59. Modeling and Optimization of Machining Problems

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In this chapter, applications of computational intelligence methods in the field of production engineering are presented and discussed. Although a special focus is set to applications in machining, most of the approaches can be easily transferred to respective tasks in other fields of production engineering, e.g., forming and coating. The complete process chain of machining operations is considered: The design of the machine, the tool, and the workpiece, the computation of the tool paths, the model selection and parameter optimization of the empirical or simulation-based surrogate model, the actual optimization of the process parameters, the monitoring of important properties during the process, as well as the posterior multicriteria decision analysis. For all these steps, computational intelligence techniques provide established tools. Evolutionary and genetic algorithms are commonly utilized for the internal optimization tasks. Modeling problems can be solved using artificial neural networks. Fuzzy logic represents an intuitive way to formalize expert knowledge in automated decision systems.

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In production engineering and particularly in the field of machining, improvements in materials, coatings, tools, and machines continuously provide potentials for improving the processes. In order to exploit these potentials, however, optimal setups of the changing processes have to be found. Since modern production processes involve many complex subsystems, as well as preceding and subsequent steps, all these systems and steps have to be adapted for achieving the optimal result.

In this chapter, it is shown that computational intelligence (CI) provides methods to assist in achieving this ambitious aim. A particular focus is on the applications of evolutionary computation (EC) in machining, but also artificial neural networks (NN) and fuzzy logic are considered. A comprehensive overview is presented by considering several subsystems, as well as the preceding and subsequent steps in the operating sequence. In this aspect, the chapters contribute to common surveys in the literature [59.1–5], which are often only focused on the modeling and optimization of the actual process.

In order to assist interested engineers in choosing a suitable method for their problem, the solutions offered by CI are structured according to the specific subproblems to be solved in a machining problem. To keep the big picture still apparent, these subproblems are integrated into the complete operating sequence in the following section. They are then discussed according to their chronological order in the sequence. The chapter is concluded with summarizing remarks on CI applications in the field of production engineering.

59.1 Elements of a Machining Process

An overview of the elements and steps to be considered when optimizing a machining process is shown in Fig. 59.1. In the focus of the considerations is the actual process. The results of this process, however, significantly depend on its elements, in particular on the mechanical properties and the dynamic characteristics of the machine, geometry, and the properties of the tools, as well as the layout of the workpiece which determines the required machining operations. All these elements can be individually optimized to improve the results of the process. For the latter, often complex numerical control (NC) paths for the machines have to be generated using computer-assisted manufacturing (CAM) software. To accomplish this, a model of the final workpiece geometry is required. If no such model is available, e.g., after manual modifications of a prototype, CI-based methods can assist in computing an optimized workpiece model for the CAM software. However, even if a model is available, the NC paths computed by the CAM software can be far from optimal due to the complexity of the process, e.g., in five-axis milling operations. In this case, the subsequent optimization of the position-dependent parameters of the NC code, such as the inclination angles α and β, and the feed rate f [59.6], can significantly increase the efficiency of the process.

When all the components of the actual process are selected and fixed therewith, the optimization of the adjustable process parameters can begin. Thereby, CI-based techniques are usually based on a self-organizing process. In order to let the self-organization take effect, a high number of experiments is required. Since a real-world experiment involves high costs, it can become necessary to use a surrogate model on which the method is applied. In this case, however, additional problems have to be solved. It has to be selected which kind of model (empirical, analytical, physical, numerical) is applied and which type or realization of this kind of model is implemented, e.g., an empirical model can be computed using artificial neural networks, Gaussian processes, or regression techniques. As soon as a model is chosen, the parameters of this model (internal coefficients, material constants, etc.) have to be adapted with respect to the given application. This often represents an additional nonlinear optimization problem which can be solved using techniques of EC.

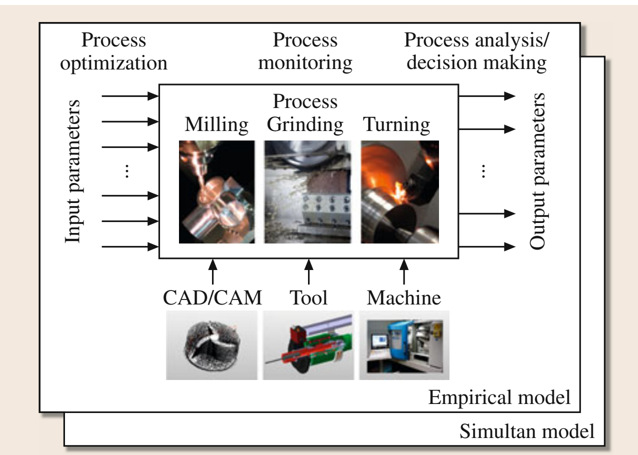

Fig. 59.1 Overview of the elements and steps of an arbitrary machining process

Moreover, the robustness of the process can be increased by a monitoring-based process control. To accomplish this, dynamic characteristics of the process, such as acoustic emission signals and force measurements, are analyzed online and control operations are initiated as soon as these characteristics show suspicious patterns. In this kind of application, however, it is necessary to automatically detect what indeed is a suspicious pattern. Fuzzy logic and NNs have proven to be capable of performing these tasks.

A lot of information can be obtained in order to analyze the process and its results. This information can either be achieved by measurements during and after the process or by performing simulation studies. They usually build the basis for the calculation of the actual objectives. In this context, machining processes have to be optimized with respect to several conflicting aims, e.g., a simultaneous minimization of tool wear and maximization of the material removal rate. Even if multiobjective optimization techniques are used, a lot of details can be lost in this formulization step. Often the first version of the objectives does not result in the desired results. Additional objectives have to be defined or preferences have to be integrated. In order to allow a deeper understanding of the process to be obtained and a refinement of the objectives to be made, an intuitive visualization and exploration of the detail information is required. For this task, again CI-based techniques can be used.

59.2 Design Optimization

The optimal design of a machine, tool, or workpiece is a great challenge in the field of production engineering. The optimization task is often conducted as an iterative manual process which is based on expert knowledge and which can be very cost and time consuming. *Roy* et al. [59.7] gave an extensive overview of the recent advances in automated and interactive design optimization. They presented a classification of the optimization problems and discussed the most important optimization approaches and techniques. In the following subsections, examples of successful applications of CI for the optimization of machine, tool, and workpiece designs are provided.

59.2.1 Optimal Design of Machines

Designing machines necessitates the consideration of multiple objectives, such as geometric accuracy and costs. *Liu* and *Liang* [59.8], for instance, presented an approach combining a modified Chebyshev programming method for the scalarization of these objectives and a particle swarm optimization algorithm for evolving the machine designs. They were dealing with reconfigurable machine tools, so not only the process accuracy and investment costs of the machine layouts, but also the configurability was considered. Significant changes in the shape of the product could thus be easily adapted. *Mekid* and *Khalid* [59.9] discussed an optimization method based on a multiobjective genetic algorithm for the design of three-axis micromilling machines. They took user requirements (for example the workspace volume), axis positions, and geometric errors of the machine into account. For the latter, they used a mathematical error model of the three-axis milling machines.

59.2.2 Tool Optimization

Designing machining tools is a very difficult optimization task since not only complex geometries, but also different machining criteria have to be taken into account [59.10]. *Abele* and *Fujara*, for example, presented a simulation approach for optimizing the drill geometry based on a genetic algorithm [59.11]. They considered not only the structural stiffness of the tool during their optimization run, but also took the coolant flow resistance and the chip evacuation capability into account. They also defined the machinability, especially the grindability of the chip flute, as constraint. In order to take all these criteria into account, different simulation approaches have to be used (Sect. 59.4). *Abele* and *Fujara* used, for example, the finite element method in order to analyze the structural stiffness. The cutting forces were computed using a semiempirical cutting force model. Additionally, a model of the grinding wheel had to be determined in order to evaluate the grindability of the optimized drill geometry. Another application was presented by *Jared* et al. [59.12] who integrated GA into the computer-aided design software CATIA. In one of their case studies, the volume and the tip deflection of a cutting tool were minimized by automatically parameterizing length and angles between segments of a 2-D (two-dimensional) profile which were then extruded to the actual tool.

59.2.3 Workpiece Layout Optimization

The layout of products can usually be described as multiobjective optimization problem. For example, the design of aerospace structures always faces a tradeoff between the stiffness and the weight of the products [59.13]. The layout of a cooling system, e.g., for a turbine blade [59.13] is a tradeoff between the machining quality, the cooling effect, and the production costs. *Weinert* et al. [59.14–17] developed a simulation system for optimizing the layout of mold temperature control systems in order to minimize the production cycle times and costs, and to maximize the product quality. They developed an efficient simulation system in order to evaluate the effect and homogeneity of the tempering of the design layout and to estimate the manufacturing costs [59.18]. Using fast but sufficiently accurate evaluation methods, a computer-aided optimization of the temperature control system based on multiobjective optimization methods, like NSGA-II [59.19] and SMS-EMOA [59.20], became possible [59.21–24]. Nevertheless, this optimization task is very complex and the engineer's experience is still necessary. Due to this, *Biermann* et al. [59.25] combined the computer-aided optimization system with the possibility of user interaction so that a visual real-time manipulation of target functions is possible. *Dürr* and *Jurklies* [59.26] presented a fuzzy expert system in order to use the expert knowledge in a computer-assisted way.

59.3 Computer-Aided Design and Manufacturing

In the modern construction process, computer-aided design (CAD) software is used for all design tasks – for example for the model of the workpiece. This model is the basis for the generation of the NC paths by CAM software. However, if only a physical prototype exists or manual modifications of the original model have been performed, methods to compute a respective model are required. To accomplish this, the original object is scanned and a point-based representation is obtained. From this point data, a new CAD model has to be calculated or the original model has to be adapted. This process is called *surface reconstruction* or *reverse engineering*.

When a model of the workpiece is available, NC paths can be generated based on CAM software for most machining processes. For complex five-axis milling processes, however, the results of standard CAM software are not always optimal with respect to the requirements of the specific machine and process. In this case, CI-based techniques can be used to improve the NC paths generated by the CAM software.

59.3.1 Surface Reconstruction

The optimization of the visual quality of triangulations with respect to different quality criteria was successfully performed using evolutionary algorithms by *Weinert* et al. [59.27]. Based on an initial triangulation, as provided by the software of the scanning system, edges were flipped in order to minimize the total length of all edges, the surface area, the sum of angles between normals, and the total absolute curvature. It was found that the latter is best suited for generating visually smooth surfaces.

Small tolerances in the representation of the original object, however, result in a huge number of required scan points. Current scanners are able to provide this dense and precise set of scan points, but the resulting triangulations become very large and difficult to handle. Approximating triangulations tackle this problem. The number of control points for the triangles is independent of the size of the point set and usually considerably smaller than the number of scan points. *Weinert* et al. [59.28] documented the capabilities of a standard evolution strategy to optimize the control point positions of approximating triangulations. In order to avoid an uncontrolled expansion of the triangulation, balancing strategies based on mass–spring systems were integrated.

Unfortunately, even approximating triangulations produce a nonsmooth surface and are therefore not convenient for the later computation of NC paths. *Nonuniform rational B-splines* (NURBS) [59.29] are another popular mathematical model for free-form surfaces in CAD software. The most important advantages of NURBS over triangulations are their smoothness, their compact definition, the possibility for an intuitive local manipulation, as well as the ability to combine NURBS patches to larger structures. *Mehnen* et al. [59.30, 31] applied an evolution strategy to the coordinates of the NURBS's control points in order to minimize the distance between the scan points and their projection to the NURBS. *Wagner* et al. [59.32] did the same using a real-valued genetic algorithm. They also proposed another distance indicator that is based on a sampling of the NURBS and that is much cheaper to evaluate. The use of the sampling-based distance measure in combination with a equation-solver-based hybrid real-valued genetic algorithm significantly reduced the runtime of the optimization. This approach was further enhanced [59.16] to a two-step approach, in which the single-objectively optimized solution is used as initial individual for a multiobjective optimization. As additional objective, the smoothness of the NURBS was considered. This objective was also considered by *Jared* et al. [59.12] in their GA-based optimization of NURBS in CATIA.

In addition, *Weinert* et al. [59.33] combined NURBS with constructive solid geometries [59.34] in a hybrid evolutionary algorithm/genetic programming approach. By these means, the constructional logic behind the workpiece could also be approximated.

59.3.2 Optimization of NC Paths

The five-axis milling process offers the possibilities to tilt the milling tool and, thus, to use shorter and therewith stiffer tools. This allows complex free-form surfaces to be machined in one workpiece clamping, and the engagement conditions to be adapted [59.35]. An improvement of the machining results and a reduction of the machining time can be achieved. However, in contrast to the three-axis process, the generation of the NC paths particularly for the machining of free-form surfaces is much more complex [59.6].

Weinert and *Stautner* [59.36] presented an algorithm for converting three- into five-axis milling paths in which the position of the tool tip is kept from the three-axis NC program. An optimization approach based on an evolutionary strategy was used to improve the tool movement [59.37]. To accomplish this, they developed a fast simulation system of the five-axis milling process based on a discrete dexel model of the workpiece (Sect. 59.4) [59.38].

The NC paths generated for a five-axis milling process are often not smooth enough since the kinematic behavior of the specific milling machine is not taken into account. *Zabel* et al. developed a simulation approach which is placed in the process chain between the CAM system and the real-milling process [59.39]. The five-axis tool movement is optimized taking the tool axis configuration and the dynamic behavior of the milling machine into account. For this purpose, methods of evolutionary computation and wavelet theory were combined [59.35]. In 2007, *Mehnen* et al. integrated a multiobjective optimization algorithm into this simulation system which combined the variation of a modern single-objective approach with the selection mechanism of a classical multiobjective optimization algorithm in order to optimize the tool movement [59.40].

One challenging task during the optimization of the five-axis milling process is the avoidance of collisions between the milling tool and the workpiece. *Kersting* and *Zabel* [59.6] developed an efficient simulation approach, which maps the high-dimensional restriction area on a two-dimensional matrix structure. They showed that the use of a multipopulation multiobjective evolutionary algorithm in the restriction-free area improved the corresponding Pareto fronts [59.41].

59.4 Modeling and Simulation of the Machining Process

The optimization of real-world applications using CI-based or classical optimization approaches requires that a performance value or vector can be obtained for all possible settings of the input parameters, whereby the performance values are usually calculated based on measurements during or after the actual process. In order to achieve a near-optimal result, however, far more than 100 different parameter vectors have to be evaluated – even for low-dimensional problems. This amount of real experiments is often impossible due to the costs related to them. As a possible solution, the use of empirical or physical (simulation) models can significantly reduce the number of required experiments since most of the evaluations can be performed on the model. For both kinds of approaches, CI techniques have already been successfully used. Some examples are presented in the following subsections.

59.4.1 Empirical Modeling

For the use of empirical models, real or simulated experiments are still required in order to build up a data base for the training of the model. In contrast to the direct optimization of the process, however, these experiments are performed as a block of moderate size in the beginning of the optimization. Afterward, the model allows new parameter settings to be predicted based on the information obtained from training data. The determination of near-optimal solutions can be performed on the model.

The number of empirical models is exhaustive [59.42]. Nevertheless, NNs often showed their capability to empirically model responses from machining processes. For instance, the material removal rate of an abrasive jet drilling process was successfully predicted by using an NN with back error propagation [59.43]. As input parameters, varying gas pressure, nozzle inside diameter, abrasive flow rate, size of the medium particle, and standoff distance were considered. Accordingly, the ablating depth obtained for specific values of the peak power, pulsing frequency, and overlapping in a laser drilling process could be predicted using NN [59.44]. *Casalino* et al. [59.45] showed that NN achieve higher prediction accuracies than regression techniques in predicting surface roughness and resultant forces for varying cutting speed, feed rate, and radial depth in milling. In the same line, NN were used for the prediction of the specific cutting constants resulting from different cutting speeds, feeds, inclination angles α and β, cutting depths, and cutting widths [59.46]. With respect to tool wear, the wheel life of a cylindrical grinding wheel was modeled using a feedforward backpropagation NN. A direct prediction of the tool wear was also accomplished using NN [59.47, 48]. Moreover, the thermal expansion of the Y-axis ball screw was predicted based on temperature measurements at different points of the machine structure [59.49].

In addition, CI-based techniques can also indirectly be used for empirical modeling. As soon as complex empirical models, such as Gaussian processes, support vector or other kernel machines, are used, the determination of the optimal model parameters is an individual nonlinear optimization problem. Evolutionary algorithms, in particular the covariance matrix adaption evolution strategy (CMA-ES) [59.50], showed to be suitable for solving these problems [59.51, 52].

59.4.2 Physical Modeling for Simulation

In cases where sufficient knowledge about the physical laws of the process is available, simulation models based on equations representing these physical laws are likely to be superior to the very general formulations of the empirical models. Nevertheless, also these models have parameters that are related to the properties of the material, tool, and machine. Since these parameters can often not be measured, their values are usually set by minimizing the error between the predictions of the simulation and a training set of observations from real-world experiments. As consequence, EC is a valuable tool for calibrating simulation models which was shown to be superior to classical data fitting tools [59.53].

In an exemplary application, the dynamic behavior of manufacturing systems was characterized by its frequency response function. This function can be modeled by a superposition of decoupled damped harmonic oscillators, whereby each oscillator has three parameters (mass, natural frequency, and damping) [59.54]. In order to minimize the deviation between the measured frequency response function and one of the oscillators, an interactive approach based on evolutionary algorithms was successfully implemented [59.54].

An open issue in the simulation of machining processes is the modeling of the extremely high strain rates which can only rarely be covered by classical material models and tensile tests. As a possible solution, EC can be used as a submodule of a simulation in order to predict the deformation and flow characteristics for high strain rates. For instance, *Weinert* et al. used symbolic regression by means of a genetic programming system to evolve mathematical formulae that describe the trajectories of single particles of steel based on recordings of a high-speed camera during the turning process [59.55, 56]. *Teti* et al. [59.57] employed NN to reconstruct the stress–strain curve of the workpiece material from experimental data of tensile tests. They found out that the learned NN is capable of predicting workpiece material properties in a wide range of temperature and strain rate values. A hybrid simulation model based on physical equations and the empirical stress–strain prediction was finally proposed. Two recent overviews of hybrid models for simulation which also incorporate CI techniques were provided by *Jawahir* et al. [59.58, 59].

59.5 Optimization of the Process Parameters

In this section, possible applications of EC methods for the optimization of the actual process parameters are discussed. Since a recent survey book for the model-based optimization of process parameters exist [59.1], only a short summary of possible applications is provided. In contrast to this survey, the following presentation does not distinguish between different processes, as the aspects related to the use of EC are independent of the actual process, e.g., milling, turning, or grinding.

As already discussed in the previous section, it is mandatory to approximate the process quality indicators by means of analytical, empirical, or physical models. In the literature, no direct application of EC optimization techniques to machining processes was reported until now. Instead, polynomial or process-related equations were usually fitted to experimental data [59.60–78]. Neural networks [59.63, 79–83], other empirical models [59.51, 62, 84], and simulation models [59.85, 86] were also popular to accomplish this task.

For the actual optimization, two important decisions on the formulation of the problem have to be taken in order to choose the EC method. These decisions are concerned with the representation of the input parameters and the objectives. In most cases, continuously defined input parameters, such as feed and cutting speed, are to be optimized. This relates to techniques such as evolution strategies, particle swarm optimization, and real-valued genetic algorithms (GAs). If also discrete parameters, such as the cooling concept or tool material, are considered, special evolution strategies [59.65, 87] or binary GAs may better be suited. With respect to the objectives, it has to be decided whether a single optimal solution or a set of tradeoffs is desired. In the former case, almost all EC techniques can directly be used. Due to the complexity of production engineering problems, however, a suitable scalarization of the different objectives has to be found in order to achieve reasonable results. In the latter case of searching for an approximation of the trade-off structure, it is important that the algorithm is capable of coping with multiple objectives which have to be considered in parallel [59.51, 72, 74, 78, 79, 84, 86].

In the literature, the use of continuous input variables and single-objective formulations is established. The most popular EC methods are particle swarm optimization (PSO) [59.63, 68, 75, 76, 81–83, 85, 88] and standard GA or evolutionary algorithm (EA) [59.60, 62, 64, 67, 69, 77, 80]. The use of specifically designed heuristics [59.71, 75, 89] is rather uncommon. Nevertheless, the formulation of the problem and the design of the algorithm should aim at incorporating as much knowledge as possible into the optimization [59.16].

Unfortunately, the generality of CI-based techniques often results in problem formulations which are not completely sophisticated. An important factor often neglected when optimizing production engineering problems is the uncertainty about the external process variables, e.g., properties of the tool or material. Although modern algorithms are capable of incorporating them into the optimization [59.90], only a few applications actually take these uncertainties into account [59.70]. More specifically, two sources of uncertainty can be considered [59.91]: perturbations in the input variables, e.g., due to online control, and environmental uncertainties, such as outdoor temperature, humidity, and the already mentioned external process variables. A detailed overview of such factors can be found in the literature [59.92]. A comprehensive survey of possible problem formulations and respective optimization approaches was presented by *Beyer* and *Sendhoff* [59.91]. In production-engineering applications, however, classical statistical methods are usually used to cope with these problems. The potential of CI-based techniques has not yet been exploited.

59.6 Process Monitoring

The analysis of different process variables – like for example the cutting forces, acoustic emission, or temperatures – allows conclusions about the process-dependent state of the machining processes and its components (tools, machines, workpieces, etc.) to be drawn and provides the possibility for an adaptive process control [59.93]. The idea of process monitoring is to measure, visualize, and analyze the values of these variables during the machining process. *Teti* et al. [59.93] gave an extensive overview of *advanced monitoring of machining operations* describing sensor systems for machining, signal processing, monitoring scopes, and the decision-making support systems. In order to evaluate the measured values, cognitive computing methods – for example genetic algorithms, fuzzy logic, or NNs – can be used. In contrast to the rule-based fuzzy logic approach, NNs do not store the knowledge in an explicit form. A survey of the successful applications of these techniques for the advanced monitoring of machining operations was provided by *Teti* et al. [59.93]. It is thus omitted in this section.

59.7 Visualization

In the field of production engineering, the complex optimization problems are often characterized by multiple objectives and restrictions. Additionally, the decision space can be high dimensional – like for example in the case of optimizing NC paths (Sect. 59.3.2) [59.6]. In order to analyze the optimization problems and the applied optimization approach, an intuitive visualization of the data resulting from the evolutionary process is advisable [59.94]. For this purpose, *Pohlheim* [59.95] reviewed several visualization techniques in order to obtain a better understanding of the optimization process of real-world problems. He recommended the use of three diagrams in order to analyze the optimization algorithm: A convergence diagram, visualization of the change of the best individual during the optimization approach, and a diagram of the objective values of all individuals in the population of all generations.

Müller et al. discussed techniques for an *intuitive visualization and interactive analysis of Pareto sets ap-*

plied on production engineering systems [59.94]. They analyzed different visualization and analysis methods in order to gain insight into both the optimization problem and the optimization algorithm, and to support an intuitive decision-making process. For this purpose, they presented a simultaneous visualization of the decision and the objective space. An interactive navigation through the solution sets supports the user to detect specific process characteristics [59.94]. This also helps to redesign the objective formulation in cases where the optimization results are not in agreement with the actual preferences of the decision maker.

In order to support the trade-off analysis in multiple dimensions, *Obayashi* and *Sasaki* [59.96] presented a visualization approach based on self-organizing maps (SOMs). The idea is to map from the high-dimensional objective function space to two-dimensional map units. They showed the applicability of this approach analyzing two multiobjective aerodynamic design problems [59.96].

The *innovization* approach of *Deb* [59.97] provides an automated identification of design principles by searching for common features of the optimal trade-offs in a multiobjective optimization problem. These features are provided by means of analytical relations between the design variables. A successful application of innovization in machining was already reported [59.78]. Another possibility to learn about the structure of the objectives and the effect of the input parameters is provided by visualizations and analyses based on the surrogate models of the process (Sect. 59.4) [59.51, 98].

59.8 Summary and Outlook

This chapter focused on applications of CI in the optimization of machining problems. For this purpose, the whole process chain – from the design of a machine, tool, or workpiece, as well as the corresponding optimization of process parameters, to the process monitoring and subsequent analysis of the results – was taken into account. Different modeling and simulation techniques, which are necessary to optimize real-world problems, were discussed. Successful examples in the field of production engineering were compiled to present the applicability of the CI methods. In conclusion, evolutionary and genetic algorithms are general and powerful solvers for nonlinear optimization tasks, artificial neural networks can be used for continuous modeling problems, and fuzzy logic provides an intuitive way to represent expert knowledge.

Unfortunately, the generality of CI-based techniques often results in problem formulations which are not completely sophisticated. For instance, possibilities of creating good initial solutions, uncertainty in the design variables, and specific aspects of the quality indicators resulting in undesirable scalarizations, are often neglected. EC provides the means to appropriately consider these aspects. A proper analysis of the results can assist in identifying such pitfalls and in improving the problem formulation.

References

59.1 E. Venkata Rao: *Advanced Modeling and Optimization of Manufacturing Processes* (Springer, Berlin, Heidelberg 2011)

59.2 D. Dasgupta, Z. Michalewicz: *Evolutionary Algorithms in Engineering Applications* (Springer, Berlin, Heidelberg 1997)

59.3 W. Banzhaf, M. Brameier, M. Stautner, K. Weinert: Genetic programming and its application in machining technology. In: *Advances in Computational Intelligence: Theory and Practice*, ed. by H.-P. Schwefel, I. Wegener, K. Weinert (Springer, Berlin, Heidelberg 2003) pp. 194–244, Chap. 7

59.4 I. Mukherjee, P. Ray: A review of optimization techniques in metal cutting processes, Comput. Ind. Eng. **50**(1-2), 15–34 (2006)

59.5 H. Aytug, M. Khouja, F.E. Vergara: Use of genetic algorithms to solve production and operations management problems: A review, Int. J. Prod. Res. **41**(17), 3955–4009 (2003)

59.6 P. Kersting, A. Zabel: Optimizing NC-tool paths for simultaneous five-axis milling based on multi-population multi-objective evolutionary algorithms, Adv. Eng. Softw. **40**(6), 452–463 (2009)

59.7 R. Roy, S. Hinduja, R. Teti: Recent advances in engineering design optimisation: Challenges and future trends, CIRP Ann. Manuf. Technol. **57**(2), 697–715 (2008)

59.8 W. Liu, M. Liang: A particle swarm optimization approach to a multi-objective reconfigurable machine tool design problem, IEEE Cong. Evol. Comput. (2006) pp. 2222–2229

59.9 S. Mekid, A. Khalid: Robust design with error optimization analysis of CNC micromilling machine, 5th CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2006) pp. 583–587
59.10 H. Schulz, A.K. Emrich: Optimization of the chip flute of drilling tools using the principle of genetic algorithms, 2nd CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2000) pp. 371–376
59.11 E. Abele, M. Fujara: Simulation-based twist drill design and geometry optimization, CIRP Ann. Manuf. Technol. **59**(1), 145–150 (2010)
59.12 G. Jared, R. Roy, J. Grau, T. Buchannan: Flexible optimization within the CAD/CAM environment, CIRP Int. Seminar Intell. Comput. Manuf. Eng. (1998) pp. 503–508
59.13 R. Roy, A. Tiwari, J. Corbett: Designing a turbine blade cooling system using a generalised regression genetic algorithm, CIRP Ann. Manuf. Technol. **52**(1), 415–418 (2003)
59.14 J. Mehnen, K. Weinert, H.-W. Meyer: Evolutionary optimization of deep drilling strategies for mold temperature control, 3rd CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2002)
59.15 T. Michelitsch, J. Mehnen: Evolutionary optimization of cooling circuit layouts based on the electrolytic tank method, 4th CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2004)
59.16 K. Weinert, A. Zabel, P. Kersting, T. Michelitsch, T. Wagner: On the use of problem-specific candidate generators for the hybrid optimization of multi-objective production engineering problems, Evol. Comput. **17**(4), 527–544 (2009)
59.17 J. Mehnen, T. Michelitsch, K. Weinert: Production engineering: Optimal structures of injection molding tools. In: *Emergence, Analysis and Optimization of Structures – Concepts and Strategies across Disciplines*, ed. by K. Lucas, P. Roosen (Springer, Berlin, Heidelberg 2010) pp. 75–90
59.18 T. Michelitsch, J. Mehnen: Optimization of production engineering problems with discontinuous cost-functions, 5th CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2006) pp. 275–280
59.19 K. Deb, A. Pratap, S. Agarwal, T. Meyarivan: A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Trans. Evol. Comput. **6**(2), 182–197 (2002)
59.20 N. Beume, B. Naujoks, M. Emmerich: SMS-EMOA: Multiobjective selection based on dominated hypervolume, Eur. J. Oper. Res. **181**(3), 1653–1669 (2007)
59.21 J. Mehnen, T. Michelitsch, T. Bartz-Beielstein, N. Henkenjohann: Systematic analyses of multi-objective evolutionary algorithms applied to real-world problems using statistical design of experiments, 4th CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2004)
59.22 J. Mehnen, H. Trautmann: Integration of expert's preferences in pareto optimization by desirability function techniques, 5th CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2006) pp. 293–298
59.23 T. Michelitsch, T. Wagner, D. Biermann, C. Hoffmann: Designing memetic algorithms for real-world applications using self-imposed constraints, Proc. 2007 IEEE Congr. Evol. Comput. (2007) pp. 3050–3057
59.24 D. Biermann, R. Joliet, T. Michelitsch, T. Wagner: Sequential parameter optimization of an evolution strategy for the design of mold temperature control systems, Proc. 2010 IEEE Congr. Evol. Comput. (2010) pp. 4071–4078
59.25 D. Biermann, R. Joliet, T. Michelitsch: Interactive manipulation of target functions for the optimization of mold temperature control systems, 2nd Int. Conf. Manuf. Eng., Qual. Prod. Syst. (2010) pp. 239–244
59.26 H. Dürr, I. Jurklies: A fuzzy expert system assist the CAD/CAM/CAE process chain in the tool and mould making industry, 3rd CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2002)
59.27 K. Weinert, J. Mehnen, F. Albersmann, P. Drerup: New solutions for surface reconstruction from discrete point data by means of computational intelligence, CIRP Int. Seminar Intell. Comput. Manuf. Eng. (1998) pp. 431–438
59.28 K. Weinert, J. Mehnen, M. Schneider: Evolutionary optimization of approximating triangulations for surface reconstruction from unstructured 3D Data, Proc. 6th Jt. Conf. Inf. Sci. (2002) pp. 578–581
59.29 L. Piegl, W. Tiller: *The NURBS Book* (Springer, Berlin, Heidelberg 1997)
59.30 K. Weinert, J. Mehnen: NURBS-surface approximation of discrete 3D-point data by means of evolutionary algorithms, 2nd CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2000) pp. 263–268
59.31 T. Beielstein, J. Mehnen, L. Schönemann, H.-P. Schwefel, T. Surmann, K. Weinert, D. Wiesmann: Design of evolutionary algorithms and applications in surface reconstruction. In: *Advances in Computational Intelligence: Theory and Practice*, ed. by H.-P. Schwefel, I. Wegener, K. Weinert (Springer, Berlin, Heidelberg 2003) pp. 164–193
59.32 T. Wagner, T. Michelitsch, A. Sacharow: On the design of optimisers for surface reconstruction, Proc. 9th Annu. Genet. Evol. Comput. Conf. (2007) pp. 2195–2202
59.33 K. Weinert, T. Surmann, J. Mehnen: Evolutionary surface reconstruction using CSG-NURBS-Hybrids, Proc. Genet. Evol. Comput. Conf. (2001) pp. 1456–1463
59.34 C.M. Hoffmann: *Geometric & Solid Modeling* (Kaufmann Publ., San Mateo 1989)
59.35 K. Weinert, A. Zabel, H. Müller, P. Kersting: Optimizing NC tool paths for five-axis milling using evolutionary algorithms on wavelets, 8th Annu. Genet. Evol. Comput. Conf. (2006) pp. 1809–1816
59.36 K. Weinert, M. Stautner: Generating multiaxis tool paths for die and mold making with evolutionary algorithms, Lect. Notes Comput. Sci. **3103**, 1287–1298 (2004)

59.37 K. Weinert, M. Stautner: A new system optimizing tool paths for multi-axis die and mould making by using evolutionary algorithms, production engineering, Res. Dev. **12**(1), 15–20 (2005)

59.38 A. Zabel, M. Stautner: Optimizing the multi-axis milling process via evolutionary algorithms, Berichte aus dem IWU, 8th CIRP Int. Workshop Model. Mach. Oper. (2005) pp. 363–370

59.39 A. Zabel, H. Müller, M. Stautner, P. Kersting: Improvement of machine tool movements for simultaneous five-axes milling, 5th CIRP Inter. Semin. Intell. Comput. Manuf. Eng. (2006) pp. 159–164

59.40 J. Mehnen, R. Roy, P. Kersting, T. Wagner: ICS-PEA: Evolutionary five-axis milling path optimisation, 9th Annu. Genet. Evol. Comput. Conf. (2007) pp. 2122–2128

59.41 D. Biermann, A. Zabel, T. Michelitsch, P. Kersting: Intelligent process planning methods for the manufacturing of moulds, Inter. J. Comput. Appl. Technol. **40**(1/2), 64–70 (2011)

59.42 T. Hastie, R. Tibshirani, J. Friedman: *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 2nd edn. (Springer, Berlin, Heidelberg 2009)

59.43 M. Gheorghe, C. Neagu, S. Antoniu, C. Ionita: Modeling of abrasive jet drilling by applying a neural network method, 2nd CIRP Int. Seminar Intell. Comput. Manuf. Eng. (2000) pp. 221–226

59.44 S.L. Campanelli, A.D. Ludovico, C. Bonserio, P. Cavalluzzi: Artificial neural network modelling of the laser milling process, 5th CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2006) pp. 107–111

59.45 G. Casalino, A.D. Ludovico, F.M.C. Minutolo, A. Rotondo: On the numerical modelling of a milling operation: Data recoveringand interpolation, 5th CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2006) pp. 193–197

59.46 P. Clayton, M.A. Elbestawi, T.I. El-Wardany, D. Viens: An innovative calibration technique using neural networks for a mechanical model of the 5-Axis milling process, 2nd CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2000) pp. 391–396

59.47 G. Casalino, A.D. Ludovico: Tool life estimation in single point turning using artificial neural networks, 4th CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2004)

59.48 G. Ambroglio, D. Umbrello, L. Filice: Diffusion wear modelling in machining using ANN, 5th CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2006) pp. 69–73

59.49 C. Bruni, A. Forcellese, F. Gabrielli, M. Simoncini: Thermal error prediction in a machining center using statistical and neural network-based models, 4th CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2004)

59.50 N. Hansen, A. Ostermeier: Completely derandomized self-adaptation in evolution strategies, Evol. Comput. **9**(2), 159–195 (2001)

59.51 D. Biermann, K. Weinert, T. Wagner: Model-based optimization revisited: Towards real-world processes, Proc. 2008 IEEE Congr. Evol. Comput. (2008) pp. 2980–2987

59.52 O. Kramer: Covariance matrix self-adaptation and kernel regression – perspectives of evolutionary optimization in kernel machines, J. Fundam. Inform. **98**(1), 87–106 (2010)

59.53 T. Özel, Y. Karpat: Identification of constitutive material model parameters for high-strain rate metal cutting conditions using evolutionary computational algorithms, Mater. Manuf. Process. **22**, 659–667 (2007)

59.54 D. Biermann, T. Surmann, G. Kehl: Oscillator model of machine tools for the simulation of self excited vibrations in machining processes, 1st Int. Conf. Process Mach. Interact. (2008) pp. 23–29

59.55 K. Weinert, M. Stautner: Reconstruction of particle flow mechanisms with symbolic regression via genetic programming, Proc. Genet. Evol. Comput. Conf. (2001) pp. 1439–1443

59.56 K. Weinert, M. Stautner, J. Mehnen: Automatic generation of mathematical descriptions of cutting processes from video data, production engineering, Res. Dev. **9**(2), 55–58 (2002)

59.57 R. Teti, G. Giorleo, U. Prisco, D. DAddona: Integration of neural network material modelling into the FEM simulation of metal cutting, 3rd CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2002)

59.58 I.S. Jawahir, X. Wang: Development of hybrid predictive models and optimization techniques for machining operations, J. Mater. Process. Technol. **185**(1–3), 46–59 (2007)

59.59 A.D. Jayal, I.S. Jawahir: Analytical and computational challenges for developing predictive models and optimization strategies for sustainable machining, 7th CIRP Int. Conf. Intell. Comput. Manuf. Eng. (2010)

59.60 G. Celano, S. Fichera, E.L. Valvo: Optimization of cutting parameters in multi pass turning operations for continuous forms, 2nd CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2000) pp. 417–422

59.61 C.W. Lee, Y.C. Shin: Evolutionary modelling and optimization of grinding processes, Intern. J. Prod. Res. **38**(12), 2787–2813 (2000)

59.62 X. Wang, Z.J. Da, A.K. Balaji, I.S. Jawahir: Performance-based optimal selection of cutting parameters and cutting tools in multi-pass turning operations using genetic algorithms, 2nd CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2000) pp. 409–414

59.63 V. Tandon, H. El-Mounayri, H. Kishawy: NC end milling optimization using evolutionary computation, Int. J. Mach. Tools Manuf. **42**(5), 595–605 (2002)

59.64 X. Wang, I.S. Jawahir: Web-based optimization of milling operations for the selection of cutting conditions using genetic algorithms, 3rd CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2002)

59.65 C.W. Lee, T. Choi, Y.C. Shin: Intelligent model-based optimization of the surface grinding process for heat-treated 4140 steel alloys with aluminum oxide grinding wheels, J. Manuf. Sci. Eng. **125**(1), 65–76 (2003)
59.66 K. Vijayakumar, G. Prabhaharan, P. Asokan, R. Saravanan: Optimization of multi-pass turning operations using ant colony system, Inter. J. Mach. Tools Manuf. **43**(15), 1633–1639 (2003)
59.67 X. Wang, A. Kardekar, I.S. Jawahir: Performance-based optimization of multi-pass face-milling operations using genetic algorithms, 4th CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2004)
59.68 Y. Karpat, T. Özel: Hard turning optimization using neural network modeling and swarm intelligence, Trans. North Am. Manuf. Res. Inst. **33**, 179–186 (2005)
59.69 T.-H. Hou, C.-H. Su, W.-L. Liu: Parameters optimization of a nano-particle wet milling process using the Taguchi method, response surface method and genetic algorithm, Powder Technol. **173**(3), 153–162 (2007)
59.70 J.L. Vigouroux, L. Deshayes, S. Foufou, L.A. Welsh: An approach for optimization of machining parameters under uncertainties using intervals and evolutionary algorithms, CIRP J. Manuf. Syst. **5**(36), 395–399 (2007)
59.71 A.R. Yildiz: A novel hybrid immune algorithm for global optimization in design and manufacturing, Robot. Comput. Integr. Manuf. **25**(2), 261–270 (2009)
59.72 R. Roy, J. Mehnen: Dynamic multi-objective optimisation for machining gradient materials, CIRP Ann. Manuf. Technol. **57**(1), 429–432 (2008)
59.73 F. Cus, J. Balic, U. Zuperl: Hybrid ANFIS-ants system based optimisation of turning parameters, J. Achiev. Mater. Manuf. Eng. **36**(1), 79–86 (2009)
59.74 R. Datta, K. Deb: A classical-cum-evolutionary multi-objective optimization for optimal machining parameters, Nat. Biol. Inspir. Comput. (2009) pp. 607–612
59.75 A.R. Yildiz: A novel particle swarm optimization approach for product design and manufacturing, Inter. J. Adv. Manuf. Technol. **40**(5-6), 617–628 (2009)
59.76 A.N. Sait: Optimization of machining parameters of GFRP pipes using evolutionary techniques, Int. J. Precis. Eng. Manuf. **11**(6), 891–900 (2010)
59.77 A.M. Zain, H. Haron, S. Sharif: Application of GA to optimize cutting conditions for minimizing surface roughness in end milling machining process, Expert Syst. Appl. **37**(6), 4650–4659 (2010)
59.78 K. Deb, R. Datta: Hybrid evolutionary multi-objective optimization of machining parameters, Eng. Optim. **44**(6), 685–706 (2011)
59.79 A.A. Krimpenis, P.I.K. Liakopoulos, K.C. Giannakoglou, G.-C. Vosniakos: Multi-objective design of optimal sculptured surface rough machining through pareto and nash techniques, 6th Conf. Evol. Determ. Methods Des. Optim. Contr. Appl. Ind. Soc. Probl. (2005)
59.80 I.N. Tansel, B. Ozcelik, W.Y. Bao, P. Chen, D. Rincon, S.Y. Yang, A. Yenilmez: Selection of optimal cutting conditions by using GONNS, Inter. J. Mach. Toolls Manuf. **46**(1), 26–35 (2006)
59.81 F. Cus, U. Zuperl, V. Gecevska: High speed end-milling optimisation using particle swarm intelligence, J. Achiev. Mater. Manuf. Eng. **22**(2), 75–78 (2007)
59.82 U. Zuperl, F. Cus, V. Gecevska: Optimization of the characteristic parameters in milling using the PSO evolution technique, J. Mech. Eng. **6**, 354–368 (2007)
59.83 F. Cus, U. Zuperl: Particle swarm intelligence based optimisation of high speed end-milling, Arch. Comput. Mater. Sci. Surf. Eng. **1**(3), 148–154 (2009)
59.84 T. Wagner, H. Trautmann: Integration of preferences in hypervolume-based multiobjective evolutionary algorithms by means of desirability functions, IEEE Trans. Evol. Comput. **14**(5), 688–701 (2010)
59.85 E.L. Valvo, B. Martuscelli, M. Piacentini: NC end milling optimization within CAD/CAM system using particle swarm optimization, 4th CIRP Int. Semin. Intell. Comput. Manuf. Eng. (2004) pp. 357–362
59.86 E. Borsetto, N. Gramegna: Multi-objective optimization of machining process using advantedge FEM tool, 7th CIRP Int. Conf. Intell. Comput. Manuf. Eng. (2010)
59.87 R. Li, M.T.M. Emmerich, J. Eggermont, T. Bäck, M. Schütz, J. Dijkstra, J.H.C. Reiber: Mixed-integer evolution strategies for parameter optimization, Evol. Comput. **21**(1), 29–64 (2013)
59.88 R.V. Rao, P.J. Pawar: Parameter optimization of a multi-pass milling process using non-traditional optimization algorithms, Appl. Soft Comput. **10**(2), 445–456 (2010)
59.89 Z.G. Wang, M. Rahman, Y.S. Wong, J. Sun: Optimization of multi-pass milling using parallel genetic algorithm and parallel genetic simulated annealing, Int. J. Mach. Tool. Manuf. **45**(15), 1726–1734 (2005)
59.90 R. Roy, Y.T. Azene, D. Farrugia, C. Onisa, J. Mehnen: Evolutionary multi-objective design optimisation with real life uncertainty and constraints, CIRP Annu. Manuf. Tech. **58**(1), 169–172 (2009)
59.91 H.-G. Beyer, B. Sendhoff: Robust optimization – A comprehensive survey, Comput. Method. Appl. Mech. Eng. **196**(33/34), 3190–3218 (2007)
59.92 S. Mekid, T. Ogedengbe: A review of machine tool accuracy enhancement through error compensation in serial and parallel kinematic machines, Int. J. Precis. Technol. **1**(314), 251–286 (2010)
59.93 R. Teti, K. Jemielniak, G. O'Donnell, D. Dornfeld: Advanced monitoring of machining operations, CIRP Ann. Manuf. Technol. **59**, 717–739 (2010)
59.94 H. Müller, D. Biermann, P. Kersting, T. Michelitsch, C. Begau, C. Heuel, R. Joliet, J. Kolanski,

M. Kröller, C. Moritz, D. Niggemann, M. Stöber, T. Stönner, J. Varwig, D. Zhai: Intuitive visualization and interactive analysis of pareto sets applied on production engineering. In: *Success in Evolutionary Computation*, Studies Computational Intelligence, Vol. 92, ed. by A. Yang, Y. Shan, L.T. Bui (Springer, Berlin, Heidelberg 2008) pp. 189–214

59.95 H. Pohlheim: Understanding the course and state of evolutionary optimizations using visualization: Ten years of industry experience with evolutionary algorithms, Artif. Life **12**(2), 217–227 (2006)

59.96 S. Obayashi, D. Sasaki: Evolutionary multi-criterion optimization. In: *Visualization and Data Mining of Pareto Solutions Using Self-Organizing Map*, ed. by C. Fonseca, P. Fleming, E. Zitzler, L. Thiele, K. Deb (Springer, Berlin Heidelberg 2003) pp. 796–809

59.97 K. Deb: *Innovization: Discovering Innovative Solution Principles Through Optimization* (Springer, Berlin, Heidelberg 2011)

59.98 B. Sieben, T. Wagner, D. Biermann: Empirical modeling of hard turning of AISI 6150 steel using design and analysis of computer experiments, Prod. Eng. Res. Dev. **4**(2-3), 115–125 (2010)