CIRP Journal of Manufacturing Science and Technology 9 (2015) 57–68

Contents lists available at ScienceDirect

CIRP Journal of Manufacturing Science and Technology

journal homepage: www.elsevier.com/locate/cirpj

Review

Survey on the use of computational optimisation in UK engineering companies

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ARTICLE INFO

Article history:
Available online 22 January 2015

Keywords:
Computational optimisation
Engineering optimisation
Optimisation algorithms

ABSTRACT

The aim of this work is to capture current practices in the use of computational optimisation in UK engineering companies and identify the current challenges and future needs of the companies. To achieve this aim, a survey was conducted from June 2013 to August 2013 with 17 experts and practitioners from power, aerospace and automotive Original Equipment Manufacturers (OEMs), steel manufacturing sector, small- and medium-sized design, manufacturing and consultancy companies, and optimisation software vendors. By focusing on practitioners in industry, this work complements current surveys in optimisation that have mainly focused on published literature. This survey was carried out using a questionnaire administered through face-to-face interviews lasting around 2 h with each participant. The questionnaire covered 5 main topics: (i) state of optimisation in industry, (ii) optimisation problems, (iii) modelling techniques, (iv) optimisation techniques, and (v) challenges faced and future research areas. This survey identified the following challenges that the participant companies are facing in solving optimisation problems: large number of objectives and variables, availability of computing resources, data management and data mining for optimisation workflow, over-constrained problems, too many algorithms with limited help in selection, and cultural issues including training and mindset. The key areas for future research suggested by the participant companies are as follows: handling large number of variables, objectives and constraints particularly when solution robustness is important, reducing the number of iterations and evaluations, helping the users in algorithm selection and business case for optimisation, sharing data between different disciplines for multi-disciplinary optimisation, and supporting the users in model development and post-processing through design space visualisation and data mining.

Contents

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http://dx.doi.org/10.1016/j.cirpj.2015.01.003
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Introduction

The aim of this research is to capture current practices in the use of computational optimisation in UK engineering companies and identify their current challenges and future needs. By focusing on practitioners in industry, this work complements current surveys in optimisation that have, on the whole, concentrated solely on published literature.

The survey undertaken for this research addresses the following four focus areas to:

- Capture the current real-life applications of optimisation in industry
- Identify the domains where optimisation is applied
- Define the key optimisation problem features
- Obtain the techniques used to solve each optimisation problem feature
- Identify the challenges faced by industry and future research areas

In the following section of the paper, an examination of existing surveys on this subject is made. This paper then presents the methodology followed and the results of this survey with an accompanying analysis. The paper concludes with future directions for this research.

Related research

Optimisation can be considered as the process of finding "feasible solutions which correspond to extreme values" of one or more given objectives [1]. Computational optimisation techniques have been widely applied to a variety of disciplines. A search conducted by the authors (based on a survey of 390 documents, shortlisted for detail to 51 documents, that outline industrial optimisation problems) showed that the power industry has the highest usage of optimisation (32%). The automotive industry represents 12%, the construction industry 10% and in the fourth position is the electric industry with 6%. The fifth position is shared by the chemical, materials, aerospace, food and Information System industries with 4% each. Finally, production, retail, surgical, water, electronic, banking, logistics and transport industries have same share (2%) and these have been grouped under others category (16% in total). The results are shown in a graphical form in Fig. 1.

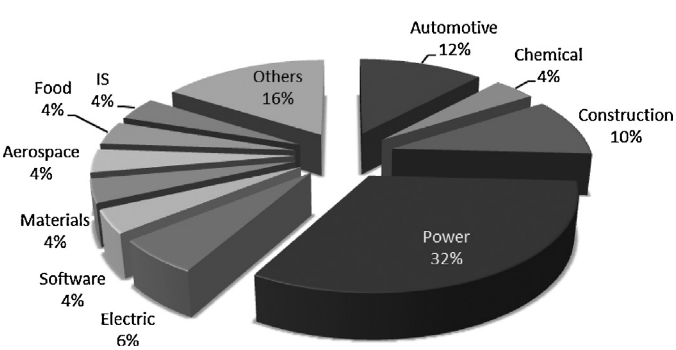

Fig. 1. Use of computational optimisation in industrial sectors (based on literature survey).

To establish the starting reference for the survey undertaken for this work, four related surveys reported in literature have been examined. Firstly, Roy et al. [2] conducted a survey of 9 engineers from five UK-based companies, from aerospace, automotive and steelmaking industry. Its purpose was to investigate issues related to engineering design optimisation in industry. The second survey [3] was conducted with 324 members of the Evolutionary Community; its aim was to understand trends in the field of Evolutionary Computation. Agte et al. [4] presented the state-of-the-art, trends, developments and industrial applications in Multidisciplinary Design Optimisation (MDO), based on the opinion of nearly 70 professionals from academia, industry and government. The literature based survey of Boussaïd et al. [5] made a comparison of some of the main metaheuristics approaches. By focusing on practitioners in industry from multiple industry sectors and investigating the full range of optimisation techniques, this work complements current surveys in optimisation that have mainly concentrated on selected problem domains and optimisation techniques.

Research methodology

This survey was carried out using a questionnaire administered through face-to-face interviews lasting around 2 h with each participant. The questionnaire covered 5 main topics:

1. State of optimisation in industry: This section identified how widely optimisation is used in industry, how well optimisation is integrated with the design process, and which evaluation and optimisation packages are the most popular.
2. Optimisation problems: This section identified the features of optimisation problems (such as constraints, multiple objectives and computational expense) and the domains in industry that experience these features (such as design, manufacturing and assembly).
3. Modelling techniques: This section identified the modelling techniques used in industry when dealing with optimisation problems.
4. Optimisation techniques: This section identified the optimisation techniques used in industry and their strengths and weaknesses in handling various problem features. It also captured the importance of each problem feature in terms of the effort required to deal with it.
5. Challenges faced and future research areas: This section captured the key industrial challenges in optimisation and the requirements for future research.

The questionnaire was validated with 5 researchers within Cranfield University before starting with the implementation of the survey. Once the questionnaire was approved, the interviews were conducted on each survey participant.

In the completion of the survey, 17 experts and practitioners were interviewed; they were drawn from the following industry sectors:

- Aerospace Original Equipment Manufacturers (OEMs) (airframe)
- Aerospace OEM (power)

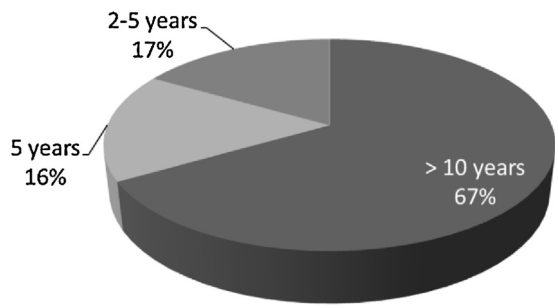

Fig. 2. Percentage of industry sectors with different years of experience in using optimisation.

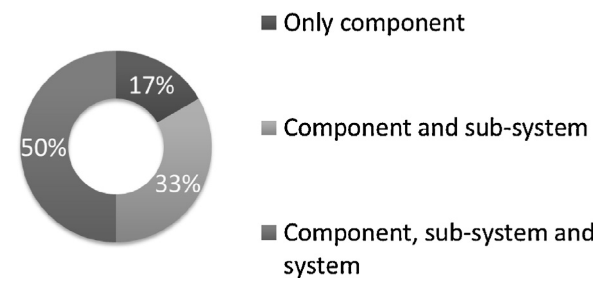

Fig. 3. Percentage of companies using optimisation at different configuration levels.

- Automotive OEM
- Power OEM
- Steel manufacturing sector
- Small- and medium-sized design, manufacturing and consultancy companies
- Optimisation software vendors

The interviewees represented eight engineering companies. Face to face interviews were undertaken with each of the participants, with each interview lasting 2 h. The questionnaire contained both closed- and open-ended questions. On average 3 h of analysis was required for each hour of interview. In the presentation of the results with closed-ended questions, graphs and charts were utilised. For open-ended questions, a categorisation of responses using an analysis protocol was made.

Survey results

State of optimisation in industry

This section focused on: (i) how widely optimisation is used in industry, (ii) how well optimisation is integrated with the design process, and (iii) which evaluation and optimisation packages are the most popular. The first question asked in the survey concerned the number of years that the participants' organisation had been using optimisation. From Fig. 2 it can be seen that that the majority (67%) of industry sectors have more than 10 years of more experience. It was also found that SMEs tend to be relatively inexperienced in this field.

The next question asked about the configuration level to which optimisation was applied whether optimisation was applied at a system, sub-system or component level. From Fig. 3 it can be seen that only 50% of companies deal with system level optimisation whereas all companies deal with optimisation at the component level.

Fig. 4 displays the results of a question about how well optimisation is integrated into the design process. For automotive and aerospace (power) companies optimisation is very well integrated into the design process. This issue is more of a concern for aerospace (airframe) companies who report lower integration levels due to the complexity of their design processes. It was also found by this survey that a wide range of integration capabilities are provided by software vendors.

In a question about the software that organisations use for optimisation it was found that all companies use commercial packages (shown in Fig. 5). Popular commercial packages were named as Matlab, ModelCenter, Isight, HyperWorks and modeFRONTIER. There is an increase in the use of optimisation add-ons to Excel due to their simplicity. Overall, there is a decrease in the use of in-house packages and an increase in the use of open source packages, particularly in the last five years.

Optimisation problems

This section focused on: (i) features of industrial optimisation problems (such as multiple objectives, constraints and computational expense), and (ii) domains in industry that experience these features (such as design manufacturing and assembly). Design and manufacturing are the most common problem domains for optimisation (as shown in Fig. 6); though, optimisation is increasingly being applied to a range of problems in industry. A number of new problem domains are emerging for optimisation, such as maintenance, project management and supply chain.

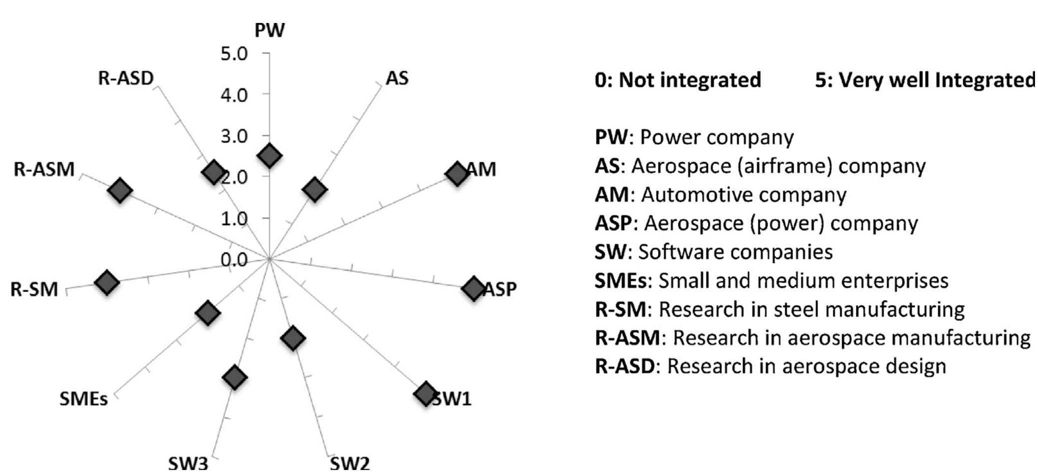

Fig. 4. Levels of integration with the design process.

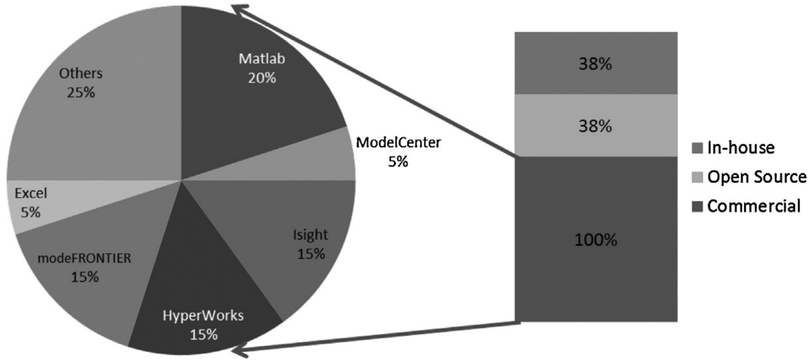

Fig. 5. Percentage of companies using different optimisation packages.

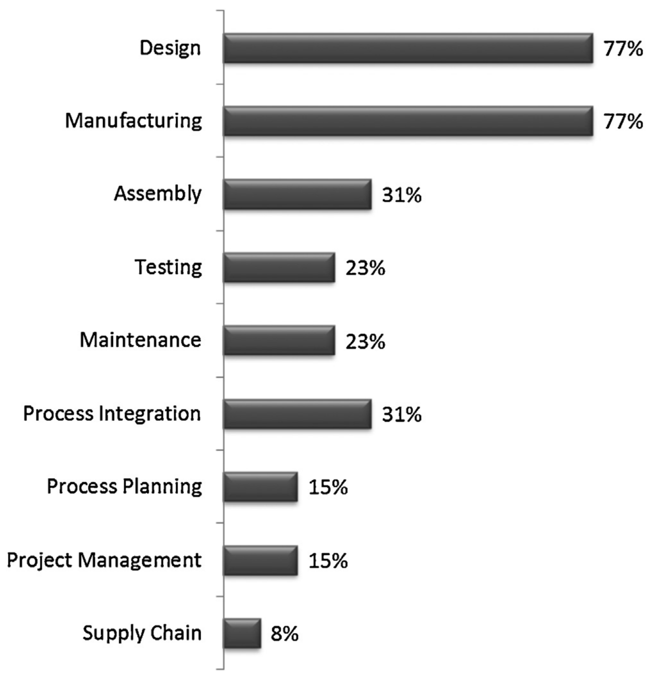

Fig. 6. Percentage of companies using optimisation in different domains.

In terms of problem features most commonly faced by organisations, multiple objectives and constraints are the most frequently encountered. Various new problem features are being handled, such as interactive optimisation and qualitative optimisation (Fig. 7).

The type of problem features faced differs depending on the industry sector in question. For aerospace airframe (shown as the first graph in Fig. 8) multiple objectives and global search are the most common problem features faced. It is also true that constraints and robust search are also important for this sector. Multiple objectives are important for this sector because it needs to deal with weight and at least one other objective in its optimisation problems. Global search is important due to the importance of efficiency for this sector. Constraints and robust search are important due to the need to look for feasible optimal solutions that can perform well in a range of conditions.

With aerospace power (shown as graph 2 in Fig. 8) constraints and computational expense are the most common problem features faced, with many other features sharing equal importance due to the long history of the use of optimisation in this sector. Constraints are important for this sector due to the need to look for feasible solutions. Computational expense is important because the optimisation algorithms used in this sector need to be linked with expensive evaluations, such as Computational Fluid Dynamics (CFD).

The automotive sector (shown as graph 3 in Fig. 8) results showed that constraints are the most common problem features. As with

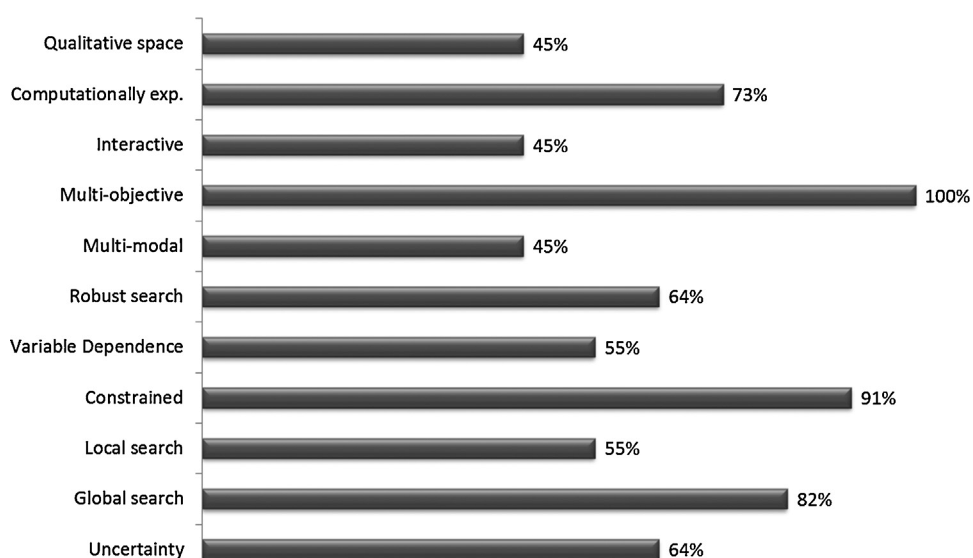

Fig. 7. Percentage of companies using optimisation with different features.

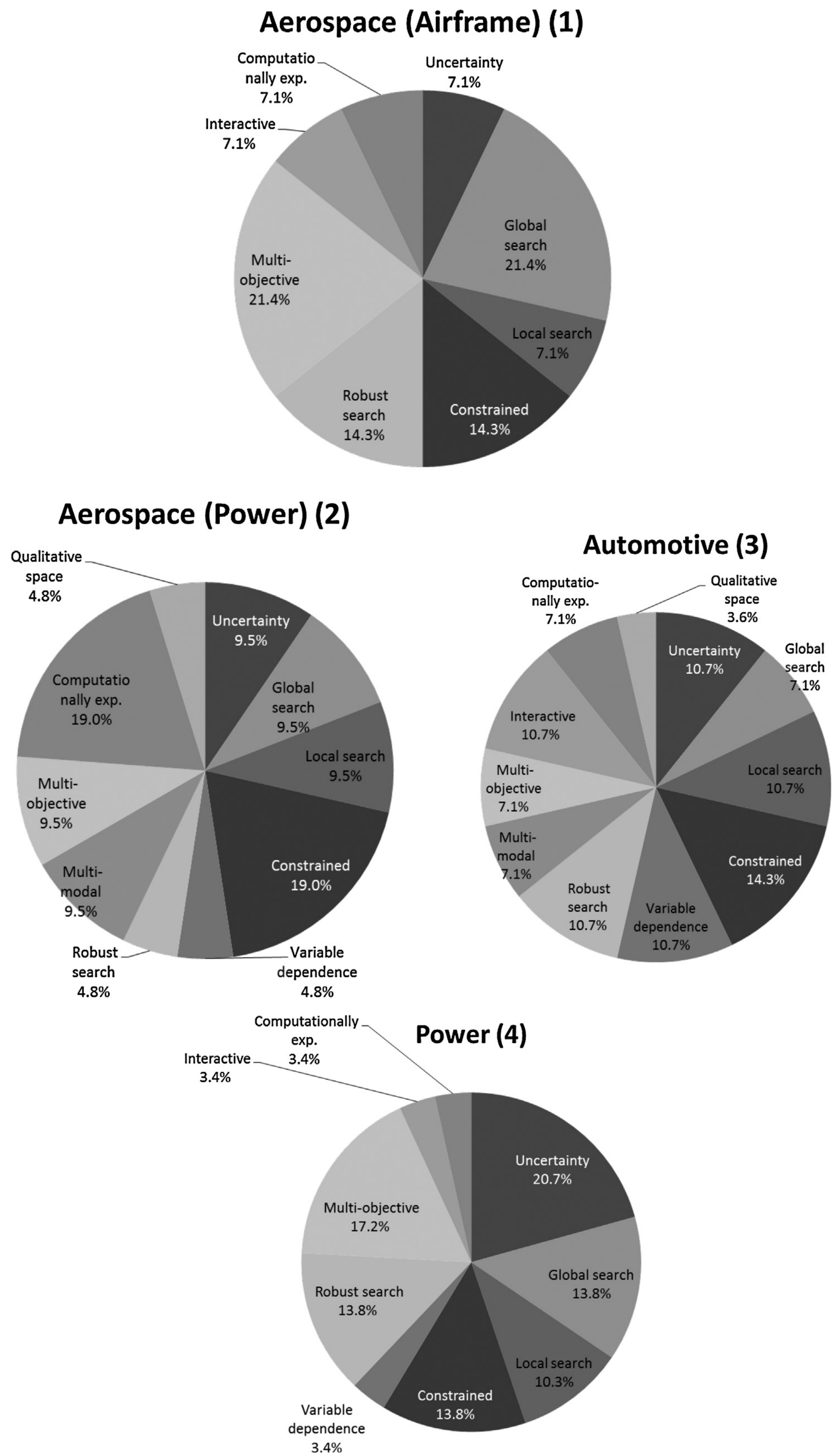

Fig. 8. Percentage of optimisation problem features faced by different industry sectors.

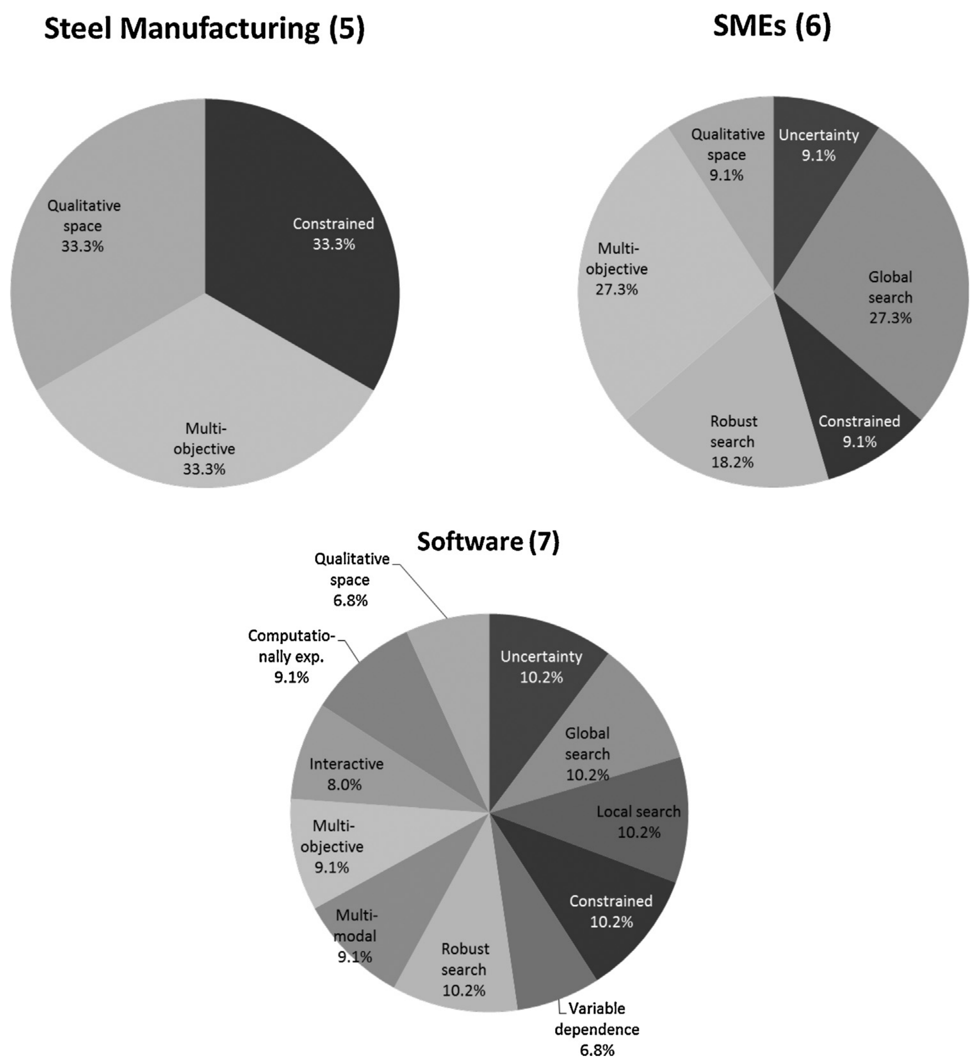

Fig. 8. (*Continued*).

aerospace power this sector also deals with a range of other problem features due to the long history of the use optimisation in this sector. Constraints are the most important for this sector due to the need to meet the requirements imposed by standards and system fit.

Multiple objectives and uncertainty are the most common problem features faced by the power sector (shown as graph 4 in Fig. 8). Global search, constraints and robust search are also important for this sector. Multiple objectives are important for this sector because it needs to deal with power efficiency and at least one other objective in its optimisation problems. Uncertainty is important because the power equipment and grid need to operate optimally in a range of conditions. Global search is important due to the importance of efficiency for this sector. Constraints and robust search are important due to the need to look for feasible optimal solutions that can perform well in a range of conditions.

Steel manufacture encounters only 3 problem features: multiple objectives, constraints and qualitative objectives (shown as graph 5 in Fig. 8). Multiple objectives are important for this sector because it needs to deal with throughput and at least one other objective in its optimisation problems. Constraints are important due to the need to look for feasible solutions. Qualitative objectives are important since the link between the quality of final cross-section of steel and manufacturing process parameters is best described using rules rather than mathematical or computational models. This sector deals with only 3 problem features because the operating conditions once set in a steel factory are maintained for many years.

SME design, manufacturing and consultancy companies (shown as graph 6 in Fig. 8) face a number of optimisation problems with multiple objectives, global search and robustness cited as the most common. On the whole SMEs deal with a smaller number of problem features than the OEMs. Multiple objectives are important for this sector because it needs to deal with cost and at least one other objective in its optimisation problems. Global search is important in since this sector deals heavily with topology optimisation applied for additive layer manufacturing. Robustness is important so that the solutions can perform well in a range of conditions.

The final sector, the software industry (shown as graph 7 in Fig. 8), deals with a large range of optimisation problems with equal importance. This is because these software vendors need a range of capabilities that they can provide to their clients.

Modelling techniques

This section focused on: (i) modelling techniques used in industry when dealing with optimisation problems and (ii) modelling and simulation approaches, design of experiments, feasibility analysis and approximations of surrogates. Another important subject surveyed in the questionnaire was the use of

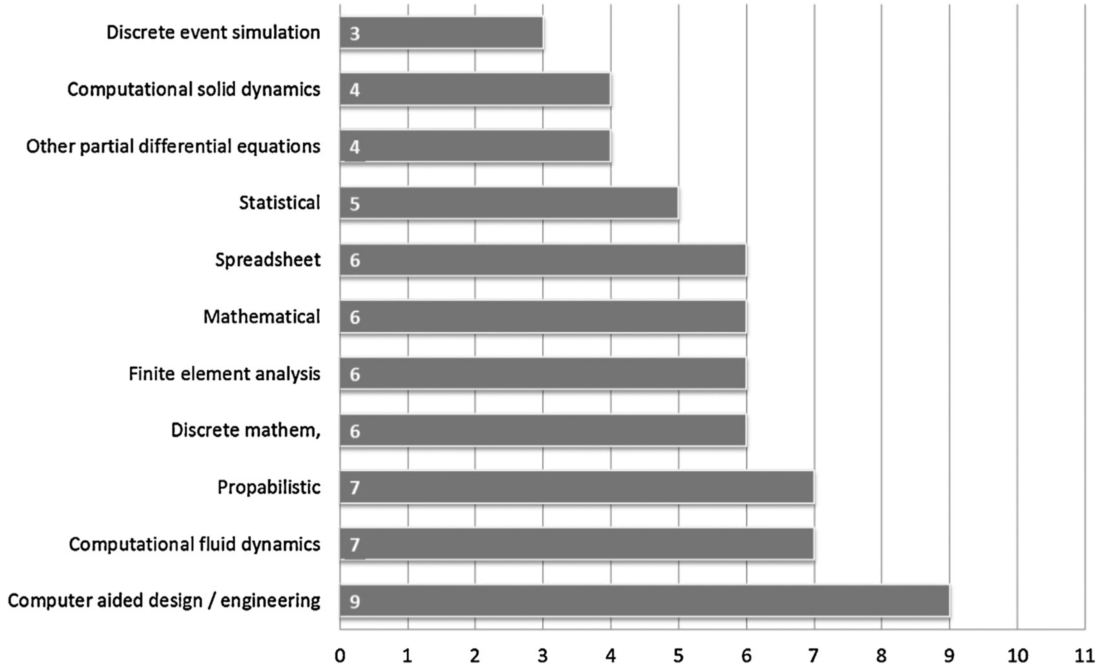

Fig. 9. Modelling and simulation approaches used by companies.

modelling for optimisation problems. In Fig. 9 it can be seen that CAD/CAE, CFD and probabilistic models are the most popular methods used for simulation and modelling. Though, various other methods such as spreadsheets & mathematical models are also used. CAD/CAE and CFD are used for engineering design optimisation problems, and probabilistic models are used for handling uncertainty in optimisation problems. Spreadsheets are finding increasing use due to the emergence of simple optimisation add-ons to Excel. Discrete maths is being used for scheduling problems.

The number of companies using different approaches for approximations & surrogates can be seen in Fig. 10, with quadratic models, kriging and linear models being the most popular due to their simplicity. Various other approaches for approximations and surrogates are used including neural networks and splines.

Optimisation techniques

This section focused on: (i) optimisation techniques used in industry, (ii) their strengths and weaknesses in handling various problem features, and (iii) importance of each problem in terms of the effort required to deal with it. An examination of the techniques companies use for multi-objective optimisation shows that metaheuristic techniques are the most popular, with NSGA-II singled out as the most widely used (shown in Fig. 11). The breakdown of metaheuristics techniques is heavily dominated by evolutionary algorithms. It is interesting to note the emergence of particle swarm optimisation (PSO) for discrete and constrained problems.

When considering global search, metaheuristics techniques were also the most popular. As shown in Fig. 12, evolutionary algorithms

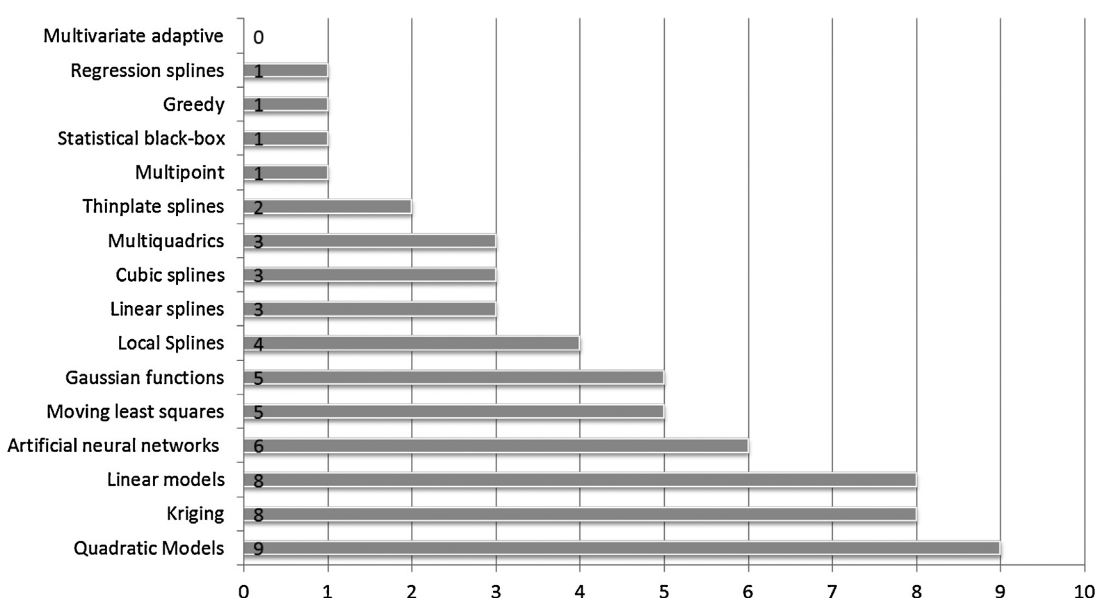

Fig. 10. Number of companies using different approaches for approximations and surrogates.

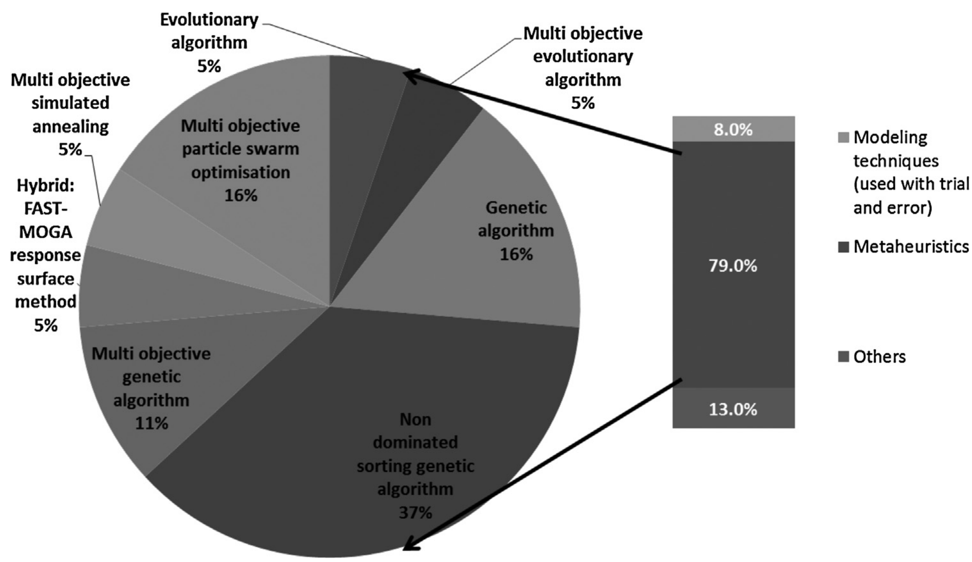

Fig. 11. Percentage of companies using different techniques for multi-objective optimisation.

are the most popular among metaheuristics techniques. For classical techniques approximations and kriging are the most popular.

From Fig. 13 it can be seen that metaheuristics techniques are the most popular for handling constraints. Such techniques routinely make use of evolutionary and particle swarm algorithms. It is interesting to note that the penalty function is not the most popular category.

For companies who encounter high computational expense problems with regularity modelling techniques are the most commonly applied methods (shown in Fig. 14). Surrogates/metamodels are the most popular among modelling methods.

For the use of robust search techniques, modelling techniques are the most popular, with sensitivity analysis used most often (shown in Fig. 15).

Probabilistic techniques are the most popular modelling techniques for problems involving uncertainty (shown in Fig. 16). Among metaheuristics techniques evolutionary algorithms are the most popular.

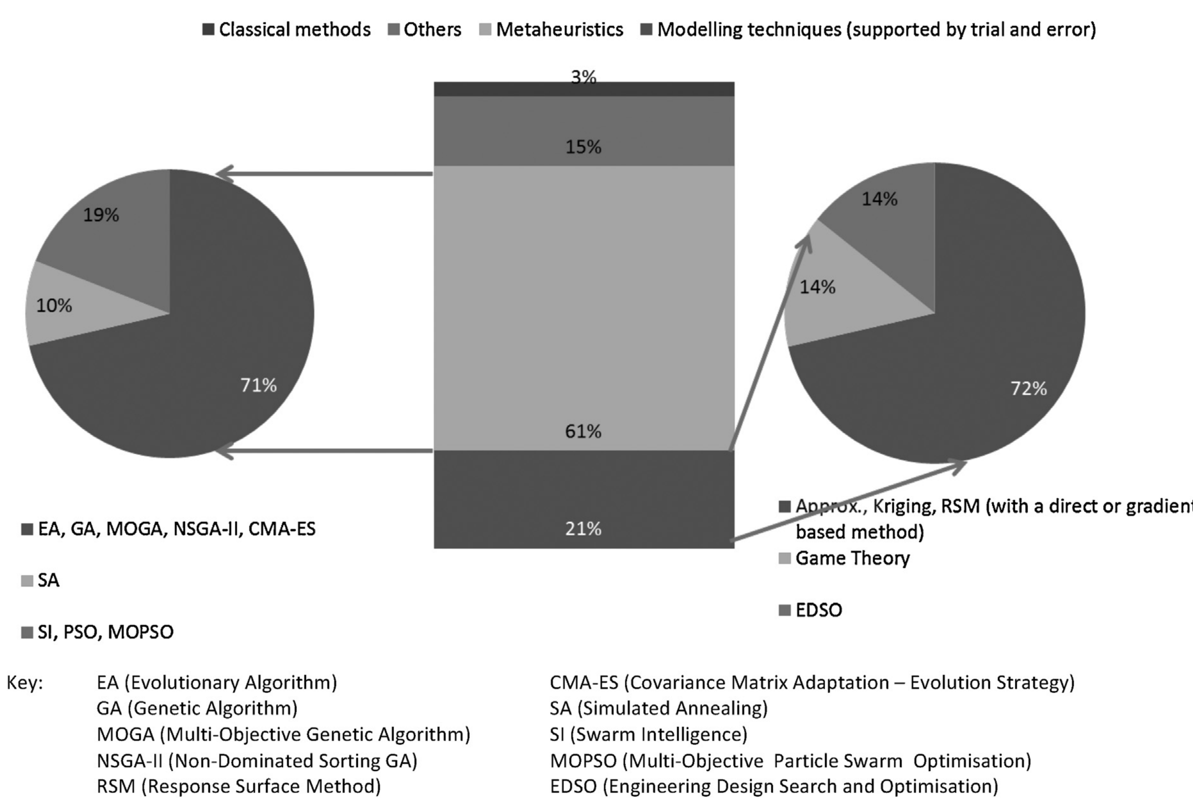

Fig. 12. Percentage of companies using different techniques for global search.

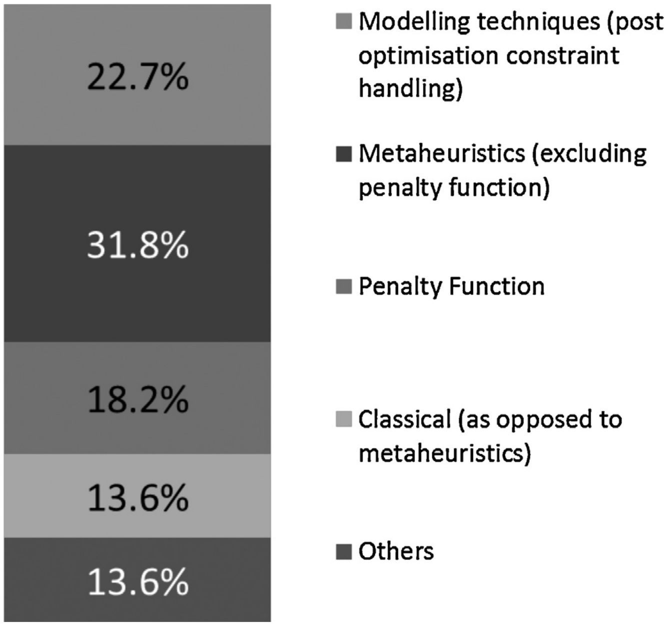

Fig. 13. Percentage of companies using different techniques for handling constraints.

Fig. 17 shows a comparative analysis of the techniques used for different problem types broken down by company type. Constraints, multiple objectives, global search and computational expense have a high frequency of occurrence in industry, and robust search and uncertainty have low frequency of occurrence in industry.

Challenges faced and future research areas

This survey identified the following challenges that the participant companies are facing in solving optimisation problems: large number of objectives and variables, availability of computing resources, data management and data mining for optimisation workflow, over-constrained problems, too many algorithms with limited help in selection, and cultural issues including training and mindset.

The key areas for future research suggested by the participant companies are as follows: handling large number of variables, objectives and constraints particularly when solution robustness is important, reducing the number of iterations and evaluations, helping the users in algorithm selection and business case for optimisation, sharing data between different disciplines for multi-disciplinary optimisation, and supporting the users in model development and post-processing through design space visualisation and data mining.

Discussion

General use of optimisation

Optimisation is an everyday task in engineering companies. 60% of the companies have been using optimisation for more than 10 years; however, 40% only use optimisation in less than the 50% of the departments within the organisation. Current practices in industry indicate that those companies using optimisation in a specific configuration level also use it in the previous levels. Specifically, 25% of the companies only optimise at component level, 38% in component and sub-system levels and 38% in all three configuration levels.

The deployment of integration packages/tools enables the integration of optimisation in the design process. However, there are other main limitations that hinder this integration. Some of these are: existence of manual processes, necessity of data management, immature development of optimisation in manufacturing, the lack of user training and support, as well as issues related to technical functionalities, certification and design rules. Regarding the optimisation packages, all companies used commercial software. The most frequently used optimisation packages are Matlab, Isight, HyperWorks and modeFrontier.

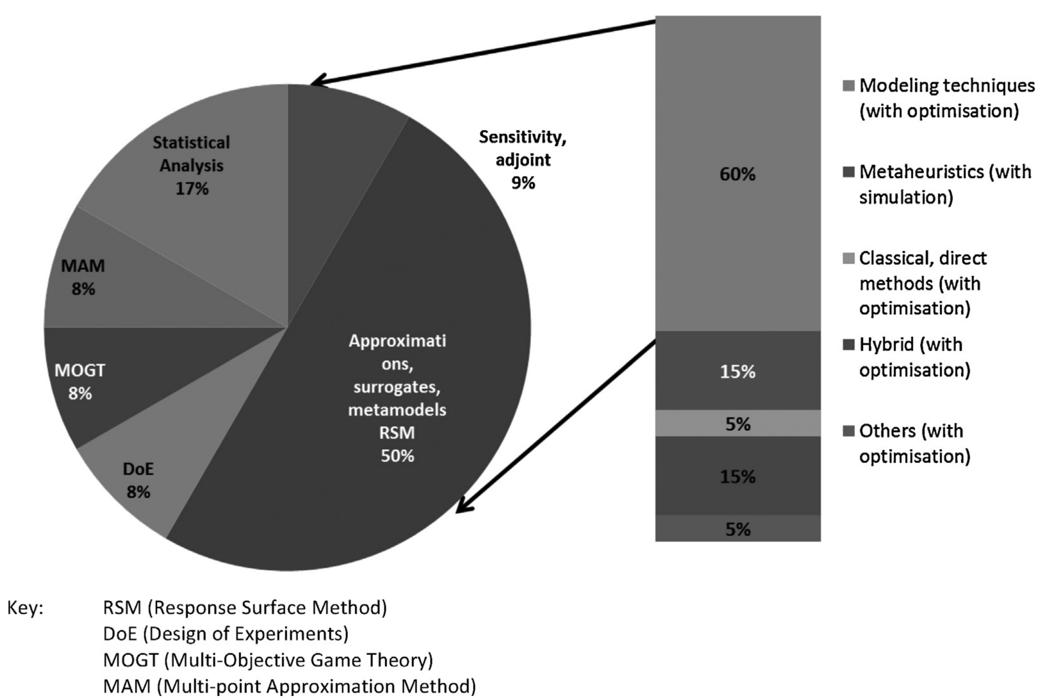

Fig. 14. Percentage of companies using different techniques for high computational expense problems.

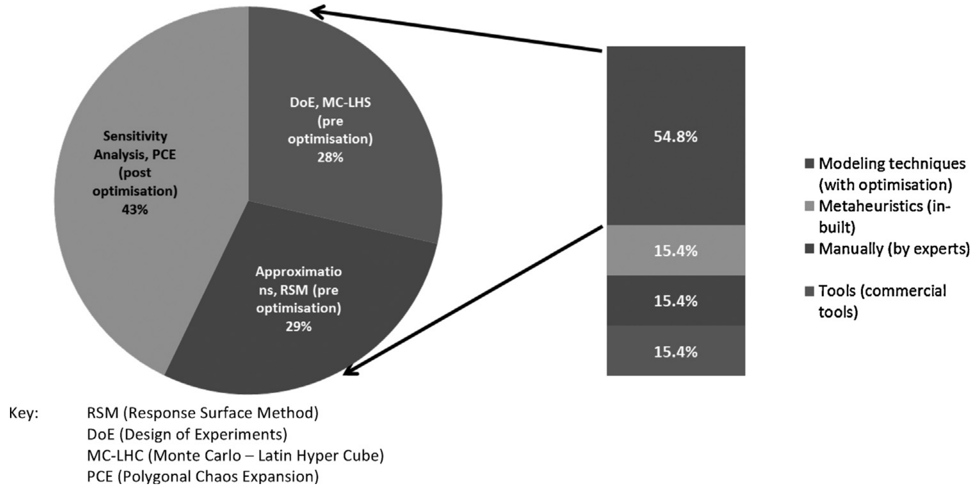

Fig. 15. Percentage of companies using different techniques for robust search.

Optimisation problems

Optimisation is applied to design and manufacturing by 77% of organisations, to assembly and process integration by 31% and to testing and maintenance by 23%. The most commonly tackled features among organisations are multi-objective (100%) problems, constrained (92%), and computationally expensive problems (77%). Specifically, in design optimisation the most common problems require multi-objective and global search techniques, faced by 100% of the organisations; whereas in manufacturing optimisation the most common problem feature are problems with constraints (90%) and multi-objective problems (80%).

Optimisation and modelling techniques

Modelling approaches are used globally by all the companies surveyed, among the specific techniques, CAD/CAE, CFD and FEA are the most used. Modelling techniques that are the most used to solve uncertain problems are; mainly, probabilistic models (42%) and DoE (33%). 90% of the organisations optimise global search problems in more than 50% of the cases. The most common techniques used to solve this type of problem are metaheuristics, among which the Evolutionary Algorithms (EA, GA, MOGA, NSGA-II and CMA-ES) are used in 71% of the cases. 100% of the companies face constraints in more than 50% of the problems they encounter. More precisely, 65% of organisations deal with constraints in more than 90% of cases.

Regarding robust search problems, the evaluation time is much longer than other standard problems. The vast majority of the companies face robustness problems in less than 50% of the cases. Modelling techniques are generally used to solve them. 100% of the companies face multi-objective problems in more than 50% of the problems encountered. The most common techniques used to solve this kind of problem are metaheuristics, where NSGA-II is the most used.

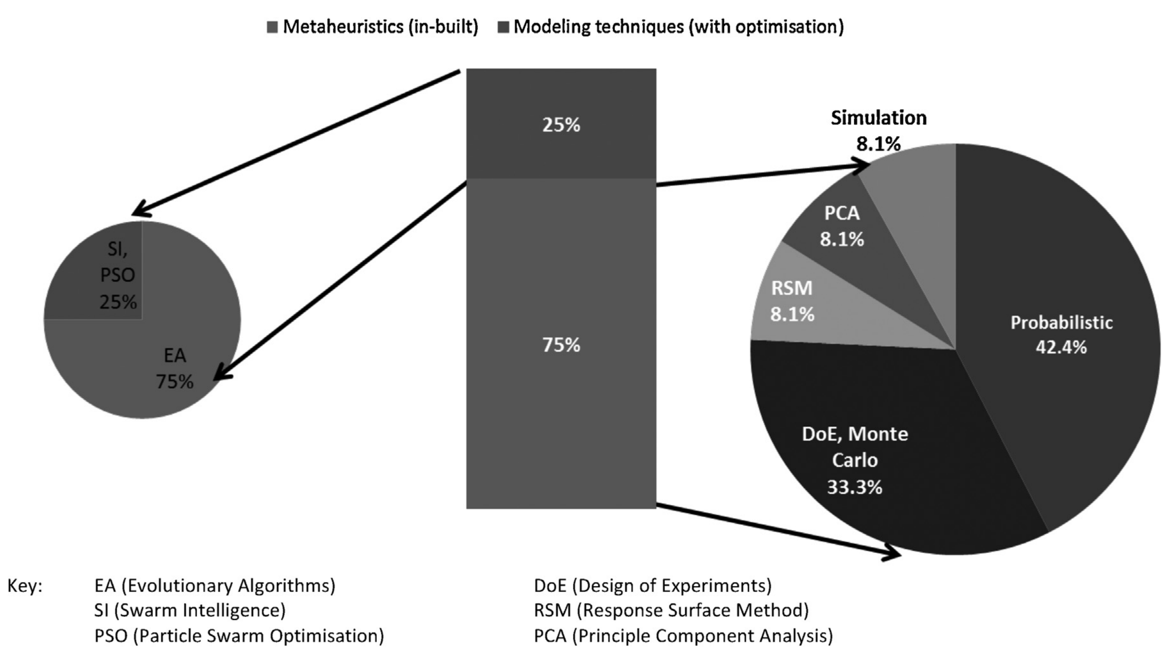

Fig. 16. Percentage of companies using different techniques for handling uncertainty.

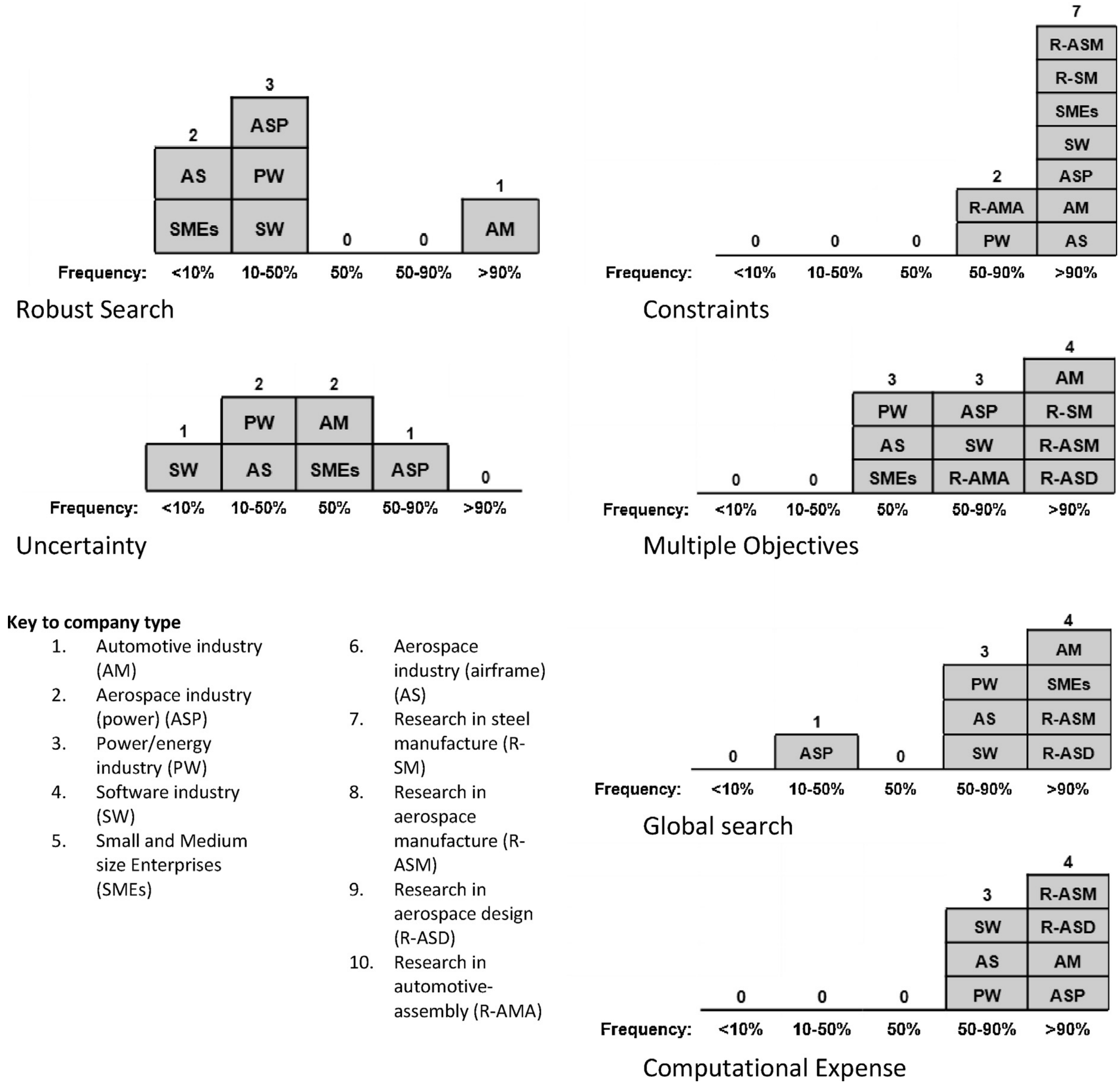

Fig. 17. Comparative analysis of the techniques broken down by company type.

While almost half of the companies need tacit expert knowledge in less than 10% of the problems, the other remaining companies require it in almost all their optimisation problems. The main drawback of all techniques is the dependency on expert knowledge to select the best solution. 100% of the companies optimise computationally expensive problems in more than 50% of the cases. 60% of techniques used to address computationally expensive problems are modelling techniques, from which 50% are approximations/surrogates.

Conclusions

The results of the survey carried out in this research demonstrate that domains such as design, manufacturing, assembly, process integration, testing and maintenance are using optimisation. In fact optimisation is applied to manufacturing as much as to design (77% of the companies). It was identified by this research that the challenge of having to select one technique to solve a specific problem from the wide range of techniques available is a problem faced by many organisations. This issue has in part been addressed by the results featured in this paper, which may be used as a selection guideline based on current practices in surveyed engineering companies. For example, the identification of the most suitable techniques to effectively tackle uncertainty and robustness optimisation problems has been addressed in this work. In the case of uncertainty, modelling techniques are most commonly used to solve such problems; mainly, probabilistic models and DoE. In the case of robust search problems modelling techniques are generally used. Future work in this area will involve a survey covering a wider range of engineering sectors; it would be useful to include other industries such as chemical, construction, food, materials, electric, and water. The geographic region of the survey participants could also be widened to competitive countries. Additional work could be carried out to help users in their selection of algorithms and in building the business case for optimisation. In addition this research has highlighted that users could be better supported in model development and post-processing through the use of design space visualisation and data mining; and it has underlined the need for the sharing of data between different disciplines for multi-disciplinary optimisation.

This paper has captured and presented the current practices in the use of computational optimisation in several engineering companies from power, aerospace, automotive, software development, steel manufacturing and SMEs consultancy industries. As such this research acts as a resource for manufacturing companies already using or considering the use of optimisation techniques.

Acknowledgements

The authors would like to thank Alstom Power and the Engineering and Physical Sciences Research Council (EPSRC – under grant EP/M506813/1) for their funding support. The authors also thank the UK engineering companies who have participated in this survey.

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