ICSPEA: Evolutionary Five-Axis Milling Path Optimisation

Jörn Mehnen
Decision Engineering Centre
Cranfield University
Cranfield
Bedfordshire MK43 0AL, UK
j.mehnen@cranfield.ac.uk

Rajkumar Roy
Decision Engineering Centre
Cranfield University
Cranfield
Bedfordshire MK43 0AL, UK
r.roy@cranfield.ac.uk

Petra Kersting
Department of Machining Technology (ISF)
University Dortmund
44227 Dortmund, Germany
pkersting@isf.de

Tobias Wagner
Department of Machining Technology (ISF)
University Dortmund
44227 Dortmund, Germany
wagner@isf.de

ABSTRACT

ICSPEA is a novel multi-objective evolutionary algorithm which integrates aspects from the powerful variation operators of the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) and the well proven multi-objective Strength Pareto Evaluation Scheme of the SPEA 2. The CMA-ES has already shown excellent performance on various kinds of complex single-objective problems. The evaluation scheme of the SPEA 2 selects individuals with respect to their current position in the objective space using a scalar index in order to form proper Pareto front approximations. These indices can be used by the CMA-part of ICSPEA for learning and guiding the search towards better Pareto front approximations. The ICSPEA is applied to complex benchmark functions such as an extended n-dimensional Schaffer's function or Quagliarella's problem. The results show that the CMA operator allows ICSPEA to find the Pareto set of the generalised Schaffer's function faster than SPEA 2. Furthermore, this concept is tested on the complex real-world application of the multi-objective optimization of five-axis milling NC-paths. An application of ICSPEA to the milling-path optimisation problem yielded efficient sets of five-axis NC-paths.

Categories and Subject Descriptors

J.6 [**Computer-Aided Engineering**]: Computer-Aided Manufacturing (CAM); G.1 [**NUMERICAL ANALYSIS**]: G.1.6 Optimization

General Terms

Algorithms

GECCO'07, July 7–11, 2007, London, England, United Kingdom.

Keywords

Multi-objective Optimisation, Mechanical Engineering, CMA-ES, SPEA 2, Evolutionary Computing

1. INTRODUCTION

Multi-objective parameter optimisation can be a very challenging task especially when real-world problems have to be solved. Therefore, new concepts have to be introduced using powerful operators that help in solving even very complex problems. ICSPEA (Integrating CMA-ES and SPEA 2) is a new multi-objective evolutionary algorithm, which uses the variation operators of the CMA-ES [11] and the Strength Pareto evaluation concept of SPEA 2 [3]. The Covariance Matrix Adaptation (CMA) shows advantageous features and makes the CMA-ES the best known single-objective stochastic optimiser [1]. SPEA 2 uses a scalar quality index to describe multi-objective properties of a set of possible Pareto solutions. This index is based on Pareto dominance and takes also the distribution and the spread of the currently approximated Pareto front into account. This makes SPEA 2 a good multi-objective evolutionary algorithm. Laumanns, Rudolph, and Schwefel showed [15] that the variation operator has a strong influence on the approximation quality of a Pareto front. ICSPEA follows this idea by joining the covariance matrix adaptation with the Strength Pareto evaluation. The CMA variation has been successfully integrated in a MOEA by Igel et al. [13]. Here, to overcome the drawbacks of a step size control in an elitist strategy, the step size mechanism had to be replaced by a success rule criterion. ICSPEA is an approach that completely utilizes the scheme proposed by Hansen [11]. It is introduced to overcome some drawbacks of the conventional SPEA 2 variation operators and to test the CMA concept in a multi-objective environment.

In the following, the idea of ICSPEA will be introduced. A comparison of ICSPEA and SPEA 2 using the multi-objective generalized Schaffer's function is discussed in order to discover the influence of the CMA variation operator in ICSPEA. The ability of the algorithm to find Pareto front approximations for benchmark function of Quagliarella is shown. The real-world problem of five-axis milling is introduced. A mathematical description of the two main objectives of the problem is given. The results were generated using a milling simulator. This paper addresses scientists interested in the concept of ICSPEA as well as mechanical engineers with multi-objective real-valued problems.

2. THE ICSPEA

Developing efficient learning schemes that are able to handle sparse data in order to achieve optimal solutions in unknown problem domains is the main objective of optimisation algorithm design. There exist two key elements in optimisation algorithms: first is the variation of possible solutions and second is the selection of promising new solutions. If no a-priori knowledge about a problem is available at all, stochastic search schemes seem the only sensible techniques for choosing possible solutions in an unknown search space. The more points are tested, the more knowledge is available and should be used as efficiently as possible for the definition of promising solutions. Evolutionary Algorithms (EA) are intrinsically stochastic search heuristics that are able to solve even very complex optimisation problems. The Evolution Strategy (ES) [20] is – together with Genetic Algorithms (GA) [9] – surely one of the most famous paradigms for stochastic general purpose optimisation. Developed in the early 1970's it uses a Gaussian distribution for the variation of a set of possible solutions called parent individuals. The variation process in an ES is self-adaptive, i.e. the mutation operator learns from beneficial choices of search directions. For this learning process each surviving individual carries its own history in its genes. On the extreme this history lasts only one generation. In 1981 Schwefel extended the original ES by a new variant, which adapts the learning scheme with respect of the success in the direction of the coordinate axis. Individuals in an ES with correlated mutations can adapt their steps sizes in any arbitrary direction of the search space. Here, each surviving individual carries its own promising coordinate axis dependent step sizes together with an additional rotation matrix in its genes [20, 2]. Objective values, step sizes as well as the correlation matrix undergo evolutionary adaptation.

In 1996 Hansen and Ostermeier proved several disadvantages of the Evolution Strategy with correlated mutations [10]. They proposed a variant with covariance matrix adaptation, the CMA-ES. This algorithm uses a derandomised learning strategy of the search directions. It utilises a longer history of several subsequent improvements and estimates a general beneficial search direction. This history is stored in two so called evolution paths, which are used to adapt a covariance matrix and a global step size, respectively. The covariance matrix concept properly turns the search into promising directions during mutation. The global step size defines the variance of the multivariate normal distribution controlled mutation. For a formal description of the CMA-ES and its operators refer to [11].

The CMA-ES is a very good single-objective optimisation algorithm. Its effectiveness comes from the advanced variation operator and learning scheme. Its application to multi-objective problems is possible, if solutions can efficiently be evaluated in a multi-objective sense using scalar indices for each single solution. Actually, this indexing concept is used in many multi-objective evolutionary algorithms (MOEA). The most prominent MOEA of this class are NSGA-II [6], SMS-EMOA [8], and SPEA 2 [24].

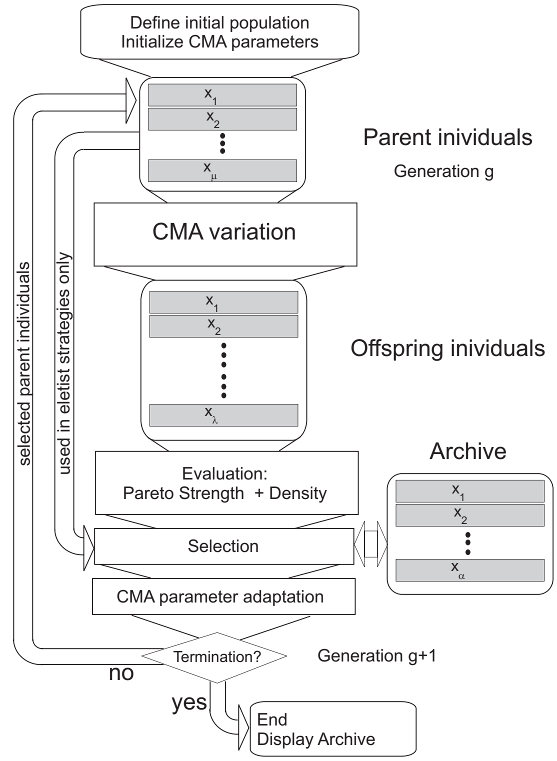

Figure 1: Sketch of the general structure of ICSPEA.

2.1 Concept

For ICSPEA, SPEA 2 was selected as a prototype. SPEA 2 uses the well accepted Strength Pareto evaluation concept. This method has superior properties with respect to Pareto front approximation and solution spread [24]. The population handling of parent and offspring individuals has certain similarities with the Evolution Strategy. An additional archive is used for storing current non-dominated solutions. The multi-objective quality of each solution is evaluated taking the number of dominated individuals and the distance between the other individuals into account. Strength and distance form a scalar index which is used for the selection of promising offspring individuals to form the new parent generation. It is possible to use the archive as an additional information source. Currently, the archive is used as an external memory for saving non-dominated individuals, i.e. the latest Pareto front approximation. The current implementation utilises a non-elitist strategy, where only individuals from the surplus of offspring are evaluated and selected. SPEA 2, as implemented in PISA [3] and utilises the SBX variation operator [7] with polynomial mutation. Using the correct variation operator is very crucial for the evolutionary process. As [15] pointed out, especially in multi-objective environments the application of effective mutation operators is necessary to avoid early stagnation near the true Pareto front. The idea of ICSPEA is to combine the evaluation operator of SPEA 2 and its population management concept with the effective variation operator of the CMA-ES. A sketch of the layout of ICSPEA is shown in figure 1. An exact mathematical description of ICSPEA can be found in [17] and [21]. The generation of new offspring individuals is based on the original CMA variation concept by Hansen and Ostermeier [11]. For ICSPEA, the Strength Pareto evaluation method [3] was embedded in the CMA-ES algorithm available in the SHARK program library [12]. Additionally, the definition of the density function has been changed slightly in ICSPEA [17].

3. BENCHMARK FUNCTIONS

First, the application of ICSPEA to typical benchmark functions is discussed. In the single-objective case, the ES as well as the CMA-ES have been comprehensively tested on the sphere model and elliptic functions [20, 2, 11]. Schaffer's function [19] can be seen as a multi-objective counterpart. The **Generalised Schaffer's Function** has a decision space with dimension $n \geq 1$. A first generalised version using $n = 2$ was suggested by [14]. The Pareto set is $x_1 \in [0, 2]$ and $x_2 = \ldots = x_n = 0$.

$$\text{Generalised Schaffer}: \quad \begin{array}{l} f_1(\mathbf{x}) = \sum_{i=1}^{n} x_i^2 \\ f_2(\mathbf{x}) = (x_1 - 2)^2 + \sum_{i=2}^{n} x_i^2 \end{array} \qquad (1)$$

with
$x_1, x_2 \in [-10^6, 10^6]^n$.

The two-criteria **Quagliarella's function** [18] has a concave Pareto front. The problem is strongly nonlinear. In the tests with ICSPEA, the number of dimensions was set to $n = 3$. The area of feasible solutions is $[-100.0, 100.0]^n$.

$$\text{Quagliarella}: \quad \begin{array}{rcl} f_1(\mathbf{x}) & = & \sqrt{\frac{A_1}{n}}, \\ f_2(\mathbf{x}) & = & \sqrt{\frac{A_2}{n}} \end{array} \qquad (2)$$

with

$$\begin{array}{l} A_1 = \sum_{i=1}^{n} [(x_i^2) - 10\cos[2\pi(x_i)] + 10] \\ A_2 = \sum_{i=1}^{n} [(x_i - 1.5)^2 - 10\cos[2\pi(x_i - 1.5)] + 10] \\ -5.12 \leq x_i \leq 5.12, n = 16. \end{array} \qquad (3)$$

Convergence assessment

Due to the fact that the Pareto sets of the generalised Schaffer's function is known by construction, the average distance of all current solutions in the archive of size α to the set $[0, 2] \times 0.0^{n-1}$ can be taken for estimating the convergence speed [21]. Like in single-objective optimisation, the distance of the solutions to the known best solutions is calculated. Here, the measure MeSCH_n [17] determines the average distance of the approximation of the true Pareto set. Small values with a minimum at 0.0 indicate a good approximation quality.

$$d(\mathbf{x_i}) = \begin{cases} (\mathbf{x_{i1}} - 2) & \text{if} \quad (\mathbf{x_{i1}} > 2) \\ -\mathbf{x_{i1}} & \text{if} \quad (\mathbf{x_{i1}} < 0) \\ 0.0 & \text{if} \quad (0 \leq \mathbf{x_{i1}} \leq 2) \end{cases} \qquad (4)$$

$$\text{MeSCH}_n = \frac{1}{\alpha} \sum_{i=1}^{\alpha} \sqrt{d(\mathbf{x_i})^2 + \sum_{j=2}^{n} \mathbf{x_i}_j^2} \qquad (5)$$

A convergence measure for Quagliarella's function has not been done. References on quality assignments for Pareto fronts can be found in [4, 5, 16].

3.1 Parameter Settings

In order to compare the results obtained with ICSPEA, Pareto fronts were calculated using SPEA 2 from the well tested and accepted software package PISA [3]. In PISA, the SPEA 2 algorithm uses a fixed $k = 1$. In the experiments the specific SPEA 2 parameters $p_m = \frac{1}{n}$, $p_c = 0.5$, $\eta_m = 20$, and $\eta_m = 15$ were used and the SBX-variation operator was applied.

The dimension of the decision space in the generalised Schaffer's problem is $n = 20$. Quagliarella's problem was tested with $n = 3$. The number of individuals in the populations were the same for ICSPEA and SPEA 2. The sizes of parent, offspring, and archive populations were set to $\mu = 5$, $\lambda = 50$, and $\alpha = 60$, respectively. All runs were repeated 50 times, 400 generations per single run. In the analysis, all results were taken into account to get main statistical data such as median or quartiles. The individuals of the first population were initialised randomly within the complete feasible subspace.

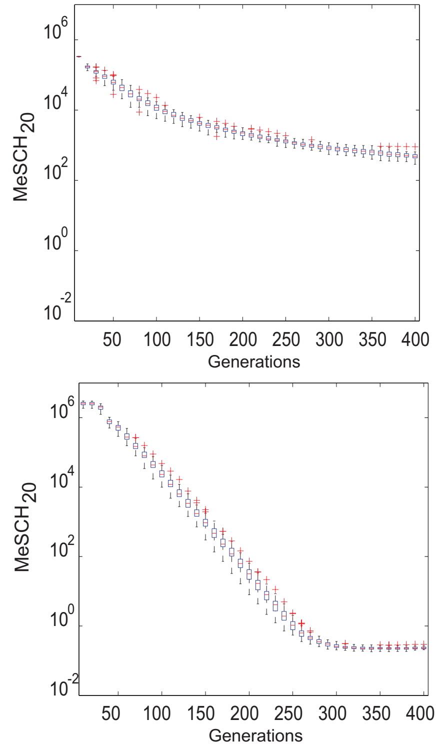

Figure 2: Convergence of SPEA 2 (above) and ICSPEA (below) when applied to the 20-dimensional generalised Schaffer's function.

3.2 Results

Figure 2 shows the results of the application of ICSPEA and SPEA 2 to the generalised Schaffer's problem. The values on the ordinate axis are scaled logarithmically. The distribution of the qualities MeSCH_{20} of fifty runs is displayed using box and whisker plots. The boxes have lines at the lower quartile, median, and upper quartile values. The whiskers show the extent of the rest of the data. Outliers have values beyond the ends of the whiskers.

Both algorithms approximate the Pareto front correctly. ICSPEA shows a fair linear convergence during the first about 250 generations. For high dimensions of n, it is difficult to get very small values for MeSCH_{20} because every

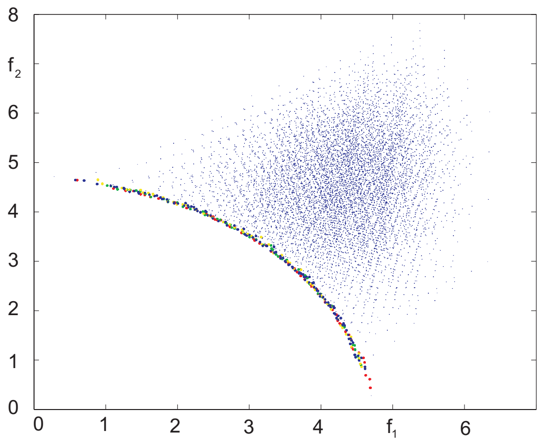

Figure 3: Pareto front approximations of Quagliarella's function found with ICSPEA. Five runs are plotted.

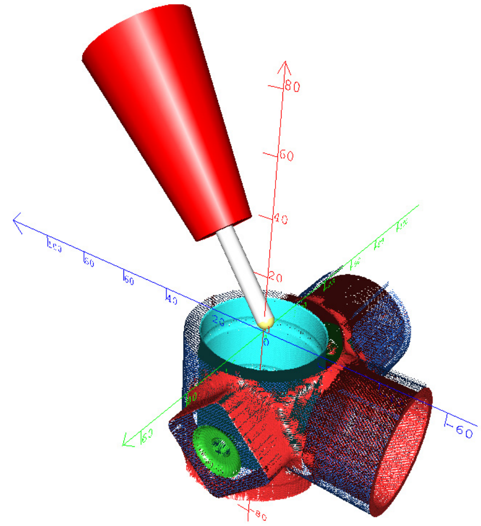

Figure 4: Five-axis milling of a connector.

slight deviation from the optimum is accounted for with squared error values added up n times. Small deviations appear because the density criterion indents to spread the Pareto front as much as possible. This causes overshoots at the borders of the Pareto front and introduces a slight constant error.

The linear convergence of ICSPEA is due to the CMA variation concept. This shows the comparison of the graphs in figure 2. SPEA 2 differs from ICSPEA mainly in the SBX variation operator but behaves strongly different in the convergence. CMA and SBX just follow different self adaptation concepts. The boxes and whiskers, i.e. quantiles and outliers, are very small for both algorithms indicating that both methods are working very reliable on the generalized Schaffer's function.

Figure 3 shows that ICSPEA is also able to approximate concave Pareto fronts. Neither the evaluation scheme nor the CMA operator seems to have a general influence on the approximation of concave fronts. The figure shows the approximation of five runs. Additionally, a regular sampling of the decision space with step size 0.3 in all three dimensions is displayed. All five Pareto front approximations in figure 3 are quite similar and approximate the true Pareto front equally good.

4. OPTIMISING FIVE-AXIS MILLING

Milling is a machining process of cutting small chips from a workpiece surface using defined cutting edges, which are attached to a rotating tool. In the three-axis case, the tool is able to move at any position in the workspace. Only the tool's orientation is fixed. In five-axis milling the tool can additionally be tipped. Five-axis milling is especially designed for workpieces with deep cavities, steep 90° walls, or undercuts such as dies for large crank shafts or micro injection moulds. These geometries cannot be machined optimally with three-axis strategies. Furthermore, the five-axis process offers the possibility of using shorter and stiffer milling tools with only less tendency of deflection. The orientation of the milling tool relative to the workpiece surface has a relevant impact on the quality of the machined surface. Five-axis milling allows adjusting the orientation of the milling tool according to the respective objectives that are necessary during the current machining situation. Figure 4 shows an example of a deep cylindrical cavity with steep walls. The object shown is a connector node used in lightweight constructions.

There are several objectives in five-axis milling that have to be fulfilled the same time, e.g. devation from the normal vector, harmony of movement, process forces, process time etc. Here only the first two of them are discussed exemplarily.

Deviation from the Normal Vector

Largely simplified, during milling the main axis of the milling tool should be nearly parallel to the normal vector of the current workpiece surface. In practice and simulation, the milling tool is kept slightly inclined to avoid inefficient cutting conditions at the tool tip. The milling simulation used here for the experiments is able to calculate the normal vectors at any time at any point of the surface efficiently. The following equations give a more formal description of the first objective f_1.

$\mathbf{n}_i \in \mathbb{R}^3$ are normal vectors at the workpiece surface determined at each discrete step of the NC-path and $\mathbf{x}_i \in \mathbb{R}^3, i = 1, \ldots, k, k \in \mathbb{N}$ are current orientation vectors of the main axis of the milling tool at each respective NC-step. The angles α_i between $\mathbf{n}_i$ and $\mathbf{x}_i$ can be calculated as follows:

$$\alpha_i = acos\left(\frac{<\mathbf{n}_i, \mathbf{x}_i>}{||\mathbf{n}_i||||\mathbf{x}_i||}\right). \tag{6}$$

The first quality criterion f_1 sums up all differences α_i between the vectors, i.e.

$$f_1 = \frac{1}{k}\sum_{i=1}^{k} |\alpha_i|. \tag{7}$$

The values of f_1 are normalized to be independent from the number k of NC-steps. The desired value should be as small as possible. The minimum is 0.0 if all vectors are aligned.

The sketch on figure 5 illustrates schematically calculation for objective f_1.

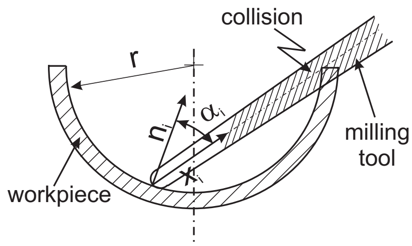

Figure 5: Calculation of the deviation α_i of the tool's main axis $\mathbf{x}_i$ from the normal vector $\mathbf{n}_i$ (side view). The collision between tool and workpiece is a violation of a geometric constraint.

Harmony of Movement
The spindle of a five-axis milling machine should be moved as less as possible in order to reduce oscillations. These oscillations may cause chatter marks on the surface of the workpiece. A turn of the spindle implies a change of subsequent orientations of the tool's main axis, i.e. a difference between $\mathbf{x}_i$ and $\mathbf{x}_{i+1}$. The smaller these differences the better the harmonic movement of the spindle. A minimum of 0.0 is reached if all $\mathbf{x}_i$ are in parallel. Therefore, the second fitness criterion f_2 is

$$f_2 = \frac{1}{k}\sum_{i=1}^{k} |\beta_i| \tag{8}$$

with

$$\beta_i = acos\left(\frac{< \mathbf{x}_i, \mathbf{x}_{i+1} >}{||\mathbf{x}_i||||\mathbf{x}_{i+1}||}\right). \tag{9}$$

The values of f_2 are normalized again to be independent from the number k of NC-steps.

Functions f_1 and f_2 are contradictory for curved NC-paths. On the one hand the spindle should follow the normal vectors as good as possible to keep advantageous engagement conditions. On the other hand, it should change its orientation as less as possible to reduce oscillations caused by the spindle movement. Machining e.g. a full circle like in figure 6, both criteria cannot reach a minimum at the same time.

Constraints
Collisions are a key issue in five-axis milling. Any contact between tool shaft or spindle with the workpiece must be avoided because this causes a deterioration of the surface quality, may cause tool breakage or even damages of the machine. Therefore, any collision has to be detected during the simulation. Collisions are constraints that depend on the continuously changing geometry of the tool. Additional constraints are caused due to the restricted orientation of the spindle. For any violation of a constraint the simulator calculates a specific penalty value. This penalty is designed to lead the search process smoothly back into the feasible regions. The continuously dynamically changing constraints are one of the main issues that make the optimisation of five-axis milling a very difficult task. In figure 5 a collision between workpiece and tool shaft is shown.

Of course, realistic milling simulations are much more complex [23, 22]. The two quality criteria described here may give a slight impression of the restricted real-value multi-objective parameter optimisation problem ICSPEA had to face.

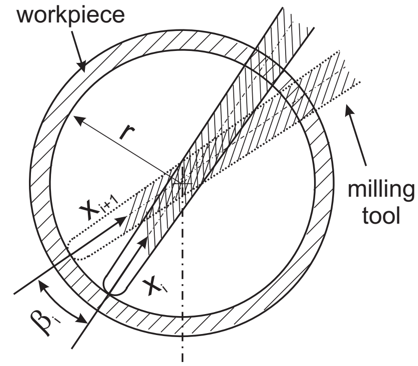

Figure 6: Calculation of the harmony β_i between two subsequent NC-steps $\mathbf{x}_i$ and $\mathbf{x}_{i+1}$ (top view).

4.1 Experimental Setup

All experiments with ICSPEA were performed using 10,000 generations. Each optimisation run was repeated 10 times. The initial global step size is $\sigma_{(0)} = 0.1$. The parent population size is $\mu = 10$ and the number of offspring $\lambda = 50$. The archive size is $\alpha = 20$. A special function for the estimation of the Pareto front density is applied as described in [21, 17]. All initial solutions start in the space of feasible region, i.e. all initial solutions are valid NC machining paths. A solution in ICSPEA is coded by a set of subsequent vectors $\mathbf{x}_i \in \mathbb{R}^3, i = 1, \ldots, k$ following the k discrete steps of an NC-path. In the examples k equals 10. The NC-path describes the milling path of an arc of the inner circle of a spherical mould (see figure 8).

4.2 Results and Discussions

For the analyses, ICSPEA was integrated into the milling process simulator [23]. For each single solution a complete milling simulation of the respective NC-path was carried out and the two quality values f_1 and f_2 were calculated. Figure 7 shows the results of three example runs.

The results of the optimisation runs indicate that the actually unknown true Pareto front may have a generally convex shape. Taking only f_1 and f_2 and no restrictions into account, the Pareto front for a machined quarter circle (see figures 6 and 5) is truly convex. Constraints and shape of the milling path have a major influence on the shape of the Pareto front and complexity of the problem. Especially, if an optimal solution is at the border of the constrained area, optimisation becomes very difficult. This problem appears e.g. if the tool shaft is forced to come very close to the workpiece surface in order to follow optimal engagement conditions. Optimising close to a constraint means that it is very likely that several solutions may be infeasible. These individuals are 'lost' and, thus, make only a minor contribution to the search process. Some results at the Pareto front found by ICSPEA have quite small f_2 values. This corresponds to milling paths with a strong harmonic character. An example solution of an extremely harmonic movement of the machine is displayed in the lower part of figure 8. In this example the main axis of the tool shaft are nearly all in parallel. This NC-path is perfectly valid and the machine movement is very stable but the engagement conditions are not optimal.

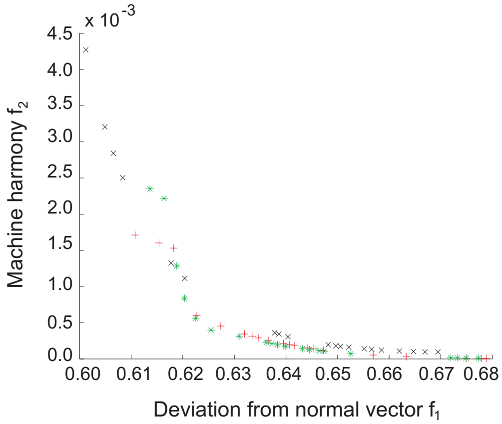

Figure 7: Pareto fronts for the optimisation of the five-axis milling path calculated with ICSPEA. Three Pareto fronts are plotted, each denoted by a plus, asterisk, and cross, respectively.

Small values of f_1 indicate small deviations from the normal vectors. The tool follows mainly the shape of the workpiece surface. An example is shown in the top of figure 8. The engagement conditions of solutions with small f_1 values should be preferred if the machine movement could be neglected. In practice a good compromise between harmony, i.e. less machine wear and reduced machine oscillations, and engagement, i.e. less tool wear and improved surface quality, should be found.

One can see from figure 7 that the solutions in f_1 direction are two factors larger than in f_2 direction. Due to the fact that both problems nearly have the same complexity, it may be possible that during the early stages of the optimisation, ICSPEA prefers searching in f_2 direction. Furthermore, it should be pointed out, that the initialisation of the search may also have an influence on the search result. The solutions displayed in figure 7 all have different feasible start conditions and differ slightly in position along the Pareto front.

All solutions found by ICSPEA are feasible. The simulator guarantees that only feasible solutions are passed on to the user. Additionally, automatic post processing steps convert the data into processable machine specific NC-paths. Depending on current external practical demands, the user can choose any solution from the Pareto front and visualise and test the solutions using the simulator. An intuitive graphical online visualisation of every single solution, i.e. each NC-path corresponding to a solution along the Pareto front, may help an engineer finding his/her preferred milling strategy.

5. CONCLUSIONS

ICSPEA is a novel multi-objective optimisation algorithm that combines the most effective ingredients from CMA-ES and SPEA 2 in one single multi-objective optimisation algorithm. The advantages of this concept are empirically discussed using benchmark functions. Empirical experiments with a generalised Schaffer's problem show that combining CMA-ES variation and SPEA 2 fitness evaluation yield significant improvements when compared to the standard SPEA 2. The advantageous features of SPEA 2 with respect to approximation and distribution properties of the Pareto front are inherited. A milling-path optimisation problem was selected as a specially challenging real-world application example. ICSPEA generated various compromise solutions from which a user can choose either more harmonic or better engagement properties. This allows the engineer to adapt more easily to changing practical demands. ICSPEA was successful in various tests and fulfilled the engineer's demands. Nevertheless, a more rigorous theoretical analysis of the algorithm has to follow.

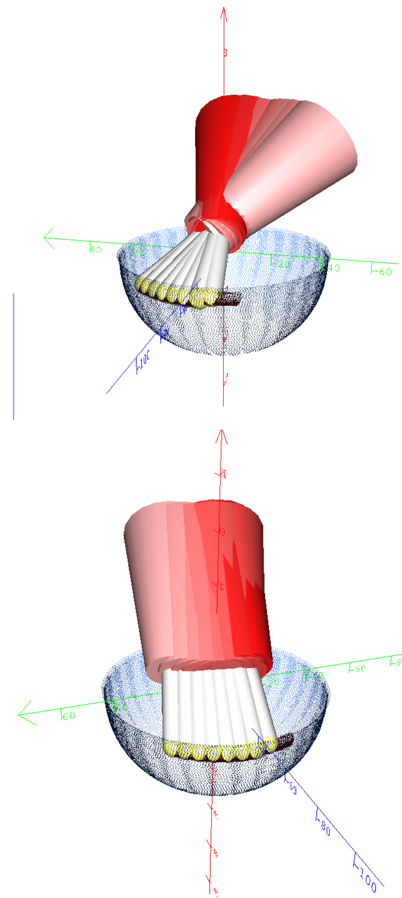

Figure 8: Two optimisation results. In the top figure the normal vectors are emphasised while in the lower figure the harmony is predominant.

6. ACKNOWLEDGMENT

This work is the result of a collaboration of the University of Dortmund (Germany) and Cranfield University (UK). The application of the milling process refers project C15, which is part of the *Collaborative Research Center 'Computational Intelligence' (SFB 531)*. Project D5 from the *Collaborative Research Center SFB/TR TRR 30* strongly supported the discussions regarding ICSPEA and PISA. Both SFB projects are supported by the *Deutsche Forschungsgemeinschaft (DFG)*. Many thanks to Igor Tipura, who did a great job in implementing ICSPEA. Many thanks also to Prof. Dr. Günter Rudolph (LS 11, Computer Science Department, Dortmund) for strongly encouraging this work.

7. REFERENCES

[1] A. Auger and N. Hansen. A Restart CMA Evolution Strategy With Increasing Population Size. In *Proceedings of the IEEE Congress on Evolutionary Computation, CEC 2005*, pages 1769–1776. IEEE, Vol. 2, 2005.

[2] H.-G. Beyer and H.-P. Schwefel. Evolution strategies. A comprehensive introduction. *Natural Computing*, 1:3–52, 2002.

[3] S. Bleuler, M. Laumanns, L. Thiele, and E. Zitzler. PISA — A Platform and programming language independent Interface for Search Algorithms. In *EMO2003*, pages 494–508, 2003.

[4] C. Coello Coello, D. van Veldhuizen, and G. Lamont. *Evolutionary Algorithms for Solving Multi-Objective Problems*. Kluwer Academic Publishers, New York, 2002.

[5] Y. Collette and P. Siarry. *Multiobjective Optimization. Principles and Case Studies*. Cost Engineering in Practice. Springer, Berlin, 2003.

[6] K. Deb. *Multi-Objective Optimization using Evolutionary Algorithms*. Wiley, New York, 2001.

[7] K. Deb and R. Agarwal. Simulated Binary Crossover for Continuous Search Space. *Complex Systems*, 9:115–148, 1995.

[8] M. Emmerich, N. Beume, and B. Naujoks. An EMO Algorithm Using the Hypervolume Measure as Selection Criterion . In *Evolutionary Multi-Criterion Optimization*, Lecture Notes in Computer Science, pages 62–76, Berlin, 1995. Springer.

[9] D. Goldberg. *Genetic Algorithms ins Search, Optimization, and Machine Learning*. Addison-Wesley, Reading, 1989.

[10] N. Hansen and A. Ostermeier. Adapting arbitrary normal mutation distributions in evolution strategies: The covariance matrix adaptation. In *Proceedings of the 1996 IEEE International Conference on Evolutionary Computation*, pages 312–317, Piscataway, New Jersey, 1996. IEEE Press.

[11] N. Hansen and A. Ostermeier. Completely Derandomized Self-Adaptation in Evolution Strategies. *Evolutionary Computation*, 9(2):159–195, 2001.

[12] C. Igel. Shark library http://shark-project.sourceforge.net/. 2007.

[13] C. Igel, N. Hansen, and S. Roth. The Multi-Objective Variable Metric Evolution Strategy, Part I. Technical Report IR-INI 2005-04, Institut für Neuroinformatik, Ruhr-Universität Bochum, Germany, 2005.

[14] M. Laumanns, G. Rudolph, and H.-P. Schwefel. A Spatial Predator-Prey Approach to Multi-Objective Optimization: A Preliminary Study. In T. Bäck, A. Eiben, M. Schoenauer, and H.-P. Schwefel, editors, *Parallel Problem Solving From Nature - PPSN V*, pages 241–249, Berlin, 1998. Springer.

[15] M. Laumanns, G. Rudolph, and H.-P. Schwefel. Mutation Control and Convergence in Evolutionary Multi-Objective Optimization. In R. Matousek and P. Osmera, editors, *Proceedings of the 7th International Mendel Conference On Soft Computing (MENDEL 2001)*, pages 24–29, Brno, Czech Republic, 2001. University of Technology.

[16] J. Mehnen. *Mehrkriterielle Optimierverfahren für produktionstechnische Prozesse*. Vulkan Verlag, Essen, Germany, 2005. Habilitationsschrift.

[17] J. Mehnen, T. Wagner, P. Kersting, I. Tipura, and G. Rudolph. ICSPEA: Integrating CMA-ES and SPEA 2. Technical Report to be published, Department of Machining Technology (ISF), University Dortmund, Germany, 2007.

[18] D. Quagliarella and A. Vicini. Sub-population Policies for a Parallel Multiobjective Genetic Algorithm with Applications to Wing Design. In *1998 IEEE International Conference On Systems, Man, And Cybernetics*, volume 4, pages 3142–3147, San Diego, California, October 1998. Institute of Electrical and Electronic Engineers (IEEE).

[19] J. Schaffer. Multiple Objective Optimization with Vector Evaluated Genetic Algorithms. In *Genetic Algorithms and their Applications: Proceedings of the First International Conference on Genetic Algorithms*, pages 93–100. Lawrence Erlbaum, 1985.

[20] H.-P. Schwefel. *Evolution and Optimum Seeking*. John Wiley, New York, 1995.

[21] T. Wagner and J. Mehnen. ICSPEA: Integrating CMA-ES and SPEA 2. In *Late Breaking Papers at the Conference on Evolutionary Multiobjective Optimization, EMO 2007*, pages 36–40, New York, Berlin, 2007. Lecture Notes in Comp. Sciences, Springer.

[22] K. Weinert, A. Zabel, M. Müller, and P. Kersting. Optimizing NC Tool Paths for Five-Axis Milling using Evolutionary Algorithms on Wavelets. In M. K. et al., editor, *Conference Proceedings Pt. II; Genetic and Evolutionary Computation – GECCO 2006: Genetic and Evolutionary Computation Conference*, pages 1809–1816, Seattle, WA, USA, 2005. ACM New York.

[23] A. Zabel, M. Müller, M. Stautner, and P. Kersting. Improvement of Machine Tool Movements for Simultaneuos Five-Axis Milling. In R. Teti, editor, *Proceedings of the 5th CIRP International Seminar on Intelligent Computation in Manufacturing Engineering, ICME 2006, Ischia, Italy*, pages 159–164, University of Naples, Italy, 2006.

[24] E. Zitzler, M. Laumanns, and L. Thiele. SPEA 2: Improving the Strength Pareto Evolutionary Algorithm. Technical Report 103, Computer Engineering and Communication Networks Lab (TIK), ETH Zürich, 2001.