Comparison of Geometric Optimization Methods with Multiobjective Genetic Algorithms for Solving Integrated Optimal Design Problems

Bruno Sareni, Jérémi Régnier, Xavier Roboam

Laboratoire d'Electrotechnique et d'Electronique Industrielle
Unité mixte de Recherche INPT-ENSEEIHT / CNRS
BP 7122 – 2 rue Camichel – 31071 Toulouse Cedex 7 – France
{sareni, regnier, roboam}@leei.enseeiht.fr,
http://www.leei.enseeiht.fr

Abstract. In this paper, system design methodologies for optimizing heterogenous power devices in electrical engineering are investigated. The concept of Integrated Optimal Design (IOD) is presented and a simplified but typical example is given. It consists in finding Pareto-optimal configurations for the motor drive of an electric vehicle. For that purpose, a geometric optimization method (i.e the Hooke and Jeeves minimization procedure) associated with an objective weighting sum and a Multiobjective Genetic Algorithm (i.e. the NSGA-II) are compared. Several performance issues are discussed such as the accuracy in the determination of Pareto-optimal configurations and the capability to well spread these solutions in the objective space.

1 Introduction

The determination of innovative industrial solutions for complex energetic systems requires the improvement of design tools and methodologies. In particular, systems should be considered in their globality to ensure optimal performances. In effect, the local optimization of system elements independently taken, does not guarantee the optimality of the whole. In most cases, couplings existing between the elements directly affect the global efficiency. On the other hand, several aspects have to be considered at the same level in the design process such as the choice of the system architecture, the element sizing and the energy management strategy. These features are strongly coupled to global performances. Integrated Optimal Design (IOD) aims at simultaneously optimizing the architecture, the element sizing and the energy management in heterogeneous power systems. IOD necessarily leads to complex mixed variable optimization problems with multiple constraints which require the use of direct optimization methods to be solved. Therefore geometric optimization methods or stochastic approaches (such as Mutiobjective Genetic Algorithms) are suitable for this kind of problems.

In this paper, we illustrate the efficiency of these methods for solving an IOD problem. The considered case is simple but typical of this issue.

The paper is organized as follows. In the first part, the concept of IOD is developed and the main features are given. The second part is devoted to direct multiobjective optimization methods with a particular attention to the Hooke and Jeeves procedure and the Non-Dominated Sorting Genetic Algorithm (NSGA-II). The third part presents a simple example of IOD problem consisting in the optimization of motor drives for electric vehicle. Finally, the fourth part illustrates the comparison of the investigated optimization methods on this problem.

2 Integrated Optimal Design in Electrical Engineering

2.1 The Issue of Energetic System Design

The design of electrical energetic systems represents a societal challenge. The increasing demand in terms of energetic needs and efficiency requirements for energetic systems has to be fulfilled. Instead of current devices which are generally oversized in relation to their power needs, innovative systems should be now designed as accurately as possible to avoid energetic wastes. The difficulties related to the optimization of such systems are related to several features:

– these systems are characterized by a high level of complexity, being composed of multiple subsystems whose architecture and dimensioning have to be determined to reach optimal performance,
– these systems are strongly heterogeneous and multi-domain composed of elements of different physical nature (electric, mechanic, thermal) and multi-time scaled models. This leads the designer to raise the question of the level of representation for the system elements and the type of the corresponding models (analytical, numerical such as algebra-differential equations or finite element models…) in relation to a compromise associated with accuracy and computational costs.

Because of these main difficulties, the design process was generally simplified in the past using a sequential approach consisting in:

– finding the most suitable architecture for the system,
– optimizing element sizing,
– finding an optimal energy management strategy for the system.

However, couplings existing between these factors and their influence on global system efficiency require evolution toward a global optimization approach. We name this approach as Integrated Optimal Design (IOD) since it aims at concurrently optimizing in parallel, architecture, element sizing and energy management in a given system.

2.2 Electric Vehicle Example

Pure electric vehicles are typical examples of complex heterogeneous energetic systems. They are composed of several elements including the frame and the electrical traction device itself constituted by an energy supply (battery) and a static power converter which controls the electrical motor. Power is transferred to the wheel through a reducer and a mechanical transmission line. Note that the architecture of the electrical traction device can be more complicated in the case of hybrid vehicles and multi-motor solutions (i.e. one motor per wheel for example).

The electric vehicle designer is confronted with choices related to traction device architecture, element type and size (i.e. batteries, static converters, electrical motors). These choices are strongly coupled with geometrical and mechanical characteristics of the vehicle (i.e. mass and volume of the frame, drag coefficient) and to its capabilities to fulfill typical operating cycles (i.e. urban, road or highway cycles). This example is illustrated in Fig. 1.

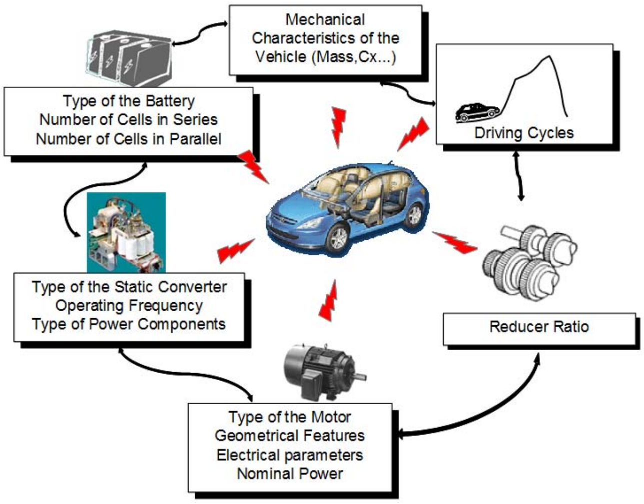

Fig. 1. Example of coupling elements in an electric vehicle

2.3 Integrated Optimal Design

IOD can be carried out thanks to global optimization techniques. The corresponding optimization problems resulting from this approach are rather complex and difficult. In particular, they are usually characterized by:

- an important number of design variables which can be discrete (e.g. the combinatorial parameters related to the system architecture or the type of the constitutive elements or materials) and/or continuous (typically, sizing parameters and energetic variables),
- multiple constraints intrinsic to each subsystems or related to the association compatibility between elements in the system,
- several objectives to optimize, typically energetic criteria (efficiency, consumption, losses), sizing factors (volume, mass) or economic costs.

Note that IOD leads to multiobjective optimization problems with mixed variables subject to several constraints.

3 Multiobjective Optimization Approaches

3.1 Multiobjective Optimization and Decision Making

Multiobjective optimization techniques aim to provide to the designer one or multiple Pareto-optimal solutions. They can be separated into three different classes [1], [2] in relation to the decision making process associated to the optimization procedure.

- *A priori approaches*: the Decision Maker combines the different objectives into a global quality function. Thus, the multiobjective problem is transformed into a standard scalar optimization problem which can be solved using traditional optimization methods. This approach includes aggregation based methods such as weighting-sum or fuzzy logic techniques, ε–constraint procedure and goal attainment method. Although they have been widely used in the past, *a priori* techniques suffer from various drawbacks. In particular, in one optimization run, they provide a single Pareto-optimal solution. Moreover, this solution is very sensitive to the scalarization of the objectives and the choice of decision parameters (e.g. weighting coefficients, target values) associated with the preferences of the Decision Maker.
- *Progressive and sequential approaches*: the optimization process and the Decision Making are intertwined. Preferences of the Decision maker are sequentially updated in function of the result of the optimization process. Note that *a priori* approaches can be iteratively used as progressive approaches as well as traditional techniques such as lexicographic method.
- *A posteriori approaches*: these approaches provide in a single optimization run a set of Pareto-optimal solutions to the Decision Maker who can choose among that set. They essentially include population based optimization methods such as Multiobjective Evolutionary Algorithms [2], [3], [4], [5], [6] or Multiobjective Particle Swarm Optimization techniques [7], [8], [9].

All these approaches require one or multiple optimization steps to obtain at least one Pareto-optimal solution. For that purpose, several minimization methods can be used (see Fig.2). However, for IOD problems, direct methods have to be preferred to avoid the hazardous computation of constraint and objective gradients in numerical models. Consequently, two different approaches have been investigated and compared as indicated in Fig.3.

3.2 The Hooke and Jeeves Procedure

The principle of Hooke and Jeeves algorithm [10] involves two successive steps :

- *exploration step* : From an initial parameter vector $\mathbf{X}_0$ (i.e. the *reference point* in the design variable space), the algorithm processes an exploration search, displacing each parameter one by one with an increment ($+\Delta_i$) while other parameters

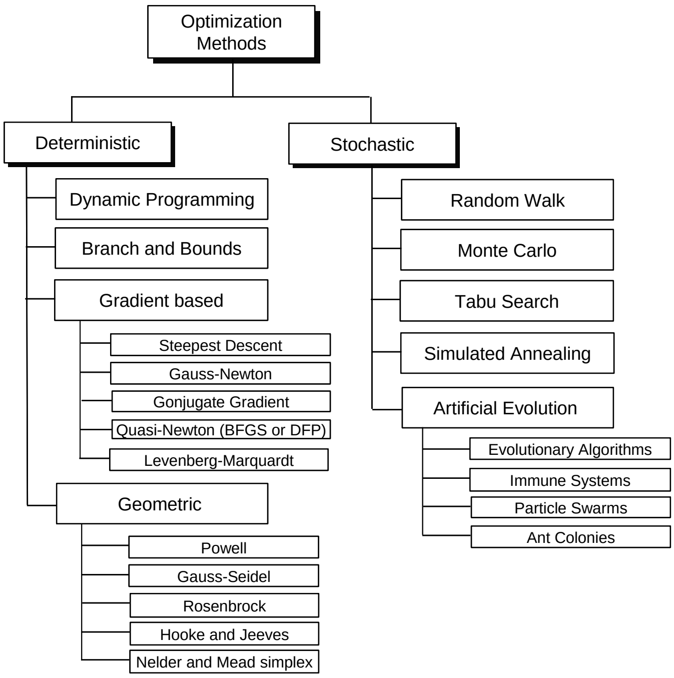

Fig. 2. Optimization Methods Classification

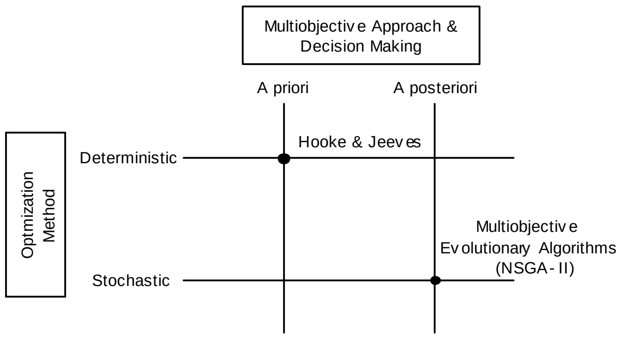

Fig. 3. Investigated Approaches

remain fixed. If the objective function is decreased the new value of the parameter is preserved. On the contrary, if the objective function is degraded, a negative increment ($-\Delta_i$) is proposed to move this parameter; if increments ($+\Delta_i$ and $-\Delta_i$) do not offer any improvement of the objective function, each parameter remains unchanged. At the end of the process, each component of the parameter vector has been moved at least one time and the objective function must be either decreased or unchanged. In this latter case, the process is reiterated with a smaller increment (typically $\Delta_i/2$).

- *extrapolation step* : when the exploration step is successful (i.e the objective function has been decreased by one positive or negative increment Δ_i) a new point $\mathbf{X}_e$ is obtained and used with the last reference point to define the new reference point as follows:

$$\mathbf{X}_0 \leftarrow 2\mathbf{X}_e - \mathbf{X}_0 \tag{1}$$

These steps are iterated until all increments Δ_i have reached a given accuracy set by the designer.

Note that this deterministic procedure is a local method which is usually used for single optimization. It can be applied on multiobjective problems by means of an aggregative approach (typically objective weighted sum).

3.3 The Non-Dominating Sorting Genetic Algorithm

Elitist Mutiobjective Genetic Algorithms (MOGAs) based on Pareto approaches have become more and more popular because of their capabilities to approximate the set of optimal trade-offs in a single run [3], [4], [5], [6]. Among all algorithms of this class, the second version of the Non-dominated Sorting Genetic Algorithm (NSGA-II) has become a solid reference. NSGA-II determines all successive fronts in the population (the best front corresponding to the non-dominated set). Moreover, a *crowding distance* is used to estimate the density of solutions surrounding each individual on a given front. In a tournament, if individuals belong to the same front, the selected one is that with the greater crowding distance. This niching index is also used in the clustering operator to uniformly distribute the individuals on the Pareto front. More details about the implementation of the algorithm can be found in [4].

4 Integrated Optimal Design of Pure Electric Vehicles

The synoptic of the traction device for the electric vehicle is described in Fig. 4. The design variables associated with each part of system are defined in Table 1. The traction device should be optimized in order to minimize the total energetic losses and the vehicle mass.

Table 1. Design variables characteristics

Design Variables	Range
Battery Voltage	$E \in [20, 500]$ [V]
Filter Inductance	$L_f \in [10^{-5}, 0.005]$ [H]
Filter Capacitor	$C_f \in [10^{-4}, 0.003]$ [F]
Converter Switching Frequency	$f_{switch} \in [500, 10\ 000]$ [Hz]
Motor Core Radius	$r \in [0.05, 0.2]$ [m]
Motor Length	$l \in [0.05, 0.4]$ [m]

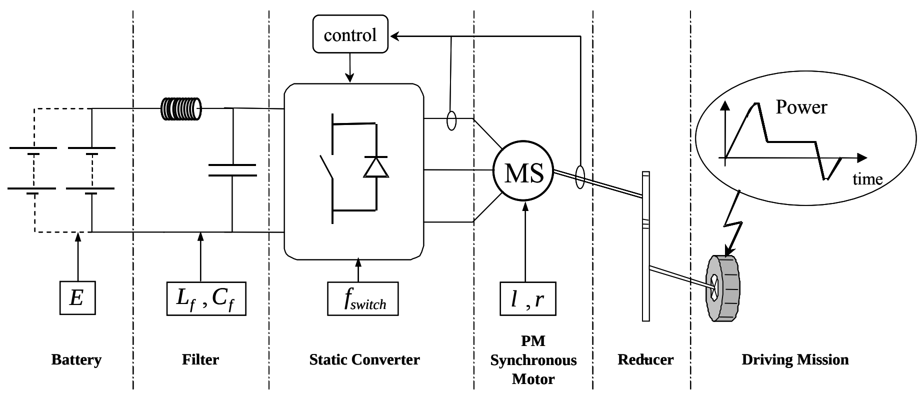

Fig. 4. Synoptic of the electric vehicle model

We will not detail the entire model of the vehicle which is rather complex and specifically belongs to the field of electrical engineering. The reader can refer to earlier publications for a complete description [11], [12], [13], [14]. However, we briefly mention in the following some of its features.

4.1 The Electric vehicle model

The driving mission. An urban mission has been chosen to optimize this system (see Fig. 5). The wheel speed reference corresponds to a vehicle speed of 50 km/h. This elementary cycle has to be 90 times repeated to ensure 1 hour of autonomy, which corresponds to a minimum embedded energy of 15 kWh.

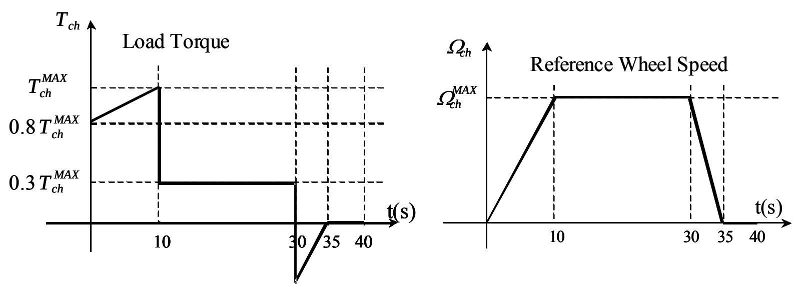

Fig. 5. Characteristics of the urban mission

The battery. Being the most commonly used in electric vehicles, a pack of 160 Ah lead acid battery is considered and its corresponding characteristics are given in Fig. 6. One simplification hypothesis deals with the internal resistance which can be considered as constant if the discharge depth is limited to 75%. Based on the vehicle autonomy requirement, 20 kWh of energy involves a minimum of 57 elementary cells.

Given that an integer number of cells must be placed in a serial/parallel architecture, a variable DC voltage causes a non-linear variation of the cell number. Joule losses in the battery can be deduced from the simulating model and the battery mass is evaluated from the mass of an elementary cell and the total number of cells.

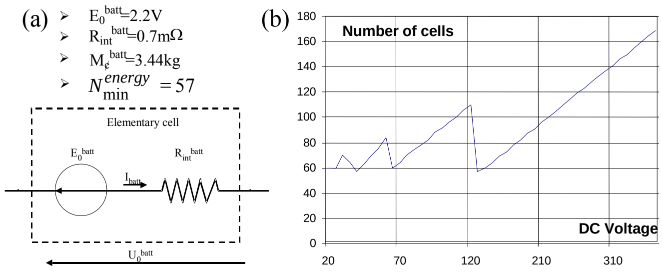

Fig. 6. Characteristics of the battery cells

The input filter. The input filter aims at reducing current ripples provided by the Voltage Source Inverter (VSI) which controls the electrical motor. If the conventional circuit model of the filter is rather simple, the sizing of its elements is complex when variable switching frequency, DC voltage and current have to be automatically handled during the optimization process. On one hand, a constraint on the natural frequency of the filter in relation to the VSI switching frequency must be fulfilled to avoid the instability of the system. On the other hand, two additional constraints must be introduced to provide a minimum voltage ripple on the filter capacitor as well as a minimum current ripple in the filter inductance. The input filter losses and its mass are neglected.

The static converter. The static converter is a classical VSI which controls a permanent magnet synchronous motor with trapezoidal electromotive forces. This kind of motor is largely used in traction applications due to its simplicity and its efficiency. In such a structure 120° rectangular currents must be imposed by the control unit. An average model of the converter is considered to reduce the computation time and a classical cascade speed-current control is implemented to provide motor torque and speed references required by the circulation cycle. Note that four technological constraints are related to the VSI and its control dynamics. Switching and conduction losses in the VSI are estimated with reference to data sheets associated to the power semiconductors. Note that the switch class is changed in relation to the DC current/voltage evolution during the IOD process. The inverter mass is neglected.

The permanent magnet synchronous motor. A sizing model of the permanent magnet synchronous motor associated with its reducer allows us to characterize the electro-mechanical behavior of the vehicle. It is defined in relation to three design variables (i.e. the motor length, the stator core radius, and the electrical voltage). The mass of the motor is evaluated from its geometrical characteristics and from the mass density of its elements (copper, iron and magnet). Joule losses are computed during the simulation of the vehicle on its course from the motor current and an additional model estimates iron losses from the motor frequency and the maximum motor flux density. Note that a thermal model of the motor is used to assess the temperature on the copper windings. This temperature must be lower than 150°C.

The vehicle dynamic. A mechanical model simulates the efforts imposed on the vehicle (i.e. vehicle weight, drag force, acceleration force) and provides torque and speed references to the electrical motor drive during the circulation cycle. Note that mechanical losses are deduced from this model.

4.2 The global design objectives and the constraint handling strategies

Two objectives have to be considered in the IOD process:

– the total losses in the vehicle during its course including Joule losses in the battery, switching and conduction losses in the VSI, iron and Joule losses in the permanent magnet motor and mechanical losses,
– the vehicle mass including a frame mass of 650 kg, the battery and motor masses.

Moreover, *twenty* constraints must be fulfilled to ensure feasible solutions. *Twelve* are related to design variables bounds, *three* concern the input filter (limitation of current and voltage ripple, compatibility of the filter natural frequency with the VSI switching frequency), *four* are associated with the control dynamics and the VSI voltage limitation, the last one depending on the maximum temperature of the copper windings in the motor. A strategy for each investigated optimization approach has been used to take these constraints into account. The HJ procedure employs for all constraints a classical exterior penalty method with fixed penalty coefficients. In the NSGA-II, constraints related to design variable bounds are implicitly fulfilled by the initialization process and the use of crossover and mutation operators which set the design variables in their nearest bound in case of violation. The other constraints are integrated by modifying the Pareto-dominance rule (see [14], [16] for more details).

5 Comparative Results

Pareto-optimal configurations for electric vehicles are determined with the HJ procedure and with the NSGA-II in association with a self-adapting recombination scheme [15]. The single objective function used in the HJ procedure is defined as the weighted sum of the two objectives. The weighting coefficients associated with the total loss objective and the vehicle mass are respectively ω_{loss} and ω_{mass}. Fourteen minimization runs are carried out with the HJ procedure using different weighting coefficients and the same feasible initial configuration for the vehicle. Note that boundary solutions of the front (run 1 and run 14 in Table 2) are first determined to normalize in the following runs mass and loss objectives by the corresponding maximum deviation. The number of objective function evaluations (n_{eval}) required in each run to reach the optimum is given in Table 2. The total number of objective function evaluations to obtain 14 Pareto-optimal solutions is about 18 000.

Table 2. Set of optimization runs for the HJ procedure

Run	1	2	3	4	5	6	7	8	9	10	11	12	13	14
ω_{mass}	0.0	0.03	0.06	0.1	0.15	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
ω_{loss}	1.0	0.97	0.94	0.9	0.85	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1	0.0
n_{eval}	1297	1281	1257	1345	1301	1352	1317	1340	1218	1276	1216	1239	1337	1386

The stochastic nature of the evolutionary algorithm requires performing the same optimization problem several times to assess the reproducibility of the results. For one optimization run, the number of objective function evaluations must be shared among the individual number (N_{ind}) and the generation number (N_{gen}). Consequently, the total number of objective function evaluations for N_{test} independent runs is $N_{test}\times N_{ind}\times N_{gen}$. Thus, the tuning parameters of Table 3 have been selected for the NSGA-II leading to 17 500 objective function evaluations for a fair comparison with the HJ procedure.

Table 3. NSGA-II tuning parameters

Number of independent runs (N_{test})	5
Population size (N_{ind})	50
Generation number (N_{gen})	70
Mutation rate for *m* design variables	1/*m*
Mutation rate for the crossover *X*-gene (see [15])	5%

Fig. 7 shows that both methods converge to the same Pareto-optimal front. Note that the NSGA-II Pareto-front plotted in this figure corresponds to a concatenation of the five Pareto-fronts obtained from the five independent runs. However, these runs have provided similar results. Therefore, NSGA-II requires 50×70=3500 objective function evaluations to obtain fifteen Pareto-optimal solutions on this design problem. With the same number of objective function evaluations, the HJ procedure only offers two Pareto-optimal solutions. This confirms the greater exploration capability of the MOGAs in comparison with local optimization methods.

The efficiency in the determination of the boundary solutions was almost equivalent with both investigated methods since the minimum loss solution has been found by the NSGA-II while the HJ procedure has detected the minimum mass solution.

The performance of both optimization methods was also characterized by two quantitative criteria. The Δ spacing factor used in [4], [14] has been evaluated in each case to assess the quality in terms of distribution homogeneity along the Pareto-optimal front. This criterion is based on consecutive distances among the solutions of the Pareto-optimal front. It characterizes the capability of the optimization method to distribute its solutions uniformly along the Pareto-optimal front. A value of zero for this metric indicates all non-dominated solutions found are equally spaced. Concerning the solution accuracy, the coverage index used in [3] was considered to compare NSGA-II and HJ efficiency.

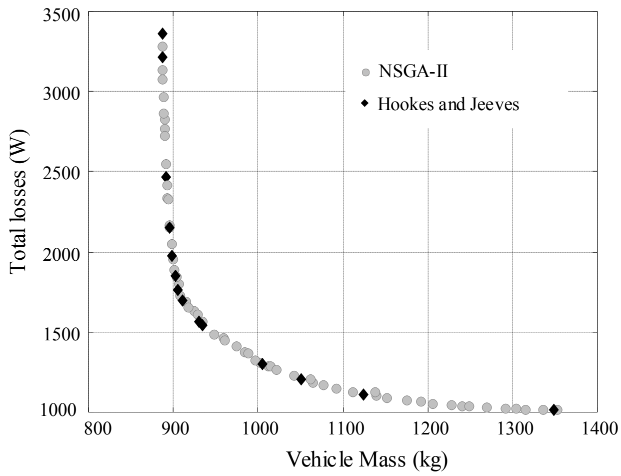

Fig. 7. Pareto-optimal solutions compared

The comparative results for both performance criteria are summarized in table 4. They show that NSGA-II ensures a better spread of Pareto-optimal solutions along the Pareto-optimal front thanks to the efficiency of its clustering operator. On the contrary, HJ procedure is characterized by a bad spread as a reason of a non-linear relation between weighting coefficients and Pareto-optimal solution distribution. Low coverage indexes indicate that NSGA-II and HJ fronts are non-covered. Most solutions found by the two different approaches are non-dominated. Consequently, the accuracy in the determination of Pareto-optimal solutions on this IOD problem was almost similar.

Table 4. Performance criteria compared

Performance criterion	NSGA-II	HJ
Spacing Δ	0.744	1.219
Coverage index (see [3])	*C*(NSGA-II/HJ) = 0.07	*C*(HJ/NSGA-II) = 0.08

6 Conclusion

In this paper, the Non-dominated Sorting Genetic algorithm and the Hooke and Jeeves procedure have been applied for solving IOD Problems. Both methods have been investigated on a simplified but typical IOD problem which consists in determining optimal configurations of motor drives for pure electric vehicles. The performance of each approach has been analyzed in terms of convergence, accuracy and diversity. With the same number of objective function evaluations, results have shown the NSGA-II superiority concerning the exploration capability and its tendency to find well spread Pareto-optimal solutions. Moreover, the NSGA-II accuracy was comparable with the well-known efficiency of the HJ deterministic procedure.

References

1. Hwang C.L. and Masud A.S.: Multiple Objective Decision Making – Methods and Applications, Heidelberg, Germany: Springer-Verlag (1979)
2. Van Veldhuizen D.A.: Multiobjective evolutionary algorithms: classifications, analyses, and new innovations. PhD Dissertation, Graduate School of Engineering, Air Force institute of Technology, Wright Patterson AFB (1999)
3. Zitzler E.: Evolutionary Algorithms for Multiobjective Optimization: Methods and Applications. PhD thesis, Swiss Federal Institute of Technology (ETH), Zurich, Switzerland (1999)
4. Deb K, Agrawal S., Pratab A., Meyarivan T.: A fast-elitist non-dominated sorting genetic algorithm for multiobjective optimization: NSGA-II. Proceeding of the Parallel Problem Solving from Nature VI Conference (2000) 849–858
5. Corne D.W, Knowles J.D., Oates M.J.: The Pareto Envelope-based Selection Algorithm for Multiobjective Optimization. In M. Schoenauer, K. Deb, G. Rudolph, X. Yao, E. Lutton, J.J. Merelo and H.P. Schwefel eds., Proceedings of the Parallel Problem Solving from Nature VI Conference, Springer (2000) 839–848
6. Zitzler E., Laumanns M., Thiele L.: SPEA2: Improving the Strength Pareto Evolutionary Algorithm. In K. Giannakoglou, D. Tsahalis, J. Periaux, P. Papailou and T. Fogarty (eds.) EUROGEN 2001, Evolutionary Methods for Design, Optimization and Control with Applications to Industrial Problems, Athens, Greece, September (2001) 12–21
7. Coello Coello C.A., Salazar Lechuga M.: MOPSO: A Proposal for Multiple Objective Particle Swarm Optimization. Congress on Evolutionary Computation (CEC'2002), Vol. 2, IEEE Service Center, Piscataway, New Jersey (2002) 1051-1056
8. Li X.: A Non-dominated Sorting Particle Swarm Optimizer for Multiobjective Optimization. In Erick Cantú-Paz et al. (editors), Genetic and Evolutionary Computation – GECCO 2003. Proceedings, Part I, Springer, Lecture Notes in Computer Science, Vol. 2723 (2003) 37-48
9. Mostaghim S., Teich J.: Strategies for Finding Good Local Guides in Multi-objective Particle Swarm Optimization (MOPSO). In 2003 IEEE Swarm Intelligence Symposium Proceedings, IEEE Service Center, Indianapolis, Indiana, USA (2003) 26-33
10. Hooke R., Jeeves J.: Direct Search Solution of Numerical and Statistical Problems. Journal of the ACM, Vol. 8, (1961) 212-229
11. Fefermann Y. : Optimisation directe de systèmes hétérogènes en Génie Electrique. PHD thesis of INP Toulouse, France (2002)
12. Fefermann Y., Roboam Y., Enjalbert J.M.: Direct optimization of Motor Drives systems for an electric vehicle. IEEE ISIE'04 Conference, Ajaccio, France (2004)
13. Fefermann Y., Randi S.A., Astier S., Roboam X.: Synthesis models of PM Brushless Motors for the design of complex and heterogeneous system. EPE'01 Conference, Graz, Austria, September (2001)
14. Régnier J.: Conception de systèmes hétérogènes en génie électrique par optimisation évolutionnaire multicritère. PHD thesis of INP Toulouse, n°2066, France (2003)
15. Sareni B., Régnier J., Roboam X.: Recombination and Self-Adaptation in Multi-objective Genetic Algorithms. Artificial Evolution: 6th International Conference, EA 2003, Marseilles, France, October 27-30, 2003. Revised Selected Papers Editors: Pierre Liardet, Pierre Collet, Cyril Fonlupt, et al., Lecture Notes in Computer Science Publisher, Springer-Verlag, Vol. 2936, (2004) 115-126

16 Régnier J., Sareni B., Roboam X., Astier S.: Optimal design of engineering systems using Pareto Genetic algorithms, 10th International Conference on Power Electronics and Applications (EPE'2003), Toulouse, France (2003)