Chapter 15
Memetic Algorithms in Engineering and Design

Andrea Caponio and Ferrante Neri

15.1 Introduction

When dealing with real-world applications, one often faces non-linear and non-differentiable optimization problems which do not allow the employment of exact methods. In addition, as highlighted in [104], popular local search methods (e.g. Hooke-Jeeves, Nelder Mead and Rosenbrock) can be ill-suited when the real-world problem is characterized by a complex and highly multi-modal fitness landscape since they tend to converge to local optima. In these situations, population based meta-heuristics can be a reasonable choice, since they have a good potential in detecting high quality solutions. For these reasons, meta-heuristics, such as Genetic Algorithms (GAs), Evolution Strategy (ES), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Differential Evolution (DE), have been extensively applied in engineering and design problems.

On the other hand, population-based meta-heuristics do not guarantee detection of the global optimum and they might either prematurely converge to solutions with a poor performance or stagnate without successfully improving upon the current best solutions. In order to overcome these problems and as a consequence of the No Free Lunch Theorem [940], engineers realized that real-world problems can be efficiently solved by means of an ad-hoc combination of algorithms. This fact led to an employment in recent years of Memetic Algorithms (MAs). As a matter of fact, MAs, if properly designed and implemented, can be a valid alternative to classical meta-heuristics in engineering and design. In some cases, MAs can lead to results which are orders of magnitude more accurate and efficient than other popular optimizers.

Andrea Caponio
Technical University of Bari, Via E. Orabona 5, 70121 Bari, Italy
e-mail: caponio@deemail.poliba.it

Ferrante Neri
University of Jyväskylä, P.O. Box 35 (Agora), 40014, University of Jyväskylä, Finland
e-mail: ferrante.neri@jyu.fi

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This chapter aims to summarize the main results in the topic of MAs successfully applied to engineering and design. Although not exhaustive, the proposed survey is supposed to give some indications about the main trends and some suggestions about the future of MAs in engineering.

This chapter is structured in the following way. Section 15.2 presents a survey on applications of MAs for real-world problems. In particular, Subsection 15.2.1 focuses on single-objective optimization problems while Subsection 15.2.2 deals with multi-objective optimization problems. Regarding single-objective, a survey on MAs in image processing is given in Subsection 15.2.1.1, in telecommunications in Subsection 15.2.1.2, in electrical and electronic engineering in Subsection 15.2.1.3, and in other fields in Subsection 15.2.1.4. Regarding multi-objective optimization, a survey on MAs in hardware design is presented in Subsection 15.2.2.1, in electrical and electronic engineering in Subsection 15.2.2.2, and in image processing and telecommunications in Subsection 15.2.2.3. Section 15.3 presents a case of study: an ad-hoc MA applied to a specific control engineering problem. Finally, Section 15.4 gives the conclusions of this work and attempts to foresee the future trends in the field.

15.2 Applications of MAs in Engineering Problems

In engineering and applied science, many decision making problems need to meet several objectives: minimize risk, maximize reliability, minimize errors or deviations from desired levels, minimize costs, and so on. The solution to these problems can be found through a single-objective or a multi-objective method: each of these approaches presents different advantages and drawbacks. Whichever of them we follow, when designing MAs, other important questions to answer are which local searchers should be employed and how they should be effectively hybridized within the evolutionary framework and in relation to each other, as highlighted in [489]. Of particular interest are the guidelines that lead to the execution and the coordination of the local searcher(s) in MAs. Some algorithms bluntly apply them to each point generated by the evolutionary framework, resulting in a very thorough search for the optimum, which, on the other hand, can also be extremely slow to converge. Some other algorithms follow instead one or more rules to choose when to launch a local searcher, possibly which one to run, and which individuals should it try to improve on: this logic leads to a less exhaustive, but generally quite faster, optimization.

In this section, we analyze various algorithmic solutions and strategies in Memetic Computing for facing engineering problems. In Subsection 15.2.1, we focus on MAs for single-objective optimization while in Subsection 15.2.2 we focus on MAs for multi-objective engineering problems.

15.2.1 Engineering Applications in Single-Objective Optimization

In single-objective optimization for real-world problems, we search for a solution corresponding to the minimum (or to the maximum) value of a single objective function. Although in real-world situations most of the problems are actually multi-objective, the problems can still be considered single-objective by constructing a fitness function that usually comprehends several different objectives into one. This means establishing an a-priori ranking of importance of the various objectives and implicitly accepting a compromise among them. For example, the scalarized approach, see [599], is a diffuse technique to aggregate various objectives: a weight factor is linked to each objective on the basis of its importance and the weighted sum is optimized. This is a very practical method that leads to a faster optimization process, while implicitly accepting that a ranking of the importance of each objective with respect to the others is already known, thus excluding some solutions that might still be interesting.

In the past years, several different single-objective meta-heuristics were developed and successfully applied to real-world problems. For instance, GAs [325], ES [354], PSO [458], and DE [787], were already widely used in real-world situations, showing extremely good performance. Furthermore, single-objective optimization becomes a mandatory choice when the time available to find a solution is limited, which often happens when dealing with real-time applications. For these reasons, single-objective MAs have been more popular than multi-objective MAs in the past and the greater part of the algorithms proposed in the literature are meant for single-objective optimization.

15.2.1.1 Memetic Algorithms in Image Processing

Many problems in image processing and analysis can be treated as optimization issues: feature extraction and recognition, filtering, image registration, and reconstruction are all situations in which, among a huge set of alternatives, we have to find the one that best solves the problem at hand.

In [888], the Memetic Differential Evolution (MDE), a hybridization of DE with the Hooke-Jeeves Algorithm (HJA) and a Stocastic Local Searcher (SLS), is proposed to design digital visual filters for flaw detection on a roll of paper produced in an industrial process. The two local search algorithms are coordinated by a rule that estimates the fitness diversity among the individuals in the current population. An improvement to this algorithm, namely Enhanced Memetic Differential Evolution (EMDE), that hybridizes the DE framework with Simulated Annealing (SA), SLS and HJA, is proposed in [889]. Particularly interesting is the rule used to coordinate the local search: every 1000 DE fitness evaluations, a measure of the fitness diversity and of the fitness values distribution within the population is computed. Then, according to a probabilistic scheme, one or more local search algorithms are run on selected individuals. In this way, according to the progress of the optimization process, the local search algorithms and the individuals selected are likely to give the best results. The performance offered by EMDE outrun those given by GA, ES, SA, DE and MDE.

In [258] a single solution population MA for the correction of illumination inhomogeneities in images is presented. In this case, the local search algorithm makes use of the gradient of the objective function. The algorithm is compared with ES, and the results show that a memetic approach is promising indeed for the problem under study.

Article [51] deals with discrete tomography reconstruction (DT), a highly multimodal problem which cannot be properly solved through standard hill-climber algorithms. On the other hand, standard GAs are also not adequate for the DT reconstruction, since they are not originally designed to work with binary matrices. A new evolutionary approach, with crossover and mutation operators designed to handle binary images, is then proposed. In addition, a stochastic hill climb method is applied to each new solution, so that during each stage of the search, all individuals represent a local optimum in the search space. This MA offers good results for several different reconstruction problems, but the thoroughness of the local search algorithm considerably slows down the optimization process, limiting its applicability to images of size 50×50 or less.

In [211], new crossover and mutation operators are designed, and a switch operator and a compactness constraint are applied to the same problem. The resulting algorithm is much more greedy than the one in [51], and is able to process 100×100 binary images in reasonable time, but compatibility between the solutions found and the inputs is not assured.

In [789], Santamaria et al. investigate the effectiveness of MAs for the construction of a 3D model of forensic objects through image registration. Several MAs, based on CHC (which stands for Cross generational elitist selection, Heterogeneous Recombination and cataclysmic mutation), DE and Scatter Search, are compared. The Powell's method, the Solis & Wets method and the crossover-based local search method are used as local search methods. These local search algorithms are integrated into the evolutionary framework by means of two different laws: in one case the local search is applied to random selected individuals, in the other case it is applied to all those offsprings which outperform their own parents. Moreover, this study highlights the importance of a proper memetic design in order to obtain high quality performance in the image registration problem.

Article [564] deals with the problem of image registration for inspection of printed circuit boards arbitrarily placed on a conveyor belt. The GA framework is hybridized with a hill-climb procedure which is applied on every individual which manages to remain the fittest for a predefined number of iterations.

In [498], Kumar et al. apply MAs to feature selection in face recognition, showing that their approach considerably outperforms the most famous *Eigenface* method.

Ali and Topchy, in [9], use a memetic approach to solve the Video Chain Optimization problem. Three different MAs are obtained by hybridizing the GA with three different local searchers: the Next-Ascent Stochastic Hill-Climbing, the NMA and the Estimation Distribution algorithm. The goal of the optimization process is to find the optimum combination of parameter settings, implementation alternatives, and interconnection schemes of several image processing algorithms, in order to deliver the best final picture quality.

In [960] a combination of the ACO and GA with simplex is presented for the problem of setting up a learning model for the "tuned" mask in texture classification: the initial candidate masks are generated by means of the GA with simplex and the

ACO is then used to search the optimal mask. New solutions are created by GA operators.

Article [670] applies the MA proposed in [355], a GA enclosing a SA-like selection scheme, to train a morphological neural network used for image reconstruction problems. The proposed method outperforms the standard training techniques in terms of quality of the reconstructed images.

15.2.1.2 Memetic Algorithms in Telecommunications

Many situations which have to be solved through optimization procedures can also be found in telecommunications. Article [810] deals with signal processing and the problem of blind signal separation, i.e. how to separate a signal from the noise that affects it. The MA described combines a standard GA with a neighborhood local search which is applied to all the new individuals generated by GA. The results encourage the use of MAs for this kind of problem.

In [814], a MA is used to solve the Routing and Wavelength Assignment problem, an NP-complete graph-theoretical problem related to optical networks. The proposed algorithm hybridizes two different heuristics, developed for this specific case, and a GA with application-specific mutation and crossover operators. The probabilities that each of these operators are applied to an individual follow a credit-assignment rule. A more recent study for the same problem is shown in [262], where two MAs are proposed. The first one, using fixed probabilities to apply recombination or mutation, runs the local search on each new solution, pursuing a steady state logic for the survival selection. The second MA proposed is a distributed version of the first one on a network of optimization processes, and allows the exchange of individuals regularly by means of an epidemic algorithm.

In [747], a MA is developed to assign cells to switches in cellular mobile networks: each new individual, generated through recombination or mutation, undergoes a tabu search algorithm. In [748], a multi-population memetic approach is presented for the same problem. Article [749] combines a multi-population compact GA with the tabu search which is applied to each newly generated individual: the proposed MA is able to find a feasible solution and to outperform two comparison optimization algorithms.

Article [441] deals with location area management, another important problem in mobile networks: after introducing an evolutionary approach and a multi-population GA, the paper proposes a MA in which the local search is used to generate the initial population and as the mutation operator.

Paper [785] proposes two hybrid approaches combining a Hopfield Neural Network, used as local search, and GAs, to solve the terminal assignment problem, which involves determining minimum cost links to form a communications network. The first algorithm uses a binary-coded GA following an elitist strategy to transmit the highest fitness individual to the next generation. Each new individual undergoes the local search and the result of the neural algorithm replaces it in the new population. The second algorithm is an integer coded version of the first one.

In [464], Kim at al. propose a novel encoding in a MA to solve the channel assignment problem in frequency division multiple-access wireless communications systems. At first, the GA is applied, and if it fails to significantly improve on the solutions for a pre-defined number of generations, the local searcher is executed on a random individual; similarly, after the local searcher is executed without any improvement for a fixed number of iterations, the GA is invoked again. Crossover and mutation operators are designed in relation to the encoding proposed for the problem under examination.

A GA-based MA for dynamic design of wireless networks is described in [257], while in [786], a MA is used to develop an efficient centralized clustering algorithm for wireless sensor networks: the proposed algorithm mixes a GA with a local searcher which is performed on each new individual.

Neri et al. implemented in [656] the Adaptive Global Local Memetic Algorithm to train a neural network used to solve the resource discovery problem in Peer to Peer networks. Training of neural networks in this context is challenging due to the large number of weights and the (great) amount of noise in the dynamic testing environment. The local searchers used in this algorithm are SA and HJA, and the coordination is done through a parameter, namely ψ, which measures the population diversity and is specially designed for flat fitness landscapes. ψ is also used to control the size of the population which is adaptively adjusted during the optimization process.

In [180], a hybridization of DE and SA, namely Annealed DE (AnDE) is used to solve the spread spectrum radar poly-phase code design problem: the AnDE is fundamentally a DE in which the worst offspring can survive according to a decreasing probability rule inspired by SA.

Article [208] presents a MA integrating ACO and SA to design reliable communication networks: specifically, the SA obtains a seed network topology to initialize the pheromone trails, while the ACO searches for the best network solution using the trails which are continuously updated during the search.

In [480] a GA in which the mutation operator is replaced by the Cut Saturation Algorithm is applied to the problem of optimal backbone design of communication networks.

Article [899] proposes four memetic approaches for frequency modulation sound parameter identification: the GA and the Queen-Bee (QB) algorithm are combined with the random optimization method, while the PSO and DE algorithm are combined with the NMA. Results show that the memetic versions of GA, QB, PSO, and DE outperform their counterparts.

Alabau et al. present a MA for the problem of radio frequency assignment in [7, 8]. In this study the authors exploit an integer coded GA, with two crossover and two mutation operators developed for the problem under study; specifically the first mutation operator uses a greedy algorithm to decide which gene to change in order to obtain the best possible result, while the second mutation operator is based on the tabu search algorithm. Furthermore, the initial population is also generated by means of a greedy algorithm.

In [901], three MAs, differing in the way the heuristic search is applied, are compared for traffic engineering in an Internet Protocol version 6 (IPv6) domain by means of routing optimization.

Article [886] proposes a serialization of GA and SA applied to broadband matching network design for antennas, while in [517] the effectiveness of the subsequent application of GA and a direct search method is investigated for the synthesis of shape-beam array antennas.

In [174] the frequency assignment problem for a GSM network is faced with a MA combining a DE with a penalty assignment strategy for unfeasible solutions, and a local searcher, designed for the problem under study, which is applied to newly generated individuals. Results show that the proposed modifications considerably improve on performance of standard DE for this kind of problems.

15.2.1.3 Memetic Algorithms in Electrical and Electronic Engineering

Evolutionary techniques have been widely employed in electric and electronic engineering in order to solve optimization problems. Lately, MAs have also been applied in the field. Leskinen et al. study the performance of two kinds of MAs on the Electrical Impedance Tomography (EIT) problem in [513]. This paper proposes a comparison of five EAs, two of which are novel MAs employing a self-adaptive DE scheme: in one of them the local search is performed on the scale factor used by DE during the optimization, while in the other it is performed on the generated individual. Results show that the MAs are more promising when the geometrical configuration makes the problem harder to solve, i.e. for more difficult optimization problems.

In [900] a hybrid GA is used for the large Unit Commitment Problem (UCP) in electric power systems, a very complex mixed combinatorial and continuous constrained optimization problem. The proposed algorithm hybridizes a binary coded GA with a modified Lamarckian local searcher.

In [874] a MA based on a GA framework is proposed for performing very large scale integrated-circuit (VLSI) automatic design. The genetic operators are used only for exploration purposes, while exploitation of the promising regions is performed by the local search algorithms. Novel crossover and mutation schemes are proposed for the VLSI design problem. The local search algorithms are applied only to promising points, i.e. points whose fitness is performing above a predetermined threshold value.

Carrano et al., in [108], solve the problem of power distribution system design under load evolution uncertainties with an immune inspired MA. The algorithm presented is a Clonal Selection Algorithm hybridized with a local search algorithm explicitly designed for networks, namely the Network Local Search. This local search is used to improve each local optimum previously detected during the search.

Article [219] presents a MA based on Evolutionary Programming (EP) and SA for the tuning of the proportional-derivative (PD) and proportional-integral-derivative (PID) multi-loop controllers for a two-degree-of-freedom robot manipulator. After each generation of EP, the SA is run on all individuals in the new population so that only the local optima take part in the search. Similarly, in [812] a MA made up of an integer-coded GA and a hill-climb algorithm is used to tune a PID controller for a servo-motor system.

Caponio et al., in [106], propose the Super Fit Memetic Differential Evolution (SFMDE) which hybridizes two different evolutionary approaches and two different local searchers. At first, a PSO algorithm is run to generate some solutions with a high performance. These solutions are then integrated within a population of an evolutionary framework. This evolutionary framework employs the structure of a DE and employs two additional local search algorithms: a Rosenbrock algorithm and the NMA. Both local search algorithms are highly exploitative in comparison with the DE framework, but the Rosenbrock algorithm, being more "thorough", is more capable to finalize the optimization, while the NMA is more keen to further improve some fairly promising solutions. To coordinate the local searchers, a parameter called χ is calculated at the end of each DE generation: the value of χ measures the population diversity and the particular fitness value of the individual displaying the best performance with respect to the others. On the basis of this metric, the algorithm adaptively increases its exploitation pressure or attempts at exploring new search directions. The viability of the SFMDE is proved through some test problems and two real-world problems: the design of a proportional-integral (PI) speed controller of a direct current electric motor, and the design of digital filters for defect detection in paper production (see [888, 889]). A similar real-world problem is addressed in [104] and summarized in greater details in Section 15.3.

In [105] the performance obtained by three mate-heuristics (DE, GA, PSO) and three MAs (MDE, FAMA, SFMDE [104, 105, 888]) is compared in order to optimally design a permanent magnet synchronous motor (PMSM) control system, realized with a Proportional-Integral (PI) scheme. This study shows that a DE-based MA can be successful for this kind of problem; in particular, SFMDE offers the best average performance on the problem examined.

Article [349] compares the results obtained by a MA, a MA with population management, and a real valued GA, in the design of a supplementary controller for high-voltage direct current links to damp oscillations in a power system. Results show that both MAs offer better solutions to the problem than the GA, but the MA with population management has better convergence characteristics.

Hazrati et al. use a MA for pricing and allocation of spinning reserve and energy in restructured power systems in [379]. The target of the optimization is to maximize the market benefits and to minimize the payments to energy and reserves. The proposed algorithm uses the SA to improve, after each generation, the best individual found by a GA framework.

In [945], a MA based on tabu search is proposed for the optimal coordination of power relays: the objective takes into account sensitivity, selectivity, reliability and speed of intervention. Results show that the proposed algorithm is fast and easily finds the optimal solution.

Articles [194, 746] implement a MA for loss reduction in power distribution systems under variable demands: the proposed algorithm optimizes the power distribution network in order to have less switch operations, which generally cause losses.

The MA is a GA, with a novel chromosome representation and crossover operators, hybridized with a local searcher, a variation of the branch-exchange procedure specific for this application, which is applied on the best solution every 50 generations.

In [921], a GA-based MA is presented for finding the optimal network structure and switching configuration in service restoration in power distribution networks. The proposed algorithm combines a two-stage GA previously applied to this kind of problem, with a local search procedure, a greedy algorithm, and an efficient maximum flow algorithm. The local search, a branch exchange algorithm, is run on all the feasible solutions after each GA iteration.

Crutchley and Zwolinski present in [173] a MA for direct current operating point analysis of non-linear circuits. In this case, a DE framework is supported by a Newton-Raphson solver which has the role of finalizing on the search and kicks in when the DE ceases to considerably improve the best solution.

In [175], a combination of GA and SA is used to compute the optimal scheduling of generator maintenance in power systems. According to a steady state logic, a new individual is always inserted in the next population when it outperforms its best parent; if this does not happen, then the probabilistic acceptance approach of the simple SA is used to decide whether or not the new solution should be included in the population.

Hidalgo et al. propose in [385] a hybrid approach for multi-FPGA (multiple Field Programmable Gate Array) system design: after a predetermined number of compact GA iterations, a local searcher tries to improve upon the best solution by randomly changing its genes.

Article [919] deals with the problem of fault diagnosis in a power transformer: in order to pursue this aim, a probabilistic neural network tuned by means of a combination of PSO and Back Propagation (BP) is used. The two algorithms are serialized so that when the PSO stops improving on the best solution, the BP algorithm is activated in order to find the global optimum.

In [23], a GA and a least square curve fitting method are combined to identify the parameters of some peculiar transistors (NMOS in this case). Also in this case the local searcher is run at the end of the optimization process, i.e. when the GA does not manage to improve on the best solution. Results show that this memetic approach outperforms a simple GA and other standard techniques used for this kind of problem. Article [943] also deals with the parameter identification of electronic devices (MOSFET).The voltage parameter identification is performed by means of a MA in which a hill-climb algorithm assists a GA in generating the first population and in performing mutation operation.

Tian et al. refers in [885] to the problem of circuit maximum power estimation. For this aim, a GA employing two problem-specific components, namely input sharing and bit climbing, has been designed.

Liu et al. optimize the design and the sizing of the power train components of hybrid electric vehicles by means of GAs combined with Sequential Quadratic Programming (SQP) in [529]. In this case the GA is run at first, and when the search slows down the SQP method is applied to 20% of individuals randomly selected among the population, and to the best individual.

In articles [101, 102], a combination of float coded GA and trust region algorithm is proposed for parameters identification of strain and dynamic hysteresis model for magnetostrictive actuators. In [340] a GA is alternated with an approximation based local searcher for the problem of optimal electromagnetic design: the SQP is used in this algorithm, and the velocity of the search is increased by using an approximated model for the local search procedure. The SQP is run cyclically after a predefined number of GA iterations.

In [403], a MA for electromagnetic topology optimization is proposed. A 2-dimensional encoding technique is introduced, along with the corresponding crossover and mutation operator. The GA is used as the main evolutionary algorithm, aided in its search by a novel on/off sensitivity method launched according to a probabilistic rule. The MA was applied to three real-world problems, proving to be a very promising optimization method in the field of electromagnetism.

Article [944] applies a GA/SA hybrid algorithm for the parameters identification of the flux linkage model for switched reluctance motors. Simulated and experimental results prove the accuracy of the model tuned by the proposed technique.

In [459] the acceptance criterion of the SA is used for chromosome selection in a binary GA. The resulting optimization algorithm is used to decide where to place measurement devices for power system state estimation.

Bui and Moon describe in [87] a MA mixing GA and a weak variation of the Fiduccia-Mattheyses algorithm, applied to each individual after crossover and mutation: this algorithm is used for partitioning electronic circuit hyper-graphs into two disjoint graphs of minimum ratio cut. The application of the proposed approach to several benchmark circuit graphs demonstrates its validity.

15.2.1.4 Other Engineering Applications of Memetic Algorithms

MAs were also applied in other fields of engineering, or for problems that do not specifically fit into the categories cited before. Article [854] proposes the use of two MAs to train a neural network for non linear system identification. The first MA is a hybrid between GA and BP, the second is a hybrid between DE and the same BP. In both cases BP is applied to each new individual generated by the evolutionary framework. The authors eventually show that the DE-BP algorithm outperforms the GA-BP and the other reference algorithms in this specific application.

In [261] a particular SA algorithm is developed for the Global Positioning System (GPS) surveying network problem. Since SA is a local searcher and has no evolutionary components, the authors speak of a *memetic SA* because they replace the canonical SA perturbation steps with an internal local search step.

Tagawa et al., in [868, 869], introduce a MA for the optimum design of surface acoustic wave filters: the Variable Neighborhood Search algorithm is applied as local searcher to each new solution and a distance-based mutation is proposed to keep diversity among the population.

Article [724] presents a memetic approach to the problem of smooth map identification in electronic control units for internal combustion engines. A simple local searcher is implemented as mutation operator in a GA framework, thus obtaining a memetic GA.

In [251] a MA incorporating two local optimization operators in a micro GA were used to solve a structural optimization problem. One local searcher is a direct search technique derived from the HJA; this algorithm is used at each generation to improve upon the offspring obtained by applying genetic operators to the population. When this algorithm gets stuck, the second local search algorithm, a hill climber, is applied to get the search out of this impasse. This approach is then applied to design a minimum weight 18-bar truss structure subject to node forces.

Article [877] presents a MA assisted by an adaptive topology Radial Basis Function (RBF) network and variable local models for airfoil shape optimization: after the evolutionary algorithm has been run, its solution is processed by a trust region approach.

Kim et al. present in [463] a MA which hybridizes a clustered GA with a neural network, local search, and random search for parameter identification of rolling element bearings. SQP is adopted as local search algorithm, and a novel random search technique is developed in order to find unexplored regions of the search space.

In [499], a hybrid between GA and tabu search is proposed to minimize production costs of thermal units: at each iteration, the tabu search is used to improve promising solutions, and the results show that the MA is fast and reliable for the problem considered.

Ong et al. propose a surrogated assisted MA for aerodynamic shape design in [679]. Alternating exact and approximated evaluation for aerodynamic performances of wing profiles, the proposed algorithm evolves the population by means of standard operators and applies to all new design points a local search strategy which implements a trust-region framework to interleave the exact and approximate models.

Article [38] provides a comparison of several evolutionary approaches to the problem of optimization of causal infinite impulse response filters with applications to perfect reconstruction quadrature mirror filter banks. Four approaches for this problem are studied. At first, a constrained genetic algorithm searches a promising valley in the fitness landscape, and then the suboptimal filter parameters obtained are further optimized using four different methods: a GA-based “creep code”, a gradient-based constrained SQP method, a Quasi-Newton method, and a non-gradient-based downhill Simplex method.

Burke et al. propose a memetic approach for the thermal generator maintenance scheduling problem in [95, 96]. More precisely, in [96], hybridizations of GA with tabu search, a basic hill-climber and a SA are compared for the problem under study, while in [95], the GA combined with tabu search is further modified to produce a multi-stage approach.

In [566], two different strategies are applied and compared for the problem of seismic image analysis. One of the MAs proposed applies the local searcher, a waveform steepest ascent, to each member of the population at every generation of GA. The second approach runs the local search to each individual after a predefined number of GA generations.

Tao, in [875], applies a MA to train a fuzzy neural network controller for a truck backer-upper. GA is chosen as the main evolutionary framework, and at each iteration, some individuals are processed by a BP algorithm while the remaining ones undergo standard genetic crossover and mutation.

In article [176], GAs are combined with a quasi-Newton method to solve the non-linear equation of a helicopter trim model. Zhang et al. in [958] try to solve the problem of inverse acceleration in robots with degrees-of-freedom less than six. The proposed approach makes use of a hybridization of a GA framework with a random search algorithm to avoid the calculation of the inverse Jacobian matrix and the second order influence coefficient matrix.

Article [972] applies a simple MA, made up of a GA and a local searcher applied to each newly generated individual, to the problem of spatial-temporal electroencephalogram dipole estimation, which is an ill-posed not fully determined inverse problem.

In article [693], a MA coupling an EA and a gradient search is designed for optimization of structures under dynamical load. In addition, an artificial neural network was used to control the parameters of the gradient-based algorithm.

15.2.2 Engineering Applications in Multi-Objective Optimization

While single-objective optimization techniques quickly provide a final unique solution, multi-objective algorithms give the chance to fully comprehend and model a problem, describing more thoroughly the connections between objectives and inputs. Multi-objective optimization eventually leads to a set of compromised solutions, known as the Pareto-optimal solution front, each of which minimizes (or maximizes) at least one objective, without simultaneously increasing (or decreasing) one or more of the others. The multi-objective approach is more thorough and usually requires more time, and, besides, once the final set is available, a decision making process is needed to select the most suitable solution. A comparative analysis between single-objective and multi-objective optimization can be found in [132].

Two important problems to solve in designing Multi-Objective Memetic Algorithms (MOMAs) are how to define a local search in a multi-objective environment, and how to optimally balance the global and the local search when dealing with simultaneous competing objectives [411]. In the following, special attention will be paid to how these problems were faced in real-world situations.

15.2.2.1 Memetic Algorithms in Hardware Design

During the design of some specific tools or hardware devices, one must satisfy many conflicting needs and one may be interested in understanding their mutual interactions. For this reason MOMAs have been widely applied to optimally plan hardware. One interesting application can be found in paper [196], where a MOMA is implemented to solve various problems of mechanical shape optimization. The study stresses the importance of a fast and good convergence and on the need to reach a final set of solutions well spread across the Pareto front. The proposed algorithm is realized by mixing a binary encoded NSGA-II [200] with a single objective local searcher, performing the weighted sum approach, which is applied to each non-dominated solution.

In [470], a multi-tiered MOMA for design of quantum cascade lasers is proposed. The evolutionary algorithm used by Kleeman et al. is the General Multi-Objective Parallel algorithm, while the local searcher used, applied after predefined generations throughout the entire process, is a multi-tiered neighborhood search, i.e. a neighborhood search algorithm which changes different alleles according to the number of generations done. The new non-dominated points returned by the local searcher are then reinserted in the population. Several strategies to apply the local search are implemented, and the results obtained are compared.

Article [835] describes the use of MOMAs in aerodynamic shape optimization through computational fluid dynamics. Song integrates within a NSGA-II framework a fitness sharing method in the design space, in addition to the fitness sharing in the objective space. The local searcher used is a single objective SA that tries to cyclically improve on each objective while treating the others as constraints. The SA is run on a certain number of points in the Pareto set: the more successful the previous local search step was, the more points will be selected.

Wang et al. in [917, 918, 919, 920] apply different MOMAs to the optimization of structures under load uncertainties. In all cases the proposed algorithm is a hybridization of multi-objective GA with HJA, but while in [917] the HJA is used as a standard local searcher applied to each solution generated by mutation operator, in [918, 919, 920] it is integrated as a worst-case scenario technique of anti-optimization, leaving to the evolutionary framework the duty to solve the multi-objective optimization. The algorithm presented in [917], is also applied in [871] to the automatic design of a compliant grip-and-move manipulator by topology and shape optimization.

15.2.2.2 Memetic Algorithms in Electric and Electronic Engineering

Electric and electronic engineering problems have also been intensely studied through multi-objective optimization techniques. Article [178] applies a MOMA to the automated synthesis of analog circuits in order to optimize circuit topologies and parameters. The evolutionary framework is implemented ad hoc and application specific crossover and mutation operators are used. The classification procedure is done through the crowded comparison operator introduced in the NSGA-II [200], and SA is applied to each new solution generated by the evolutionary framework and to non-dominated individuals after each ranking process.

In [103] the Cross-Dominance Multi-Objective MA (CDMOMA) is proposed and applied to design the control system of a direct current electric motor. The CDMOMA is composed of a NSGA-II [200] framework and two local searchers: the novel Multi-Objective Rosenbrock Algorithm (MORA) and the Pareto Domination Multi-Objective Simulated Annealing (PDMOSA) proposed in [860]. To coordinate the evolutionary framework and the two local searchers, the algorithm employs the so-called cross dominance concept after each generation. This novel concept consists of the calculation of a metric; this metric, namely λ, represents the mutual dominance between two sets of candidate solutions. This metric is then used, with the aid of a probabilistic scheme, to coordinate the MORA and the PDMOSA within the evolutionary framework. In the logic of the designer, the PDMOSA helps find non-dominated solutions in unexplored areas of the decision space, while the MORA tries to improve the individuals that already have a high quality by exploring their neighborhood. After showing the validity of the CDMOMA with several benchmark functions, the authors apply it to optimally tune a DC motor speed control system.

Mori and Yoshida, in [611], present an efficient power distribution network expansion planning method in the presence of uncertainties. The article presents a novel MOMA based on the Controlled-NSGA-II [197] combined with a local searcher run on the non-dominated points after each generation of the evolutionary framework. Results given prove the efficiency of this method for the problem under study.

In [4] a MOMA is applied to aircraft control system design. A multi-objective GA, working in the decision variable space, is supported by a local search that fine tunes the population directly in the objective space. The results of the local search process are then re-mapped into the decision space by means of an artificial neural network which is trained during the global search process.

Katsumata and Terano in [449] design a MOMA improving Bayesian optimization algorithm with tabu search and Pareto ranking. The proposed algorithm is then applied to an electric equipment configuration problem in a power plant.

In [177], a bi-objective MA is proposed for the optimal design of resonator filters of arbitrary topology. A local search algorithm assists the EA for fitness improvement of candidate circuits, refining their parameters in order to prevent good topologies with non-optimized parameters values from being prematurely discarded. Local search is run on each elite individual after the classification process, and on the topologies of new circuits after the crossover/mutation procedure.

15.2.2.3 Memetic Algorithms in Image Processing and Telecommunications

Some interesting examples of MOMAs in real-world optimization regard image processing and telecommunications problems. In article [754], the authors deal with the problem of intelligent feature extraction of isolated handwritten symbols by means of a multi-objective optimization algorithm: after coding the problem to treat it as a two-objective optimization, Radtke et al. propose a multi-objective GA hybridized with an annealed based heuristic. The MOMA follows a Pareto ranking approach, and the local searcher is applied to each individual generated by the genetic operators; at the end of each generation, the most promising individuals are stored in an archive. Results show that implementing a local searcher considerably improves the convergence speed of a stand-alone GA.

In [474], two different telecommunication problems are studied by means of several Multi-Objective Evolutionary Algorithms and one MOMA, namely the M-PAES, proposed in [472]. Numerical results show how a multi-objective approach can be very successful for this kind of problem.

Martins et al. propose a multi-objective memetic approach to the design of wireless sensor networks in [558]. The proposed algorithm is composed of a global and a local strategy. The global strategy has the role of designing the entire network of sensors, while the local one is used to repair the neighborhood of a failing node in the network.

In [530, 531], a MOMA based on a GA, is applied to the design problem of a capacitated multi-point network. During the search the generation of the new population is done by mixing four methods: an elitism reservation strategy, the shifting Prüfer vector, genetic crossover and mutation and the complete random method. Each of these strategies creates a subpopulation, and these are then merged. Comparisons between the proposed approach, the single objective GA with weighted sum approach and the vector evaluated GA (VEGA), show that the proposed MOMA finds most non-dominated solutions and offers the best performance.

15.3 A Study Case: The Fast Adaptive Memetic Algorithm

In this section, we will further discuss the study presented in [104], in which a Fast Adaptive Memetic Algorithm (FAMA) is used to design on-line and off-line the optimal control system for a Permanent Magnet Synchronous Motor (PMSM). The FAMA is an interesting example of MA applied to real-world problems. The FAMA is composed of an ES evolutionary framework with dynamic population size and two different local search algorithms, the HJA and the NMA. The local search is coordinated by means of an adaptive rule based on the concept of fitness diversity.

15.3.1 An Insight into the Problem

The performance offered by an electric motor is strictly connected to the quality of its control. Although many control structures are available, a common and convenient alternative is the Proportionate Integrator (PI)-based control. This control structure allows, despite its simplicity and low cost, high-performance if properly designed. Thus, an efficient algorithmic solution for tuning PI controllers is a very relevant topic in an industrial environment. In a nutshell, the control system of an electric motor is a device which guarantees that the motor does not encounter malfunctioning when a dynamic operation is performed. In other words, a control system is supposed to guarantee that the motor reacts quickly and accurately to an external event. For example if while a motor is working and an additional torque is suddenly applied (this is a typical scenario in industries), a good control system should ensure that the motor counterbalances the extra torque without damages to the structure. It is important to remark that with damage we do not mean only major damages which immediately compromise the functioning of the motor but also micro-damages which may significantly shorten the life of the devices.

Fig. 15.1 shows the block diagram of a vector controlled PMSM drive studied in [104].

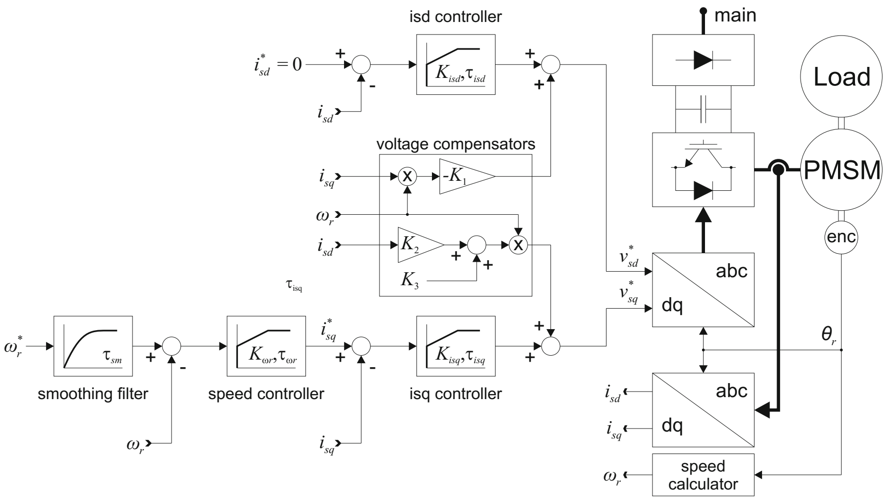

Fig. 15.1. Block Diagram of a vector-controlled PMSM drive

In [104], the main features of a good control system have been conceptualized as the capability of the motor to provide a quick and accurate response to speed command, load disturbance, and measurement noise. Thus, the PI tuning can be seen as a multi-objective optimization problem. More specifically, to evaluate the quality of each solution a training test, made of 8 speed and load torque steps, was designed. Each individual was used in this training test and its performance was given by the fitness in 15.1

$$f = \sum_{i=1}^{4} \left(a_i \cdot \sum_{j=1}^{n_{step}} f_{i,j} \right) \tag{15.1}$$

where j indicates the number of the generic speed step, i indicates the number of the performance index, and a_i is the positive normalization factor of the respective performance index $f_{i,j}$. Specifically, $f_{1,j}$ measures the speed error in the settling phase, $f_{2,j}$ is the overshoot index, $f_{3,j}$ measures the rise time, and $f_{4,j}$ takes account of the undesired d-axis-current oscillations, which increase losses and vibrations in the motor and drive.

It is interesting to notice that, since during the on-line optimization (the fitness function is not calculated by a computer but measured from an actually functioning motor) an unstable solution can be tested, to overcome the danger of possibly stressing the hardware, each performance index is constantly monitored during each experiment so that when a dangerous situation is recognized, the motor is stopped and a penalty factor is applied to the objective value.

15.3.2 Fast Adaptive Memetic Algorithm

The FAMA is a MA based on an ES framework. Initially a set of points is pseudo-randomly generated in the search space. Then, at the end of each iteration, the index ξ is calculated according to equation 15.2:

$$\xi = \begin{cases} \left|\frac{f_{best}-f_{avg}}{f_{best}}\right| & \text{if } \left|\frac{f_{best}-f_{avg}}{f_{best}}\right| \leqslant 1 \\ 1 & \text{if } \left|\frac{f_{best}-f_{avg}}{f_{best}}\right| > 1 \end{cases} \tag{15.2}$$

where f_{best} and f_{avg} are respectively the best and average fitness at the last iteration. Parameter ξ measures the diversity and, indirectly, the current state of convergence of the algorithm: the condition $\xi = 1$ means that there is a high diversity (in terms of fitness) among the individuals of the population and that the solutions are not exploited enough, while when $\xi \to 0$ the convergence is getting closer and since it could be premature, a higher search pressure is needed. According to this logic, the coefficient ξ is used to adaptively set several parameters of the optimization algorithm:

- The size of the population is set according to this rule:

$$S_{pop} = S^{f}_{pop} + S^{v}_{pop}(1-\xi) \tag{15.3}$$

  where S^{f}_{pop} is the minimum size of the population deterministically fixed and S^{v}_{pop} is the maximum size of the variable population. When $\xi = 1$ the population contains high diversity and a small number of solutions need to be exploited, if $\xi \to 0$ the population is going to converge and a bigger population size is required to increase the exploration.
- The probability of mutation is set in the following way:

$$p_m = 0.4(1-\xi) \tag{15.4}$$

Furthermore, the value of ξ is also used to decide which local searcher should be run and when: defining η as the number of the current generation, when $(\xi < 0.1)$ AND $(\eta > 8)$ the algorithm is likely to converge soon and the HJA is applied to the best performing individual to refine the final stages of the search. On the contrary, if $(0.05 < \xi < 0.1)$ AND $(\eta > 4)$, the NMA is applied on 11 individuals, i.e. the dimension of the search space $+1$, pseudo-randomly selected in the population, in order to find promising search directions. These two local search algorithms are both direct methods and can be applied to the given objective function which, being non-linear and not-differentiable, and without an explicit analytical expression (the fitness is generated by an experiment and its measures), could not have been tackled with any analytic approach. Furthermore, HJA and NMA show different and complementary behaviors: while the HJA is highly deterministic converging to the closest local optimum, the NMA retains some stochastic features, since its outcome depends on the initial sampling and the solutions are periodically sampled at random (during the shrinking phase).

The FAMA is stopped either when the number of generation η reaches a prearranged number, or when the coefficient ξ gets smaller than a predetermined value.

15.3.2.1 Experimental Results

The FAMA was compared with a pure GA and a simplex algorithm for the off-line optimization, and with a pure GA only for the on-line optimization. With off-line optimization we mean that the fitness function is calculated by means of a simulation model of the control system simulated within a computer. With on-line optimization we mean that the fitness is measured by means of experiments on an actual motor and an actual control system. The necessity of repeating the optimization twice allows an initial identification of the interesting region of the decision space which contains the optimum. The optimization must then be replicated by means of the actual devices because the model, although accurate, cannot fully simulate the real-world. As a matter of fact, similar motors of different producers can have very different responses in stress conditions. In addition, even apparently identical motors characterized by the same nameplate might have some different behaviors. Even measurement devices unavoidably influence (although in a minor way) the motor performance. For these reasons, it is important to design a specific control system tailored to the features of the available devices.

Figures 15.2 and 15.3 compare the performance trends obtained in the off-line and in the on-line case respectively. It is worth noticing that experimental results are, as expected, considerably different than the simulation results. This is due to non-linearities and uncertainties of the system, which were impossible to accurately model. In both cases, the results obtained by FAMA are strictly better than the initial commissioning and than the results offered by the other optimization techniques.

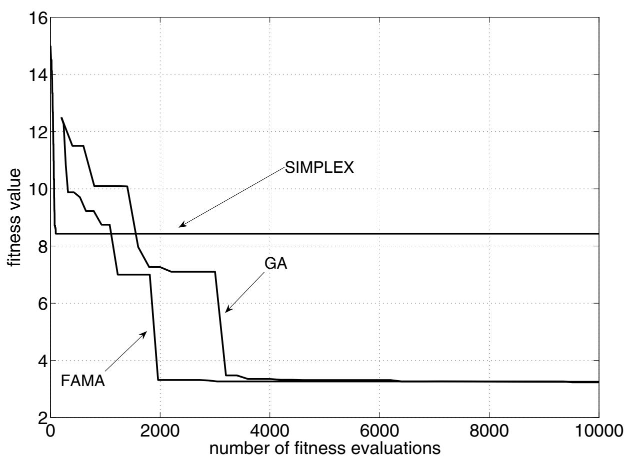

Fig. 15.2. Performance trend of three optimization methods (Simulation result)

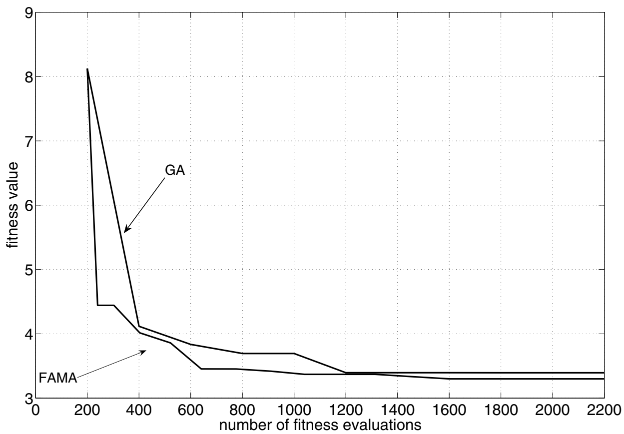

Fig. 15.3. Performance trend of two optimization methods (Experimental result)

The Fast Adaptive Memetic Algorithm presented in [104] is a good example of a MA applied to real-world optimization. Facing a non-differentiable problem which could not be solved with analytical techniques, the FAMA was designed keeping an eye on the peculiarities of the specific context under study. Nonetheless it includes some guidelines which are useful in similar conditions, i.e. when the fitness landscape is highly multi-modal and contains high gradient areas. Finally, FAMA demonstrates that the optimization performance is increased not only by the integration of a local search algorithm within an evolutionary framework, but also by a smart coordination strategy between the algorithmic components.

15.4 Conclusions

Many real-world problems are too complex to be solved by means of standard analytical techniques. In theses situations, direct search methods have become more and more popular. Specifically MAs, joining the exploration characteristics of Evolutionary Algorithms with the exploitative abilities of local searchers, have found a continuously increasing success in engineering problems.

When designing MAs, special attention must be paid to the peculiarities of the specific optimization problem to deal with. Putting together an evolutionary framework with one or more local searchers could not be enough to get good results, and a strategy to combine and harmonize the different components of a MA should be designed.

This chapter offered a panoramic view of several fields in which MAs were successfully applied so far. Researchers could see how different situations have been faced. The most interesting cases were analyzed in more depth and a specific situation, the self commissioning of electric drives for a permanent magnet synchronous motor, was described in detail.

Future trends, in accordance to the No Free Lunch Theorem, will be oriented towards the design of domain-specific MAs for addressing each engineering problem. On the other hand, this trend might lead to the design of overwhelmingly complex optimization algorithms which can require an extensive parameter tuning if minor modifications are made to the original problem (e.g. variation of working conditions). For this reason, in our view a keyword in future MA design in engineering will be "algorithmic robustness". Finally, in our opinion, it will be important that future MAs have a relatively simple structure and are fairly easy to modify and control.

Thus, we think that engineers and computer scientists will attempt to find a compromise between high performance and algorithmic flexibility. A crucial role will be played by the adaptation rules and their capability of being employed in various optimization problems, thus attempting to push towards "the outer limit" of the No Free Lunch Theorem. By giving up a marginal part of the algorithmic performance, future MAs will attempt to solve not only a very specific case but a restricted set of problems having common features. A suitable trade-off will be in our opinion a future topic of discussion. The final aim would be the implantation of "fully intelligent algorithms" which can automatically detect the suitable algorithmic components or might even be able to design the algorithms during the run time on basis of the fitness landscape response without any human decision. Although some interesting work has been already done, completely avoiding human decision within the algorithmic design phase is still very far from achievable

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