE Transactions on Evolutionary Computation* and *Evolutionary Computation*, three of the leading journals in the field of metaheuristics, respectively referred to these terms (and their derivatives) in 81%, 91% and 71% of papers during the period 2011 – 2012 (see the Appendix for details). The frequency of use of the terms varies. In all of the journals, *exploration* and *diversification* are used more frequently than *exploitation* and *intensification*, with the *IEEE Transactions on Evolutionary Computation* mentioning *diversification* in more than eight times the number of papers than for *intensification*.

Although the terms are ubiquitously employed, they do not have universally accepted definitions. Eiben and Schippers (1998) reviewed how *exploration* and *exploitation* are used in the literature on *evolutionary algorithms* (EAs). They remark that "most authors leave their definitions implicit and use the intuitive meaning of the concepts to explain the working of EAs" and "that there is no general consensus on these matters; several authors represent contradicting views".

However, they do acknowledge a few prevalent views, namely that "selection is commonly seen as the source of exploitation, while exploration is attributed to the operators mutation and recombination", "exploitation is the usage of information" and "that exploration and exploitation are opposite forces" which must be balanced. A sample of more recent papers confirms the continued expression of the first (Hansheng and Lishan, 1999; Ursem, 2002; Bosman and Thierens, 2003; Chen et al., 2009; Al-Naqi et al., 2010), second (Yen et al., 2001; Liu et al., 2007; Chen et al., 2009; Yang, 2011; Xiao et al., 2012) and third views (Hansheng and Lishan, 1999; Alba and Dorronsoro, 2005; Ortiz-Boyer et al., 2005; Tasoulis et al., 2005; Chen et al., 2009; Alam et al., 2010; Al-Naqi et al., 2010; Linhares and Yanasse, 2010). Other prevalent views in the literature, not identified by Eiben and Schippers, include: "a latent viewpoint [which] interprets exploration and exploitation as global search and local search, respectively" (Chen et al., 2009; Yuen and Chow, 2009; Khan and Sahai, 2012; Yang, 2012), that exploitation is short-term whereas exploration is long-term (Chen et al., 2011a, 2011b; Couceiro et al., 2012), and that exploitation and exploration correspond to intensification and diversification, respectively (Hansheng and Lishan, 1999; Blum and Roli, 2003; Nakamichi and Arita, 2004; Alba and Dorronsoro, 2005; Linhares and Yanasse, 2010; Ollion and Doncieux, 2011). In summary, the prevalent views propound that exploitation and exploration are, respectively:

1. local and global search
2. selection and reproduction operators
3. information utilisation and information acquisition
4. short-term and long-term strategies
5. intensification and diversification
6. opposite forces which must be balanced.

These are by no means the only views on the terminology. Many of the alternative views are less elucidatory, such as the circular:

> "*Exploitation* is the property of the algorithm to thoroughly *explore* a specific region of the search space, looking for any improvement in the best currently available solutions). *Exploration* is the property to explore wide portions of the search space, looking for promising regions, where *exploitation* procedures should be employed." (Mendes and Linhares, 2004)

Another example of an uninstructive definition is, "Exploitation is defined ... as the ability of an algorithm to step into the direction of desired improvement" (Beyer, 1998). Stepping in the desired direction of improvement is the objective of most algorithms and is not specific to exploitation. Although there is some truth to these views, they provide little value without further context or content.

A recent study (Črepinšek et al., 2013) confirms the lack of progress made in understanding the terminology. If anything, as the research community has grown, the situation has become worse as the number of views has increased with little effort being spent on separating the wheat from the chaff. Extracting the prevalent views from the literature and determining which are meaningful and consistent with each other is essential to clarifying the terminology. Without this the research community will remain unable to communicate its ideas effectively.

Demonstrating that each of the prevalent views on exploitation and exploration follow from fundamental definitions of these terms will unify, and thereby clarify, the terminology. The notion of a PFL is introduced in the following section, which is used as a basis for such definitions. In Section 4 it is demonstrated how each of the prevalent views may be deduced from the PFL.

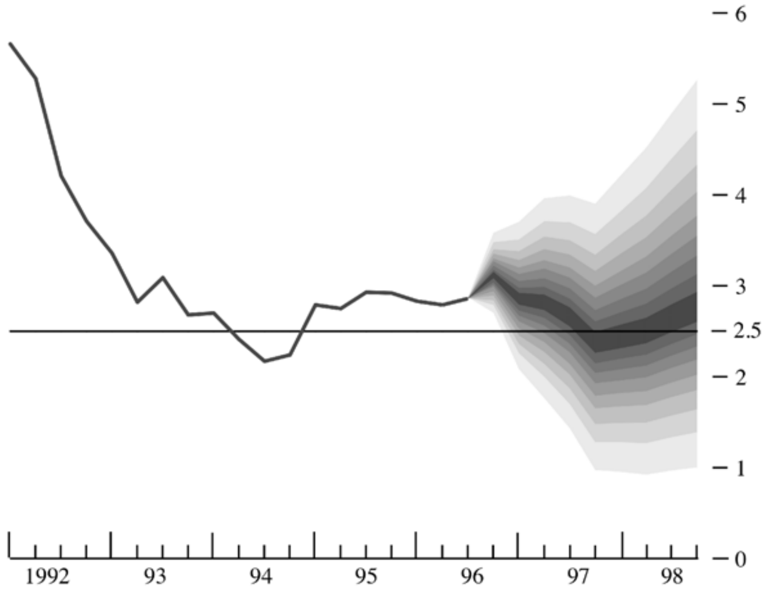
3 The PFL

The notion of the PFL was inspired by that of a *fan chart*. Fan charts have been used since 1997 by the Bank of England (1998) to describe its best prevision of future inflation graphically. The observed past data on inflation is connected by a simple line chart which diverges for future time values to represent a range of possible outcomes, with more probable outcomes having a darker shade of colour. An example of a fan chart is provided in Figure 1.

The outcome for all future time values is uncertain. Although for each time value there exists an outcome that could be calculated in the future, it is not currently known and may therefore be considered as random. This randomness is not complete, but defined by a *probability distribution* that depends on the information of the past observational data and known properties of inflation. Hence, for each future point in time there is a probability distribution of outcomes, as displayed in the fan chart.

This same notion may be applied to metaheuristics. Consider a continuous fitness function $f : \mathcal{S} \mapsto \mathbb{R}$, where $\mathcal{S} \subset \mathbb{R}^n$ is the search space of the optimisation problem. It is assumed, without loss of generality, that maximising the fitness function is the objective of the optimisation problem. The *fitness landscape* (FL) is the surface in $\mathcal{S} \times \mathbb{R}$ defined by the fitness function $(s, f(s))$, where $s \in \mathcal{S}$.

Figure 1 Fan chart of inflation in Britain



Notes: Observed past data are connected by a simple line chart until a certain time (1996), after which possible outcomes are projected. The dark band of future outcomes indicates the expected outcome, whereas less probable outcomes are displayed in lighter shades.

Source: Bank of England (1998)

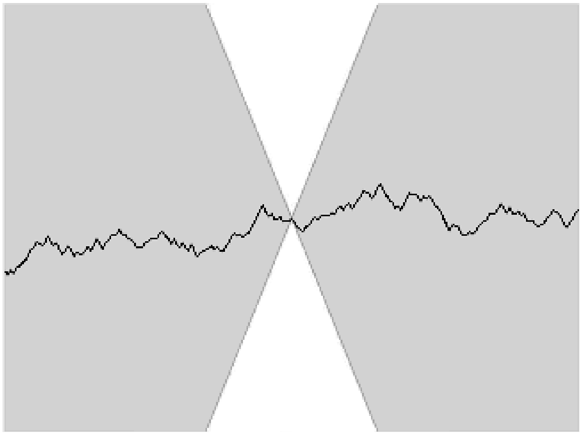
At any stage during the execution of a metaheuristic the current population (possibly consisting of a single candidate solution) is known, which is equivalent to past observational data. The known properties of the fitness function are analogous to the known properties of inflation. Together these may be used to construct the PFL, which graphically represents the fitness probability distribution of every point in the search space. In the PFL every coordinate in $\mathcal{S} \times \mathbb{R}$ is assigned a value according to a grey colour scheme. The darker a coordinate is, the larger the probability that it is in the FL.

If a candidate solution s_p is in the current population, then its fitness $f(s_p)$ is known with certainty. It is represented in the PFL by a black dot at $(s_p, f(s_p))$ with white for all coordinates in $\{s_p\} \times \mathbb{R} \backslash f(s_p)$.

The fitness of all points not in the current population is uncertain. Although for each point there exists a fitness value that can be calculated, it is not currently known and may therefore be considered as random. This randomness is not complete, but defined by a *fitness probability distribution* that depends on the information of the current population and known properties of the fitness function. Hence, for each point in the search space there is a fitness probability distribution, as illustrated in the PFL.

If a point is not in the current population, then the fitness probability distribution cannot be determined with certainty, since this would require knowing the point's fitness value, which is uncertain. This reduces the PFL to a hypothetical construct that cannot be calculated with certainty. However, the PFL does have two governing principles. Firstly, s_p is of higher than average fitness, since it has survived selection. Therefore, the *expected fitness* decreases away from s_p. Secondly, the further away a point in $\mathcal{S}$ is to s_p the larger the range of its possible fitness values, due to the (Lipschitz) continuity of the fitness function. The increase in range of possible fitness values according to the definition of Lipschitz continuity may be seen in Figure 2 [reproduced from 'Lipschitz continuity', (n.d.)]. Thus the *variance* of the fitness probability distribution increases away from s_p.

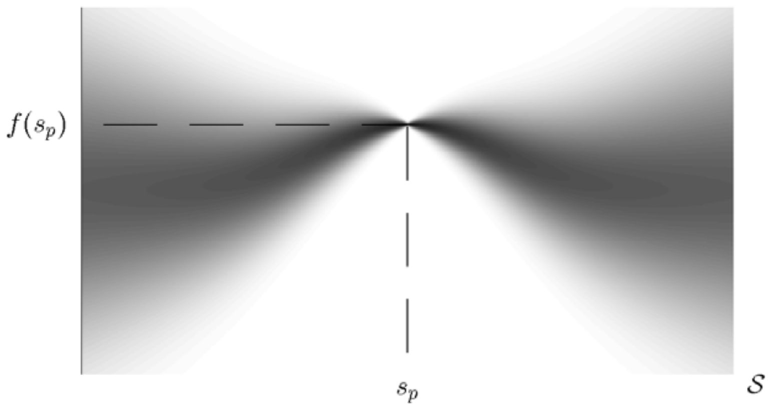
Figure 2 A Lipschitz continuous function f has the defining property that there exists a constant $K \geq 0$ such that $|f(x_1) - f(x_2)| \leq K\|x_1 - x_2\|$ for all x_1, x_2



Note: This may be represented as a double cone (shown in white) whose vertex can be translated along the search space, so that the fitness function (shown in black) always remains entirely outside the cone.

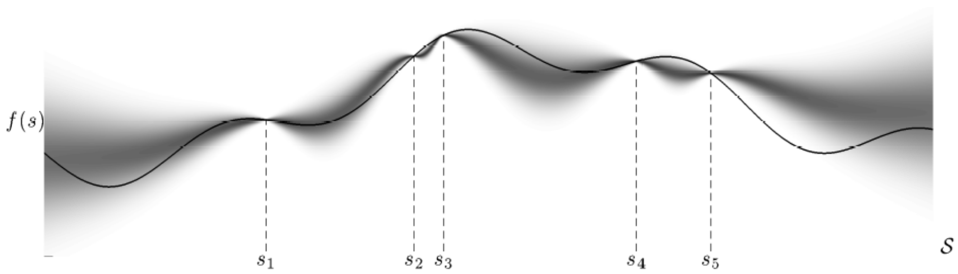
Figure 3 illustrates an example of the PFL for a population containing a single candidate solution. A single black dot is located at (s_p, $f(s_p)$), indicating that the point is definitely in the FL, whereas there is a fitness probability distribution for all other points in the search space. It is clear from the figure that the expected fitness decreases, whereas the variance of the fitness probability distributions increases, away from the candidate solution.

Figure 3 The PFL of a single candidate solution s_p



The notion of a PFL may be naturally extended to populations with multiple candidate solutions, as shown in Figure 4. It is evident that the FL agrees with the PFL at points in the current population, that is they both have single black dots corresponding to the fitness values of the points in the current population. For points not in the current population the PFL provides a good approximation of the FL, with darker points in the PFL having a higher probability of coinciding with the FL.

Figure 4 The PFL of multiple candidate solutions



Note: A possible FL is shown as a solid line, whereas the PFL is a grey distribution.

A more accurate PFL can be constructed if more properties about the particular fitness function are known. In fact, the same current population may produce different PFLs, depending on the known properties of the fitness function. For example, a PFL associated with a rough fitness function will exhibit fitness probability distributions with more variance than that associated with a smooth fitness function. If a metaheuristic has memory structures, such as a tabu search, then many features of the fitness function may be known and the fitness probability distributions might be very accurate. In fact, if the fitness values of points in previous populations have been recorded, then the fitness values of some points not in the current population are known with certainty and are represented by black dots in the PFL.

Even though the PFL cannot be constructed with certainty, there are techniques for approximating the FL, known as *meta-models* (also called *surrogate models* or *fitness approximations*) (Emmerich et al., 2002; Jin, 2005; Torczon and Trosset, 1998). Meta-models are typically used to estimate fitness values (equivalent to determining the expected fitness) of new candidate solutions if the computation of the actual fitness values is extremely time-consuming. This is done by interpolating the fitness values of all previously generated candidate solutions. One of the most popular meta-models is *Kriging* (Klein, 2009), for which the error estimation of the approximation (similar to the variance of the fitness probability distribution) may also be determined.

Although meta-models are very similar to the PFL, there are two differences. Firstly, the PFL only depends on the information of the current population and known properties of the fitness function, whereas meta-models usually use the information from all previously generated candidate solutions. Secondly, and more significantly, meta-models typically do not take into account the first principle of the PFL (that a candidate solution in the current population is of higher than average fitness). Thus, meta-models are not applicable when the current population only has one candidate solution and there is no record of the fitness values of previous points, as is the case for simulated annealing, since there are not enough points to interpolate. The PFL, on the other hand, is generally applicable. In the case of simulated annealing, the PFL would look similar to Figure 3, with the expected fitness away from the current candidate solution decreasing more sharply as the search progresses (due to the increase in the expected difference between the fitness of the current candidate solution and the average).

The PFL, unlike the FL, represents what is actually known at any stage during the execution of a metaheuristic. This makes the PFL a useful notion. Arguably the PFL is, and has always been, the fundamental concept that researchers have used implicitly to devise new metaheuristics and decide which metaheuristics to implement. The advantage of formalising this notion, with its two general principles, is that it may be used to deduce the consequences of the concept formally – specifically to define relevant terminologies. These may aid in intuiting, describing and explaining the performance of metaheuristics.

4 Unification of prevalent views

At each iteration during the execution of a metaheuristic, new candidate solutions must be generated. From the PFL definitions of *exploitation* and *exploration* can be made as follows:

- *exploit*: to generate candidate solutions at points of high expected fitness
- *explore*: to generate candidate solutions at points of high variance.

These novel definitions come directly from the notions of expected fitness and variance in the PFL and therefore share the same limitations as the PFL. Since the PFL cannot be explicitly calculated, it is impossible to determine the exact expected fitness of a point. Hence it is impossible to determine the degree of exploitation in generating a candidate solution at that point. However, it can be used to compare two points. If a point is closer to a candidate solution, then it has a higher expected fitness and generating a candidate solution at that point is more exploitative. Likewise, the closer point has lower variance and generating a candidate solution at that point is less explorative.

The prevalent views on exploitation and exploration can be deduced from the above definitions of exploitation and exploration. If the views stem from the same definitions, then they are necessarily consistent and simply represent different insights into the same phenomenon.

4.1 Local and global search

Local and global search are not themselves well defined terms. It is understood that local search refers to a search that is only able to reach a local maximum, whereas a global search may find any maximum. They may be thought of as hill climbing and pure random search (also known as uniform search), respectively. The ability to generate a candidate solution at any point in the search space, including the global maximum, is the key characteristic of a global search. By contrast, a local search is unable to generate points outside of the neighbourhood of a local maximum. Hence the essential characteristic of local search is that it only generates close to a candidate solution, whereas global search may generate far from a candidate solution.

Exploitation generates new candidate solutions at points of high expected fitness. These points are close to candidate solutions and therefore correspond to a local search. Meanwhile exploration generates at points of high variance, which are far away from current candidate solutions, corresponding to a global search.

4.2 Selection and reproduction operators

Exploitation and exploration have been used to refer to operators of an algorithm. An example are the following definitions (Bosnian and Thierens, 2003):

> "*Exploitation* indicates the parts of an EA that are concerned with the selection of a set of parent solutions from the current population and the construction of a new population given the current population, the selected set of parent solutions and the set of offspring solutions. This definition of exploitation thus includes traditional selection, but also all replacement schemes such as crowding."
>
> "*Exploration* indicates the part of an EA that is concerned with the generation of new offspring solutions from a given set of parent solutions..."

These definitions agree with the prevalent view that "selection is ... the source of exploitation, while exploration is attributed to the operators mutation and recombination".

To see how this view follows from the above definitions, the principles of the PFL are appealed to. Without selection the first governing principle of the PFL, namely that a candidate solution in the current population is of higher than average fitness, would fail. Hence exploitation, which generates at points of high expected fitness, would be impossible. Thus selection is the source of exploitation. Exploration, which generates at points of high variance, is possible without selection. This is because the second governing principle of the PFL, namely that the further away a point in $\mathcal{S}$ is to s_p the larger the range of its possible fitness values, would still hold true. Hence operators which explore, i.e., generate candidate solutions at points of high variance, would still be possible, and so exploration is attributed to the operators mutation and recombination.

4.3 Information utilisation and information acquisition

According to Chen et al. (2009), "in learning algorithms, *exploration* and *exploitation* correspond to the acquisition and utilization of knowledge, respectively". Two propositions are bound together in this claim. The first is that exploitation, as opposed to exploration, utilises knowledge and the second is that exploration, opposed as to exploitation, acquires knowledge. Both statements are true in part, but not exclusively so.

The expected fitness of a point depends on both the distance from and the fitness values of the candidate solutions in the current generation, whereas the variance just depends on the distance. Hence, exploitation (which depends on expected fitness) utilises more information than exploration (which, in turn, depends on the variance). Both do utilise information, just more so for exploitation as opposed to exploration.

Whenever a candidate solution is generated at a point and its fitness is evaluated, information is acquired about the fitness function. Both exploitation and exploration involve generating candidate solutions; therefore both acquire information. The difference is that exploitation can only generate in a local neighbourhood, whereas exploration can generate anywhere in the search space (see Section 4.1). Hence exploration can gather more information, or at least a greater range of information, than exploitation can. Again, both do acquire information, just more so for exploration than for exploitation.

4.4 Short-term and long-term strategies

The issue of short-term and long-term strategies is connected to that of information utilisation and information acquisition. The utilisation of information is of short-term benefit, while the acquisition of knowledge is advantageous in the long-term. Hence, exploitation, which utilises information, is a short-term strategy; whereas exploration, which acquires knowledge, is a long-term strategy.

A consequence of this is that exploration should be favoured toward the beginning of a search, when there are many iterations left to benefit from a long-term strategy. On the other hand, exploitation should be prioritised at the end of a search, since at that stage a short-term strategy will be more fruitful.

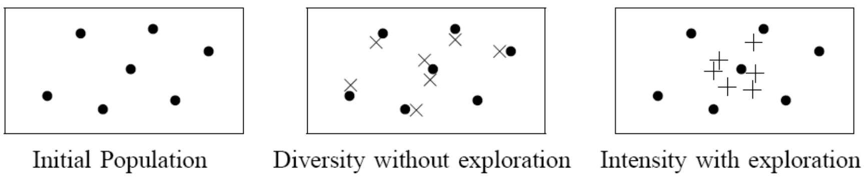
4.5 Intensification and diversification

The terms *intensification* and *diversification* are often used interchangeably with *exploitation* and *exploration*, respectively (Nakamichi and Arita, 2004; Alba and Dorronsoro, 2005). However, they have subtly different meanings, as noted by Blum and Roli (2003, p.271),

> "The term diversification generally refers to the exploration of the search space, whereas the term intensification refers to the exploitation of the accumulated search experience. These terms [(diversification and intensification)] stem from the Tabu Search field and it is important to clarify that the terms exploration and exploitation are sometimes used instead, for example in the Evolutionary Computation field, with a more restricted meaning."

The main difference is that exploitation and exploration refer to points in the search space, whereas intensity and diversity refer to the distribution of candidate solutions in the search space. This distinction is evident in Figure 5. On the left there is a plot of the initial population with possible future generations displayed in the centre, by crosses, and on the right, by plus symbols. The cross population exhibits almost no exploration yet maintains a diverse population, while the plus population is highly explorative, but results in an intense distribution.

Figure 5 Example populations in a two-dimensional search space exhibiting diversity without exploration, and intensity with exploration



The examples in Figure 5 are atypical. Exploration generates far away from candidate solutions which tends to create a diverse population, whereas exploitation generates close to candidate solutions, generally resulting in an intense population. Hence the terms *diversification* and *intensification*, meaning *the process of making diverse* and *the process* *of making intense*, respectively, are sometimes used interchangeably with exploration and exploitation.

These notions may be extended beyond the current population to the set of all candidate solutions that have been generated throughout the search. This makes the terms applicable to metaheuristics, such as tabu search, that have populations consisting of only one candidate solution, yet store multiple previously generated candidate solutions in memory structures. The terminology has evolved to reflect the different meanings, with *intensification* and *diversification* traditionally referring to the set of all candidate solutions, whereas *exploitation* and *exploration* refer to the current population. Blum and Roli (2003, p.271) confirm this usage by stating that "exploitation and exploration often refer to rather short-term strategies tied to randomness, whereas intensification and diversification also refer to medium- and long-term strategies based on the usage of memory".

4.6 Opposite forces which must be balanced

All of the above prevalent views have contrasted exploitation and exploration as opposite forces. This ultimately stems from the PFL where the expected fitness decreases away from candidate solutions, whereas the variance of the probability distributions increase. Hence exploitation and exploration have opposing tendencies, to generate close to and far from candidate solutions, respectively.

However, exploitation and exploration are not direct opposites. There may be points of high expected fitness and high variance (a moderate distance away from a candidate solution with an extremely high fitness value), or low expected fitness and low variance (close to a candidate solution with a very low fitness value).

The reason for balancing exploitation and exploration is evident from considering their extreme forms. Extreme exploitation is simple hill climbing, unable to escape the region of a local maximum, while extreme exploration is pure random search, incapable of iterative improvement. Neither of these extremes are ideal and instead a combination is required for a successful search.

Since exploitation and exploration are opposite forces, both of them can be controlled by the same operator. For instance, even though in Section 4.2 selection is argued to be the source of exploitation, it may also be used to maintain or enhance exploration via niching, preselection or fitness sharing (Mahfoud, 1992, 1996). Likewise, some reproduction operators, such as crossover, may affect exploitation.

5 Conclusions

A literature review has been conducted determining that metaheuristics research relies heavily on the terms *exploitation*, *exploration*, *intensification* and *diversification* to explain the empirical runtime performance of algorithms. It emerged from the review that the terms *exploration* and *diversification* are used more often than *exploitation* and *intensification*. Considering that a metaheuristic requires a balance between exploration and exploitation (as well as between diversification and intensification) it is striking that the use of the terminology is not more balanced. This may point to a systematic bias toward exploration, resulting in under-performing algorithms.

Six prevalent views on exploitation and exploration were identified in the literature, each expressing a different aspect of these notions. These views were unified by demonstrating that they are deducible from the novel definitions of exploitation and exploration, based on the PFL, proposed in this paper. However, it must be noted that some of the views did not agree exactly with the novel definitions, even though they did share the same sentiment. This demonstrates that the views are meaningful and reasonably consistent, and therefore may be expressed effectively in research. It also connects all of the views through their equivalence with exploration and exploitation, which reveals unintuitive correlations, such as between information usage and intensification (via exploitation), or between reproduction operators and long-term strategies (via exploration).

In order to assess (and potentially control) the balance between exploitation and exploration, they must be measured. Although some methods of measurement have been proposed in the literature (Liu et al., 2012; Črepinšek et al., 2013), how to do this is still an open question. Črepinšek et al. (2013, p.8) remark that,

> "Intrinsic to this problem is that we need to know how these two phases [(exploitation and exploration)] are identified. If in each process both phases can be clearly identified, then some direct measures can be invented. Currently, indirect measures for exploration and exploitation are mostly used".

This paper goes some of the way to identifying the characteristics of exploitation and exploration. As the PFL is a hypothetical construct that cannot be calculated with certainty, it cannot be used as a direct measure of exploitation and exploration (this possibly reflects the fact that exploitation and exploration intrinsically cannot be measured directly). However, the characteristics identified in the prevalent views may serve as 'indirect measures'. For example, diversity may be used in combination with a distance metric as a measure (Liu et al., 2012; Črepinšek et al., 2013). The 1/5-th success rule (Beyer and Schwefel, 2002) may be interpreted as a measure of whether the search is local or global, which is used to control the balance between exploitation and exploration. There may also be other characteristics which have yet to emerge in the literature that could be used. Which characteristics make for the best measure is likely to be problem-dependent and is a topic of future research.

The formalised notion of the PFL is in itself a useful contribution. It may be the case that many researchers already think about metaheuristics using a similar notion to the PFL. However, formalising the notion clarifies it and aids in understanding how metaheuristics work. Since the only requirement for the PFL is continuity, which is arguably common to all metaheuristics whatever the distance measure (García-Martinez et al., 2012, p.2129), it should be generally applicable. Future work may include formally extending the PFL to discrete problems.

The argument can be made that the ideas presented in this paper are of no practical use. Although it may be true that they are not of any direct practical use, they may still have a practical impact. Achieving a greater understanding of metaheuristics and clarifying the terminology facilitates deeper research with better communication to the research community. As argued by Goldberg (2002), graphical representations, such as the PFL, may be the appropriate type of model to progress an area of research.

Acknowledgements

The anonymous reviewers made many valuable comments that significantly improved the quality of this paper, for which we thank them sincerely.

The financial assistance of the South African National Research Foundation (NRF) towards this research is hereby acknowledged. Opinions expressed and conclusions arrived at, are those of the authors and are not necessarily to be attributed to the NRF.

References

Alam, M.S., Ul Kabir, M.W. and Islam, M.M. (2010) 'On the performance of recurring multistage evolutionary algorithm for continuous function optimization', *13th International Conference on Computation and Information Technology (ICCIT)*, pp.63–68.

Alba, E. and Dorronsoro, B. (2005) 'The exploration/exploitation tradeoff in dynamic cellular genetic algorithms', *IEEE Transactions on Evolutionary Computation*, Vol. 9, No. 2, pp.126–142.

Al-Naqi, A., Erdogan, A.T., Arslan, T. and Mathieu, Y. (2010) 'Balancing exploration and exploitation in an adaptive three-dimensional cellular genetic algorithm via a probabilistic selection operator', *NASA/ESA Conference on Adaptive Hardware and Systems (AHS)*, pp.258–264.

Bank of England (1998) 'The inflation report projections: understanding the fan chart', *Bank of England Quarterly Bulletin*, Vol. 38, No. 1, pp.30–37.

Beyer, H-G. (1998) 'On the "explorative power" of ESEP-like algorithms', *Evolutionary Programming VII: Proceedings of the Seventh Annual Conference on Evolutionary Programming*, Springer-Verlag, Berlin, pp.323–334.

Beyer, H-G. and Schwefel H-P. (2002) 'Evolution strategies – a comprehensive introduction', *Natural Computing*, Vol. 1, No. 1, pp.3–52.

Blum, C. and Roli, A. (2003) 'Metaheuristics in combinatorial optimization: overview and conceptual comparison', *ACM Computing Surveys*, Vol. 35, No. 3, pp.268–308.

Bosnian, P.A.N. and Thierens, D. (2003) 'The balance between proximity and diversity in multiobjective evolutionary algorithms', *IEEE Transactions on Evolutionary Computation*, Vol. 7, No. 2, pp.174–188.

Chen, F., Sun, X. and Wei, D. (2011a) 'Inertia weight particle swarm optimization with Boltzmann exploration', *Seventh International Conference on Computational Intelligence and Security (CIS)*, pp.90–95.

Chen, F., Sun, X., Wei, D. and Tang, Y. (2011b) 'Tradeoff strategy between exploration and exploitation for PSO', *Seventh International Conference on Natural Computation (ICNC)*, Vol. 3, pp.1216–1222.

Chen, J., Xin, B., Peng, Z., Dou, L. and Zhang J (2009) 'Optimal contraction theorem for exploration-exploitation tradeoff in search and optimization', *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, Vol. 39, No. 3, pp.680–691.

Cohen, P.R. (1995) *Empirical Methods for Artificial Intelligence*, p.249, MIT Press, Cambridge (MA).

Couceiro, M.S., Rocha, R.P., Ferreira, N.M.F. and Machado, J.A.T. (2012) 'Introducing the fractional-order Darwinian PSO', *Signal, Image and Video Processing*, Vol. 6, No. 3, pp.343–350.

Črepinšek, M., Liu, S-H. and Mernik, M. (2013) 'Exploration and exploitation in evolutionary algorithms: a survey', *ACM Computing Surveys*, Vol. 45, No. 3, pp.35:l–35:33.

Eiben, A.E. and Schippers, C.A. (1998) 'On evolutionary exploration and exploitation', *Fundamenta Informaticae*, Vol. 5, Nos. 1–4, pp.35–50.

Emmerich, M., Giotis, A., Ozdemir, M., Back, T. and Giannakoglou, K. (2002) 'Metamodel-assisted evolution strategies', in Guervas, J.J.M., Adamidis, P., Beyer H-G., Martin, J.L.F-V, and Schwefel, H-P. (Eds.): *Proceedings of the 7th International Conference on Parallel Problem Solving from Nature (PPSN VII)*, pp.361–370, Springer-Verlag, London.

García-Martinez, C., Rodriguez, F.J. and Lozano, M. (2012) 'Arbitrary function optimisation with metaheuristics: no free lunch and real-world problems', *Soft Computing*, Vol. 16, No. 12, pp.2115–2133.

Goldberg, D.E. (2002) *The Design of Innovation: Lessons from and for Competent Genetic Algorithms*, Kluwer Academic Publishers, Norwell (MA).

Griffis, S.E., Bell, J.E. and Closs, D.J. (2012) 'Metaheuristics in logistics and supply chain management', *Journal of Business Logistics*, Blackwell Publishing Ltd., Vol. 33, No. 2, pp.90–106.

Hansheng, L. and Lishan, K. (1999) 'Balance between exploration and exploitation in genetic search', *Wuhan University Journal of Natural Sciences*, Wuhan University and Springer, Vol. 4, No. 1, pp.28–32.

Jagerskupper, J. (2003) 'Analysis of a simple evolutionary algorithm for minimization in Euclidean spaces', *Proceedings of the 30th International Conference on Automata, Languages and Programming (ICALP)*, pp.1068–1079.

Jin, Y. (2005) 'A comprehensive survey of fitness approximation in evolutionary computation', *Soft Computing*, Vol. 9, No. 1, pp.3–12.

Kelly, J.P. and Osman, I.H. (1996) *Meta-heuristics: Theory and Applications*, Kluwer Academic Publishers, Norwell (MA).

Khan, K. and Sahai, A. (2012) 'A comparison of BA, GA, PSO, BP and LM for training feed forward neural networks in e-learning context', *International Journal of Intelligent Systems and Applications*, Vol. 4, No. 7, pp.23–29.

Kleijnen, J.P.C. (2009) 'Kriging metamodeling in simulation: a review', *European Journal of Operational Research*, Vol. 192, No. 3, pp.707–716.

Linhares, A. and Yanasse, H. (2010) 'Search intensity versus search diversity: a false trade off?', *Applied Intelligence*, Vol. 32, No. 3, pp.279–291.

Liu, S-H., Črepinšek, M. and Mernik, M. (2012) 'Analysis of VEGA and SPEA2 using exploration and exploitation measures', in *Proceedings of the 5th International Conference on Bioinspited Optimization Methods and their Applications*, pp.97–108.

Liu, S-H., Mernik, M. and Bryant, B.R. (2007) 'Entropy-driven parameter control for evolutionary algorithms', *Informatica: An International Journal of Computing and Informatics*, Vol. 31, No. 1, pp.41–50.

Luong, T., Melab, N. and Talbi, E. (2013) 'GPU computing for parallel local search metaheuristic algorithms', *IEEE Transactions on Computers*, Vol. 62, No. 1, pp.173–185.

Mahfoud, S.W. (1992) 'Crowding and preselection revisited', in Manner, R. and Manderick, B. (Eds.): *Parallel Problem Solving from Nature*, Vol. 2, pp.27–36, North-Holland.

Mahfoud, S.W. (1996) *Niching Methods for Genetic Algorithms*, Unpublished PhD thesis, University of Illinois, Champaign (IL).

Mendes, A. and Linhares, A. (2004) 'A multiple-population evolutionary approach to gate matrix layout', *International Journal of Systems Science*, Vol. 35, No. 1, pp.13–23.

Moscato, P. and Cotta, C. (2003) 'A gentle introduction to memetic algorithms', in Glover, F. and Kochenberger, G.A. (Eds.): *Handbook of Metaheuristics*, pp.105–144.

Nakamichi, Y. and Arita, T. (2004) 'Diversity control in ant colony optimization', *Artificial Life and Robotics*, Vol. 7, No. 4, pp.198–204.

Naudts, B. and Schippers, A. (1999) *A Motivated Definition of Exploitation and Exploration*, Technical report, University of Antwerp.

Ollion, C. and Doncieux, S. (2011) 'Why and how to measure exploration in behavioral space', *Proceedings of the 13th Annual Conference on Genetic and Evolutionary Computation (GECCO 11)*, New York (NY), pp.267–274.

Ortiz-Boyer, D., Hervas-Martinez, C. and Garcia-Pedrajas, N. (2005) 'CIXL2 – a crossover operator for evolutionary algorithms based on population features', *Journal of Artificial Intelligence Research*, Vol. 24, No. 1, pp.1–8.

Osman, I.H. and Laporte, G. (1996) 'Metaheuristics: a bibliography', *Annals of Operations Research*, Vol. 63, No. 5, pp.513–623.

Papadimitriou, C.H. and Steiglitz, K. (1982) *Combinatorial Optimization: Algorithms and Complexity*, Prentice-Hall Inc., Upper Saddle River (NJ).

Tasoulis, D.K., Plagianakos, V.P. and Vrahatis, M.N. (2005) 'Clustering in evolutionary algorithms to efficiently compute simultaneously local and global minima', *IEEE Congress on Evolutionary Computation (CEC)*, Vol. 2, pp.1847–1854.

Torczon, V. and Trosset, M.W. (1998) *Using Approximations to Accelerate Engineering Design Optimization*, Technical report, Institute for Computer Applications in Science and Engineering (ICASE).

Ursem, R.K. (2002) 'Diversity-guided evolutionary algorithms', *Proceedings of the Congress on Evolutionary Computation*, pp.1633–1640.

Watson, J.P. (2010) *An Introduction to Fitness Landscape Analysis and Cost Models for Local Search*, pp.599–623, Springer, Boston (MA).

Wikipedia, 'Lipschitz continuity' [Online] http://en.wikipedia.org/wiki/Lipschitz_continuity (accessed 5 July 2013).

Xiao, S., Rotaru, M. and Sykulski, J.K. (2012) 'Exploration versus exploitation using Kriging surrogate modelling in electromagnetic design', *COMPEL: The International Journal for Computation and Mathematics in Electrical and Electronic Engineering*, Vol. 31, No. 5, pp.1541–1551.

Yang, X-S. (2011) 'Review of metaheuristics and generalized evolutionary walk algorithm', *International Journal Bio-Inspired Computation*, Vol. 3, No. 2, pp.77–84.

Yang, X-S. (2012) 'Nature-inspired metaheuristic algorithms: success and new challenges', *Journal of Computer Engineering and Information Technology*, Vol. 1, No. 1, pp.1–3.

Yen, G., Yang, F., Hickey, T. and Goldstein, M. (2001) 'Coordination of exploration and exploitation in a dynamic environment', *Proceedings of the International Joint Conference on Neural Networks (IJCNN '01)*, Vol. 2, pp.1014–1018.

Yuen, S.Y. and Chow, C.K. (2009) 'Continuous non-revisiting genetic algorithm', *IEEE Congress on Evolutionary Computation (CEC '09)*, pp.1896–1903.

Appendix

This Appendix details the terminology count of the *Journal of Heuristics*, *IEEE Transactions on Evolutionary Computation* and *Evolutionary Computation* for the years 2011 to 2012. The total number of articles in which a term is used (in an appropriate context) over all of the journal articles considered is shown in Table 1. The final column 'Any' refers to the number of papers for which any of the terms are used. Below there are sections detailing the count for each journal.

Table 1 Total terminology count

Journal	*Paper #*	*Exploit-*	*Explor-*	*Intens-*	*Divers-*	*Any*
Journal of Heuristics	64	19	40	18	38	52
IEEE Tr. on Ev. Comp.	100	55	67	8	68	91
Evolutionary Comp.	45	22	23	5	22	32
Total	209	96	130	31	128	175
Percentage	-	46%	62%	15%	61%	84%

Journal of Heuristics

The terminology count of the *Journal of Heuristics* is shown in Table 2. If a term is used at least once in an appropriate context in an article, then there is a '1' in the corresponding cell of the table (if not, then there is a '0').

Table 2 Terminology count for the *Journal of Heuristics*

Paper #	*Exploit-*	*Explor-*	*Intens-*	*Divers-*	*Any*
1	0	0	0	0	0
2	0	0	0	0	0
3	1	1	0	0	1
4	0	0	0	0	0
5	1	1	0	0	1
6	0	1	1	1	1
7	1	1	1	1	1
8	0	1	0	1	1
9	1	1	0	1	1
10	0	1	0	1	1
11	0	1	0	1	1
12	1	1	0	1	1
13	0	0	0	1	1
14	0	0	0	0	0
15	1	0	1	1	1
16	0	0	0	0	0
17	0	1	0	0	1
18	0	0	0	0	0
19	0	0	0	0	0
20	0	1	1	1	1
21	0	0	0	0	0
22	0	0	0	0	0
23	1	1	1	1	1
24	0	1	0	0	1
25	0	0	0	1	1
26	0	0	0	1	1
27	1	0	1	1	1

Table 2 Terminology count for the *Journal of Heuristics* (continued)

Paper #	*Exploit-*	*Explor-*	*Intens-*	*Divers-*	*Any*
28	0	1	0	1	1
29	0	1	0	1	1
30	1	1	0	1	1
31	1	1	0	1	1
32	0	1	1	1	1
33	0	1	1	1	1
34	0	1	1	0	1
35	0	1	1	1	1
36	0	1	1	1	1
37	0	0	0	0	0
38	0	1	0	0	1
39	1	1	0	1	1
40	0	1	0	0	1
41	1	1	1	1	1
42	1	1	1	1	1
43	0	0	0	0	0
44	0	1	0	0	1
45	0	0	0	1	1
46	0	1	0	0	1
47	0	1	0	1	1
48	0	0	0	1	1
49	0	1	1	1	1
50	1	1	0	0	1
51	0	1	0	1	1
52	0	0	0	1	1
53	0	0	0	1	1
54	1	1	0	0	1
55	1	1	0	0	1
56	1	1	0	1	1
57	0	0	0	1	1
58	1	1	0	1	1
59	0	0	0	1	1
60	0	0	0	0	0
61	0	1	1	1	1
62	0	0	1	1	1
63	1	1	1	0	1
64	0	1	1	0	1
Sum	19	40	18	38	52
Percentage	30%	63%	28%	59%	81%

IEEE Transactions on Evolutionary Computation

The terminology count of the *IEEE Transactions on Evolutionary Computation* is shown in Table 3. If a term is used at least once in an appropriate context in an article, then there is a ‘1’ in the corresponding cell of the table (if not, then there is a ‘0’).

Table 3 Terminology count for the *IEEE Transactions on Evolutionary Computation*

Paper #	*Exploit-*	*Explor-*	*Intens-*	*Divers-*	*Any*
1	1	1	1	1	1
2	1	1	0	1	1
3	1	1	0	1	1
4	1	1	0	1	1
5	1	1	0	1	1
6	1	1	0	0	1
7	0	0	0	1	1
8	0	0	0	0	0
9	1	1	0	1	1
10	1	1	0	1	1
11	1	0	0	0	1
12	1	0	0	1	1
13	0	1	0	1	1
14	1	0	0	1	1
15	0	1	1	1	1
16	1	1	0	1	1
17	0	1	0	0	1
18	1	1	0	0	1
19	0	1	0	0	1
20	1	1	0	1	1
21	0	0	0	0	0
22	0	1	0	1	1
23	0	1	0	0	1
24	0	0	0	1	1
25	1	1	0	1	1
26	0	1	0	1	1
27	1	1	0	1	1
28	1	1	0	1	1
29	0	0	0	1	1
30	1	0	0	1	1
31	0	0	0	0	0
32	0	0	0	1	1
33	1	0	0	1	1
34	0	1	0	1	1

Table 3 Terminology count for the *IEEE Transactions on Evolutionary Computation* (continued)

Paper #	*Exploit-*	*Explor-*	*Intens-*	*Divers-*	*Any*
35	1	1	1	1	1
36	1	1	1	1	1
37	0	0	0	0	0
38	0	0	0	0	0
39	1	1	0	1	1
40	1	1	1	1	1
41	1	1	0	0	1
42	1	1	0	1	1
43	0	1	0	0	1
44	0	0	0	1	1
45	1	1	1	1	1
46	1	0	0	1	1
47	0	0	0	1	1
48	0	0	0	0	0
49	0	0	0	1	1
50	0	0	0	1	1
51	0	1	0	0	1
52	0	0	0	0	0
53	0	0	0	1	1
54	1	0	0	0	1
55	1	1	0	1	1
56	1	1	0	1	1
57	1	0	0	1	1
58	1	1	0	1	1
59	1	1	0	1	1
60	1	1	0	0	1
61	1	1	0	1	1
62	1	1	0	1	1
63	0	1	0	1	1
64	1	1	0	1	1
65	0	1	0	0	1
66	0	1	1	1	1
67	0	0	0	0	0
68	1	1	1	1	1
69	1	0	0	0	1
70	0	0	0	1	1
71	1	1	0	1	1
72	0	1	0	1	1

Table 3 Terminology count for the *IEEE Transactions on Evolutionary Computation* (continued)

Paper #	*Exploit-*	*Explor-*	*Intens-*	*Divers-*	*Any*
73	0	0	0	1	1
74	1	0	0	1	1
75	0	1	0	1	1
76	0	1	0	0	1
77	0	1	0	0	1
78	1	1	0	0	1
79	1	1	0	1	1
80	1	1	0	1	1
81	0	1	0	0	1
82	1	1	0	1	1
83	1	0	0	1	1
84	0	0	0	1	1
85	1	1	0	1	1
86	1	1	0	1	1
87	1	1	0	1	1
88	0	0	0	1	1
89	0	1	0	0	1
90	1	1	0	0	1
91	0	1	0	0	1
92	1	1	0	1	1
93	0	0	0	0	0
94	1	1	0	1	1
95	0	1	0	1	1
96	0	1	0	1	1
97	1	1	0	0	1
98	0	1	0	0	1
99	1	1	0	1	1
100	1	1	0	0	1
Sum	55	67	8	68	91
Percentage	55%	67%	8%	68%	91%

Evolutionary Computation

The terminology count of the *Evolutionary Computation* is shown in Table 4. If a term is used at least once in an appropriate context in an article, then there is a ‘1’ in the corresponding cell of the table (if not, then there is a ‘0’).

Table 4 Terminology count for *Evolutionary Computation*

Paper #	*Exploit-*	*Explor-*	*Intens-*	*Divers-*	*Any*
1	0	0	0	0	0
2	1	1	0	0	1
3	0	0	0	1	1
4	1	0	0	0	0
5	0	0	0	1	1
6	1	1	0	1	1
7	0	0	0	0	0
8	0	1	0	0	1
9	1	1	0	1	1
10	1	1	0	1	1
11	0	0	0	0	0
12	0	0	0	0	0
13	0	0	0	0	0
14	1	0	0	1	1
15	1	1	0	1	1
16	0	0	1	1	1
17	0	0	0	0	0
18	1	1	0	1	1
19	0	1	1	1	1
20	0	0	0	0	0
21	1	0	0	1	1
22	1	1	0	0	1
23	0	0	0	0	0
24	0	0	0	1	1
25	0	1	0	1	1
26	0	0	0	0	0
27	1	1	0	1	1
28	1	1	0	1	1
29	1	0	1	1	1
30	1	1	0	0	1
31	0	0	0	0	0
32	1	1	1	1	1
33	0	1	0	0	1
34	1	0	0	0	1
35	0	1	0	0	1
36	1	1	0	1	1
37	0	0	0	0	0
38	0	0	0	1	1

Table 4 Terminology count for *Evolutionary Computation* (continued)

Paper #	*Exploit-*	*Explor-*	*Intens-*	*Divers-*	*Any*
39	1	1	0	0	1
40	1	1	1	1	1
41	0	1	0	1	1
42	1	1	0	0	1
43	1	1	0	1	1
44	1	1	0	0	1
45	0	0	0	0	0
Sum	22	23	5	22	32
Percentage	49%	51%	11%	49%	71%

References from the Journal of Heuristics

1 Ouzineb, M., Nourelfath, M. and Gendreau, M. (2011) ‘A heuristic method for non-homogeneous redundancy optimization of series-parallel multi-state systems’, Vol. 17, No. 1.

2 Gouveia, L., Paias, A. and Sharma, D. (2011) ‘Restricted dynamic programming based neighborhoods for the hop-constrained minimum spanning tree problem’, Vol. 17, No. 1.

3 Bansal, R. and Srivastava, K. (2011) ‘Memetic algorithm for the antibandwidth maximization problem’, Vol. 17, No. 1.

4 Deineko, V.G., Shabtay, D. and Steiner, G. (2011) ‘On the asymptotic behavior of subtour-patching heuristics in solving the TSP on permuted Monge matrices’, Vol. 17, No. 1.

5 Lii, Z., Hao, J-K. and Glover, F. (2011) ‘Neighborhood analysis: a case study on curriculum-based course timetabling’, Vol. 17, No. 2.

6 Deng, Y. and Bard, J.F. (2011) ‘A reactive GRASP with path relinking for capacitated clustering’, Vol. 17, No. 2.

7 Aloise, D. and Ribeiro, C.C. (2011) ‘Adaptive memory in multistart heuristics for multicommodity network design’, Vol. 17, No. 2.

8 Pullan, W., Mascia, F. and Brunato, M. (2011) ‘Cooperating local search for the maximum clique problem’, Vol. 17, No. 2.

9 Karapetyan, D. and Gutin, G. (2011) ‘Local search heuristics for the multidimensional assignment problem’, Vol. 17, No. 3.

10 Hamadi, Y. and Ringwelski, G. (2011) ‘Boosting distributed constraint satisfaction’, Vol. 17, No. 3.

11 Paletta, G. and Vocaturo, F. (2011) ‘A composite algorithm for multiprocessor scheduling’, Vol. 17, No. 3.

12 Zhang, G. (2011) 'Quantum-inspired evolutionary algorithms: a survey and empirical study', Vol. 17, No. 3.

13 Van Laarhoven, J.W. and Ohlmann, J.W. (2011) 'A randomized Delaunay triangulation heuristic for the Euclidean Steiner tree problem in Rd', Vol. 17, No. 4.

14 Gilli, M. and Schumann, E. (2011) 'Optimal enough?', Vol. 17, No. 4.

15 Riise, A. and Burke, E.K. (2011) 'Local search for the surgery admission planning problem', Vol. 17, No. 4.

16 Dotu, I., Patricio, M.A., Berlanga, A., Garcia, J. and Molina, J.M. (2011) 'Boosting video tracking performance by means of tabu search in intelligent visual surveillance systems', Vol. 17, No. 4.

17 De Leone, R., Festa, P. and Marchitto, E. (2011) 'A bus driver scheduling problem: a new mathematical model and a GRASP approximate solution', Vol. 17, No. 4.

18 Goncalves, J.F., Resende, M.G.C. and Mendes, J.J.M. (2011) 'A biased random-key genetic algorithm with forward-backward improvement for the resource constrained project scheduling problem', Vol. 17, No. 5.

19 Goncalves, J.F. and Resende, M.G.C. (2011) 'Biased random-key genetic algorithms for combinatorial optimization', Vol. 17, No. 5.

20 Mateus, G.R., Resende, M.G.C. and Silva, R.M.A. (2011) 'GRASP with path-relinking for the generalized quadratic assignment problem', Vol. 17, No. 5.

21 Bengoetxea, E., Larranaga, P., Bielza, C. and Fernandez del Pozo, J.A. (2011) 'Optimal row and column ordering to improve table interpretation using estimation of distribution algorithms', Vol. 17, No. 5.

22 Ansotegui, C, Bejar, R., Fernandez, C, Gomes, C. and Mateu, C. (2011) 'Generating highly balanced sudoku problems as hard problems', Vol. 17, No. 5.

23 Toril, M., Wille, V, Molina-Fernandez, I. and Walshaw, C. (2011) 'An adaptive multi-start graph partitioning algorithm for structuring cellular networks', Vol. 17, No. 5.

24 Brueggemann, T. and Hurink, J.L. (2011) 'Matching based very large-scale neighborhoods for parallel machine scheduling', Vol. 17, No. 5.

25 Fadlaoui, K. and Galinier, P. (2011) 'A tabu search algorithm for the covering design problem', Vol. 17, No. 6.

26 Lin, C, Qing, A. and Feng, Q. (2011) 'A comparative study of crossover in differential evolution', Vol. 17, No. 6.

27 Van Peteghem, V. and Vanhoucke, M. (2011) 'Using resource scarceness characteristics to solve the multi-mode resource-constrained project scheduling problem', Vol. 17, No. 6.

28 Labadie, N., Melechovsky, J. and Calvo, R.W. (2011) 'Hybridized evolutionary local search algorithm for the team orienteering problem with time windows', Vol. 17, No. 6.

29 Abdullah, S., Turabieh, H., McCollum, B. and McMullan, P. (2012) 'A hybrid metaheuristic approach to the university course timetabling problem', Vol. 18, No. 1.

30 Czogalla, J. and Fink, A. (2012) 'Fitness landscape analysis for the no-wait flow-shop scheduling problem', Vol. 18, No. 1.

31 Mateo, P. M. and Alberto, I. (2012) 'A mutation operator based on a Pareto ranking for multi-objective evolutionary algorithms', Vol. 18, No. 1.

32 Sun, M. (2012) 'A tabu search heuristic procedure for the capacitated facility location problem', Vol. 18, No. 1.

33 Chiarandini, M., Di Gaspero, L., Gualandi, S. and Schaerf, A. (2012) 'The balanced academic curriculum problem revisited', Vol. 18, No. 1.

34 Soto, M., Rossi, A. and Sevaux, M. (2012) 'A mathematical model and a metaheuristic approach for a memory allocation problem', Vol. 18, No. 1.

35 Santamar a, J., Cordon, O., Damas, S., Marti, R. and Palma, R.J. (2012) 'GRASP and path relinking hybridizations for the point matching-based image registration problem', Vol. 18, No. 1.

36 Ribeiro, C.C. and Resende, M.G.C. (2012) 'Path-relinking *intensification* methods for stochastic local search algorithms', Vol. 18, No. 2.

37 Ben-Moshe, B. (2012) 'Geometric heuristics for rural radio maps approximation', Vol. 18, No. 2.

38 Mousavi, S.R. Babaie, M. and Montazerian, M. (2012) 'An improved heuristic for the far from most strings problem', Vol. 18, No. 2.

39 Basseur, M., Liefooghe, A., Le, K. and Burke, E.K. (2012) 'The efficiency of indicator-based local search for multi-objective combinatorial optimisation problems', Vol. 18, No. 2.

40 Rainwater, C, Geunes, J. and Romeijn, H.E. (2012) 'A facility neighborhood search heuristic for capacitated facility location with single-source constraints and flexible demand', Vol. 18, No. 2.

41 Liefooghe, A., Humeau, J., Mesmoudi, S., Jourdan, L. and Talbi, E-G. (2012) 'On dominance-based multiobjective local search: design, implementation and experimental analysis on scheduling and traveling salesman problems', Vol. 18, No. 2.

42 Kiziltan, Z., Lodi, A., Milano, M. and Parisini, F. (2012) 'Bounding, filtering and diversification in CP-based local branching', Vol. 18, No. 3.

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References from the IEEE Transactions on Evolutionary Computation

1 Das, S. and Suganthan, P.N. (2011) ‘Differential evolution: a survey of the state-of-the-art’, Vol. 15, No. 1.

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43 Sun, T-Y., Liu, C-C., Tsai, S-J., Hsieh, S-T. and Li, K-Y. (2011) 'Cluster guide particle swarm optimization (CGPSO) for underdetermined blind source separation with advanced conditions', Vol. 15, No. 6.

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59 Chow, C.K. and Yuen, S.Y. (2012) 'A multiobjective evolutionary algorithm that diversifies population by its density', Vol. 16, No. 2.

60 Bui, T.N., Deng, X. and Zrncic, CM. (2012) 'An improved ant-based algorithm for the degree-constrained minimum spanning tree problem', Vol. 16, No. 2.

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96 Gong, Y-J., Zhang, J., Chung, S-H., Chen, W-N., Zhan, Z-H., Li, Y. and Shi, Y-H. (2012) 'An efficient resource allocation scheme using particle swarm optimization', Vol. 16, No. 6.

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References from Evolutionary Computation

1 Hornby, G.S., Lohn, J.D. and Linden, D.S. (2011) 'Computer-automated evolution of an X-band antenna for NASAOs space technology 5 mission', Vol. 19, No. 1.

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15 Secretan, J., Beato, N., D'Ambrosio, D.B., Rodriguez, A., Campbell, A., Folsom-Kovarik, J.T. and Stanley, K. O. (2011) 'Picbreeder: a case study in collaborative evolutionary exploration of design space', Vol. 19, No. 3.

16 Li, J., Parkes, A.J. and Burke, E.K. (2011) 'Evolutionary squeaky wheel optimization: a new framework for analysis', Vol. 19, No. 3.

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20 Chicano, F., Whitley, L.D. and Alba, E. (2011) 'A methodology to find the elementary landscape decomposition of combinatorial optimization problems', Vol. 19, No. 4.

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42 Posik, P., Huyer, W. and Pal, L. (2012) 'A comparison of global search algorithms for continuous black box optimization', Vol. 20, No. 4.

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