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Comparative Studies on Micro Heat Exchanger Optimisation

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Abstract- Although many methods for dealing with multi-objective optimisation (MOO) problems are available [Deb01] and successful applications have been reported [Coe01], the comparison between MOO methods applied to real-world problem was rarely carried out. This paper reports the comparison between MOO methods applied to a real-world problem, namely, the optimisation of a micro heat exchanger (μHEX). Two MOO methods, Dynamically Weighted Aggregation (DWA) proposed by Jin et al. [Jin01, Jin01b] and Non-dominated Sorting Genetic Algorithms (NSGA-II) proposed by Deb et al. [Deb00, Deb02], were used for the study. The commercial computational fluid dynamics (CFD) solver called *CFD-ACE+*[1] is used to evaluate fitness. We introduce how to interface the commercial solver with evolutionary computation (EC) and also report the necessary functionalities of the commercial solver to be used for the optimisation.

1 Introduction

In the real world, there are many problems to be optimised. The problems have several objectives which generally conflict with each other. In general, such problems do not offer one optimal solution. One of the methods for dealing with such optimisation problems is *Multi-Objective Optimisation (MOO)*. Many methods for MOO have been proposed in the literatures [Deb00, Deb01, Deb02, Jin01, Jin01b].

Comparative studies of several MOO methods, often called *Performance Indices (PIs)*, have become popular in the recent years. Many PIs have been proposed for several purposes, i.e. accuracy, distribution, spread, efficiency etc. The details can be seen in the recent survey papers, for example [Zit02, Oka03]. With some of PIs, the comparison of MOO methods were carried out on several test functions, (refer [Oka03]).

The final target of the MOO technology is the optimisation of real-world problems to achieve optimal designs, optimal running conditions etc. However, optimisation should not only contribute to new and innovative designs, but must also be a tool towards better understanding its phenomena. Recently many papers reported the success of the optimisation for real-world problems [Coe01]. The comparison between different MOO methods applied to real-world problems has been rarely carried out. The reason for this might be the time-consuming fitness evaluation. In this paper, an attempt is made to compare two MOO methods applied to a real-world problem, namely the *Dynamically Weighted Aggregation (DWA)* by Jin et al. [Jin01, Jin01b] and the *Non-dominated Sorting Genetic Algorithm (NSGA-II)* by Deb et al. [Deb00, Deb02].

The real-world problem chosen for this study is the optimisation of a micro heat exchanger (μHEX). The trend towards miniaturisation has led to the use of micro devices in industry and technology. Micro heat exchangers have very high heat transfer surface area against volume ratio that leads itself to very compact designs. The micro heat exchangers are widely spread in the fields of chemical, electronic and aerospace industries. In the chemical processing industries, micro heat exchangers have been used as fuel processors, combustors and evaporators [Dro97, Hol02, Pal02], It is known that the performance of a micro-channel heat exchanger depends very much on the geometric parameters of the micro-channels [Apa90, Wei02].

The objective of this paper is to optimise a μHEX using MOO. The physical phenomena in μHEX is multi-disciplinary and involves conjugate heat transfer. In order to solve the conjugate heat transfer problem, we used a commercial computational fluid dynamics (CFD) solver called *CFD-ACE+* developed by Computational Fluids Dynamics Research Corporation in the USA [CFD02]. This CFD solver was interfaced with our in-house developed evolutionary algorithms (EAs). In this paper we shall also discuss the difficulties associated with interfacing the CFD solver with our optimisation package.

The rest of this paper is organised as follows: In section 2 some published works related to heat exchanger optimisation, multi-objective optimisation, and the comparative studies of MOO are presented. Section 3 deals with the governing equations that describe the fluid flow and heat transfer in a heat exchanger. Section 4 describes models

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and objectives. This section will go into the details of how the two software packages are interfaced to form an optimisation software block. Thus, we explain the necessary functionalities in this section. Some preliminary results obtained with DWA and NSGA-II and the discussion of these results are presented in Section 5 and 6. Finally, we conclude this paper in Section 7.

2 Related Works

2.1 Micro Heat Exchanger Optimisation

Several studies about the application of MOO have been reported [Coe01] but little have been published on optimisation of micro heat exchangers.

Rhu et al. reported numerical optimisation of a rectangular micro-channel heat sink [Rhu02]. In this paper, the random search technique [Van84] was used for searching for the optimal solution. Its objective function was the minimal thermal resistance in the micro-channel heat sink. The channel depth, the channel width, and the fin thickness of micro channel were used as design parameters. They concluded that the channel width appears to be the most crucial parameter.

Jia, and Sundén reported the optimal design of compact heat exchanger by an artificial neural network (ANN) [Jia03]. With ANN, they built up the model of a compact heat exchanger. In order to minimise the pressure drop in the heat exchanger, they optimised the density and height of fins. The optimisation was also used to maximise the temperature of heated fluid at its outlet in the compact heat exchanger. In this study the operating conditions were used as the design parameters. No details of the optimisation method are provided in the paper.

2.2 Multi-Objective Optimisation

Many methods for solving multi-objective optimisation have been proposed (see [Deb01] for an overview).

Jin et al. [Jin01, Jin01b] proposed DWA (Dynamically Weighted Aggregation) for solving multi-objective optimisation problems. In DWA, the aggregation is used as:

$$f = w_1(t)f_1 + w_2(t)f_2 \tag{1}$$

where f_1 and f_2 are objective functions. The parameters $w_1(t)$ and $w_2(t)$ are time-dependent weights with $w_1(t) + w_2(t) = 1.0$. Here, t is generation.

By changing the weights dynamically according to the generations, DWA can get not only the convex Pareto Front but in many cases also the concave one. This method is very easy to handle and shows good results on several test functions. DWA can work with small population size, that is preferable to be used on a real-world problem. Additionally, by controlling the weight, we can get the preferable part of the Pareto Front instead of the whole Pareto Front. In this paper, we use DWA as one of the multi-objective optimisers. Some theoretical analysis of DWA can be found in [Oka02].

As the second multi-objective optimiser, we use NSGA-II (Non-dominated Sorting Genetic Algorithm) proposed by Deb et al. [Deb00, Deb02]. This method often shows better performance than others on several test functions. In NSGA-II, the *Crowded Tournament Selection Operator* is used. In this selection, individuals are sorted by a non-domination rank at first. In the same rank, the crowding distance is used for sorting them. After sorting by the rank and the crowding distance, the best solutions are selected deterministically. Deb proposed two versions of NSGA-II. One is NSGA-II based on floating alleles with simulated binary crossover (SBX), and the other is with string alleles. Since DWA is based on evolution strategy (ES) with floating alleles, we use NSGA-II with string alleles.

2.3 Comparative Studies

Recently, the comparative studies of MOO methods, often called *Performance Indices (PIs)*, become popular [Oka03]. Several performance indices have been proposed in the literatures [Zit02, Oka03]. The target of MOO is to get an accurate, well-distributed, and widely spread solution set efficiently. In order to evaluate the solution set from different point of views, several PIs should be used.

In this paper, we use the hypervolume index (H) for the accuracy [Zit98], the Δ' index for distribution [Deb00], and the spread index ($\mathcal{M}_3^*$) for spread [Zit00].

The H index is the area of the dominated region by the solution set, S. The schematic image is shown in Figure 1. The larger H is better.

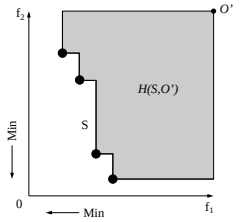

Figure 1: The definition of H index for the minimisation problem. H is the area generated by the solution set S and the defined origin O', which needs to be specified.

The Δ' index is calculated as follows: At first, the Euclidean distance d_i $(i = 1, ..., |S| - 1)$ between consecutive solutions in S are calculated. After that, the average of distance $\bar{d}$ is calculated. Finally, $\Delta(S)'$ is calculated according to the following equation:

$$\Delta(S)' = \sum_{i=1}^{|S|-1} \frac{|d_i - \bar{d}|}{|S| - 1}. \tag{2}$$

The smaller Δ' is better.

The $\mathcal{M}_3^*$ index is the Euclidean distance between the end points in S given by:

$$\mathcal{M}_3^*(S) = \sqrt{\sum_{k=1}^{2} \left\{ \max_{s \in S} f_k(s) - \min_{s \in S} f_k(s) \right\}^2} \qquad (3)$$

The larger $\mathcal{M}_3^*$ is better.

3 Micro Heat Exchanger Model

The problem under consideration is the forced convection through a micro heat exchanger. A schematic model of the micro heat exchanger is shown in Figure 2.

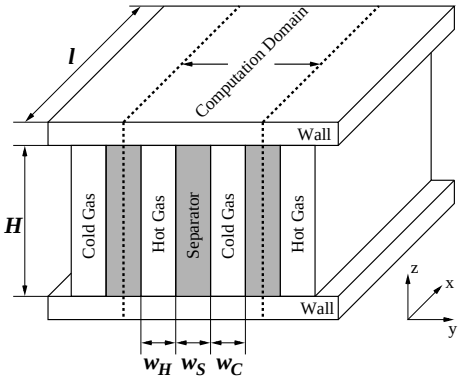

Figure 2: A schematic model of the micro heat exchanger.

It consists of two channels with hot and cold fluid flowing through alternate channels. The dimensions of the heat exchanger core are shown in Figure 2.The method described here applies to both co- and counter-flow configurations.

The following assumptions are made with regard to the flow and heat transfer in the micro-channels:

1. For the current study the hydraulic diameter of micro-channels considered was between $100\mu m$ and $1000\mu m$. The Knudsen Number for all the flows considered was less than 0.001, a necessary condition for the continuum flow assumption. The conservation equations based on continuum flow therefore apply.

2. The transport processes are steady.

3. The thermo-physical properties of the fluids are temperature dependent.

4. For overall optimal performance of the micro-channels the analyses are restricted to laminar [Tso98] and incompressible flows.

5. Thermal radiation is neglected.

The governing equations that describe flow and heat transfer in the micro heat exchangers are the Navier-Stokes and energy equations based on the continuum flow assumptions. In tensor notations these equations are:

Continuity:

$$\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x_i}(\rho u_i) = 0 \qquad (4)$$

Momentum:

$$\rho \frac{\partial u_i}{\partial t} + \rho u_j \frac{\partial u_i}{\partial x_j} = -\frac{\partial p}{\partial x_i} + \rho g_i + \frac{\partial \tau_{ij}}{\partial x_j} \qquad (5)$$

where

$$\tau_{ij} = \mu \left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} \right) + \left(\beta - \frac{2}{3}\mu \right) \frac{\partial u_k}{\partial x_k} \delta_{ij} \qquad (6)$$

Energy:

$$\rho \frac{\partial h}{\partial t} + \rho u_j \frac{\partial h}{\partial x_i} = \frac{\partial p}{\partial t} + u_i \frac{\partial p}{\partial x_i} + \phi + \frac{\partial}{\partial x_i} \left(k \frac{\partial T}{\partial x_i} \right) \qquad (7)$$

where

$$\phi = \tau_{ij} \frac{\partial u_i}{\partial x_j}. \qquad (8)$$

To predict the thermal performance of the micro heat exchanger, the Navier-Stokes and energy equations were solved in three dimensions. The above equations were solved with a commercial CFD software, CFD-ACE+ [CFD02]. A description of the numerical techniques used in solving the above equations can be found in [CFD02].

In solving the transport equations, the mass flow rate and inlet temperature of the fluids entering the channels were specified, while the gradients of the temperature and velocity components at the exit of the channels were set to zero. Adiabatic boundary conditions were imposed on the walls and the continuity of the temperature and heat flux was used as the conjugate boundary conditions to couple the energy equations for the solid and fluid phases. Finally, the no-slip boundary condition was imposed on the velocity components at the wall. In cases where geometric symmetry exists the computational domain is simplified as shown marked in Figure 2.

The nomenclature and suffix are shown in Table 1.

4 Preparation for Optimisation

4.1 Optimisation Loop with a Commercial Multi-Physics Solver

In order to evaluate the quality of a μHEX design several aspects are taken into account. In the first step a model of the micro heat exchanger is generated allowing the parameterisation of possible designs. Based on the model and the parameterisation given in a chromosome, the genotype of the

Table 1: Nomenclature and suffix

Symbol	Explanation
h	Heat transfer coefficient
H	Height of micro-channels
k	Thermal conductivity
l	Length of channel
u_i	Velocity component
w	Width
β	Bulk viscosity
g_i	Acceleration due to gravity
μ	Dynamic viscosity
ρ	Density
H (suffix)	Hot channel
C (suffix)	Cold channel
S (suffix)	Separator

individual can be generated. A multi-physics flow solver is used for the evaluation of the fitness of the design. In our case we apply the commercial flow solver CFD-ACE+. The main problem for interfacing the flow solver is the extended usage of CFD-ACE+ because CFD-ACE+ can be controlled only by a graphical user interface (GUI). Some parts can be also controlled by the programming language Python [Chu01]. By generating an interface between CFD-ACE+ and our EAs via Python, we are able to successfully control CFD-ACE+ from within the EA.

The schematic image of the connection between EC and CFD-ACE+ is shown in Figure 3.

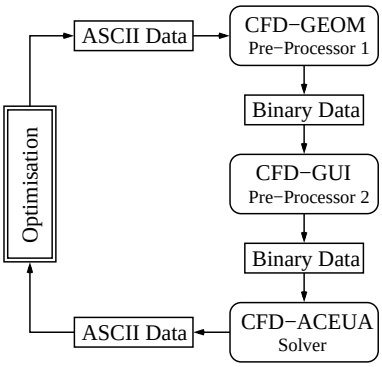

Figure 3: Connection with the commercial softwares.

From the experience with combining CFD-ACE+ with EA, we can say that in order to couple optimisation methods to a commercial solver, the commercial solver should have the following basic properties.

1. **Transparency :** It should be possible to control the flow solver and any additional functionalities with intuitive scripts which can easily be interfaced with standard programming languages like C/C++. Such scripts and interfaces should be well documented. Additionally, their results should not be capsulated.
2. **Parallelisation :** EAs can easily and efficiently be parallelised. However, current licensing policies generally do not take this type of single user multi-license usage into account, some new approaches have to be defined to keep the costs at a reasonable level.
3. **Stability :** A solver should be stable through more than 1000 runs. One instability halts a long calculation of optimisation.

In the following sections we will describe the model, defining the genotype-phenotype map and the objective function in more detail.

4.2 Select Design Parameters

The model of the μHEX was shown already in Figure 2. In this paper, we assume that the heat transfer is carried out only through the separator. The target for the optimisation is the determination of an optimal shape of the separator in order to maximise heat transfer and to minimise pressure drop at the same time.

To simplify the problem, the height H and the length L in Figure 2 are fixed. Additionally, the cross-sectional area of gas channels, i.e. Hw_H and Hw_C, are also fixed by engineer's request.

The boundary of the separator is determined by two *Non-Uniform Rational B-splines* (*NURBS*) [Pie97] like shown in Figure 4. In the optimisation the control points of one of the splines are adapted and stored in the chromosome of each individual. The second spline is generated by the given thickness t in Figure 4.

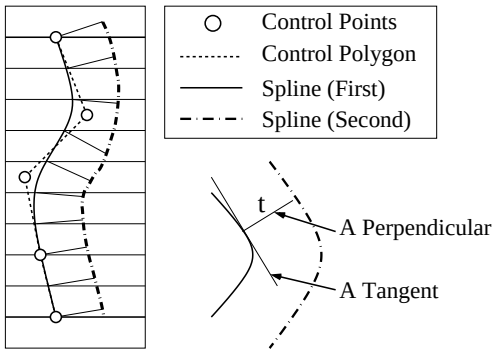

Figure 4: NURBS representation of the separator boundaries.

4.3 Select Objective Functions

The objectives for the optimisation are to maximise the heat transfer and to minimise the pressure drop in the hot gas channel and in the cold gas channel. To use minimisation strategy, we multiply the heat transfer by -1. This objective function is termed as f_1. In order to use bi-objective optimisation, we define the second objective function as:

$$
\begin{aligned}
f_2 &= P_{Hot}^{drop} + P_{Cold}^{drop} \\
&+ \max(0.0, P_{Hot}^{drop} - 1000.0) \\
&+ \max(0.0, P_{Cold}^{drop} - 1000.0).
\end{aligned} \tag{9}
$$

Here, P_{Hot}^{drop} and P_{Cold}^{drop} are the pressure drops in the hot gas channel and in the cold gas channel, respectively. The third term and the forth are the penalty terms. In the μHEX, the pressure drop in both channels has to be less than 1000.0 Pa. If the pressure drop violates this boundary, the penalty will be added to the objectives.

The pressure drops, P_{Hot}^{drop} and P_{Cold}^{drop}, are calculated as follows:

$$
P^{drop} = P_{Total}^{Inlet} - P_{Total}^{Outlet} \tag{10}
$$

$$
\begin{aligned}
P_{Total} &= P_{Static} + P_{Dynamic} \\
&= P_{Static} + \frac{1}{2}\rho v^2.
\end{aligned} \tag{11}
$$

Here, P_{Total}^{Inlet} and P_{Total}^{Outlet} describe the total pressure at the inlet and at the outlet, respectively. The total pressure is calculated by the sum of the static pressure and the dynamic pressure. The dynamic pressure is calculated by the density of the gas ρ and the velocity v in the direction along the channel.

4.4 Infeasible Models and Solver Errors

Due to the representation of the separator surface by a spline curve, it is possible to describe physically infeasible structures, e.g. by having loops in the spline curve. In this case, the individual is simply removed from the population. Even if the structure is physically feasible, the flow solver is not able to evaluate reliable results in some cases. The reasons for that can be non stationary flow conditions or the unfavourable computational grids which are the result of the automatic grid generation. In order to identify this cases, convergence properties of the flow solver are utilised. If the convergence rate is below a given threshold, the individual is also removed from the population.

4.5 Terminal Conditions

The whole optimisation is restricted by a total number of fitness evaluations of $n_{total} = 2520$. This is equivalent to about one week of calculation time on a PC-cluster (Pentium-III 850 MHz, Dual-CPUs, Memory 1GB) with 16 CPUs.

5 Results

5.1 Pareto Front by DWA

We use the DWA method with a standard evolution strategy [Jin01, Jin01b]. In the standard evolution strategy, the mutation of the design parameters is carried out by adding a normally distributed random number with zero mean and variance σ^2 ($N(0, \sigma_i^2)$). In evolution strategies the step sizes σ are encoded together with the design parameters in the chromosome of the individual and they are adapted together with the design parameters.

The standard evolution strategy can be described as follows:

$$
\vec{x}(t) = \vec{x}(t-1) + \vec{z}(t) \tag{12}
$$

$$
\sigma_i(t) = \sigma_i(t-1) \exp(\tau' z) \exp(\tau z_i) \,; i = 1, ..., n, \tag{13}
$$

where $\vec{x}(t)$ is an n-dimensional parameter vector, $\vec{z}$ is an n-dimensional random vector with $\vec{z} \sim N(\vec{0}, \vec{\sigma}(t)^2)$, z and z_i are $N(0,1)$ distributed random values. The parameters, τ and τ', are set to standard values of

$$
\tau = \frac{1}{\sqrt{2n}} \;\;,\;\; \tau' = \frac{1}{\sqrt{2\sqrt{n}}} \tag{14}
$$

Here, n is the number of design parameters. The other parameters in DWA are shown in Table 2. The history of the weights in DWA is described in Figure 5.

Table 2: Parameters in DWA.

Number of parents	2
Number of offsprings	14
Strategy	Without elitist

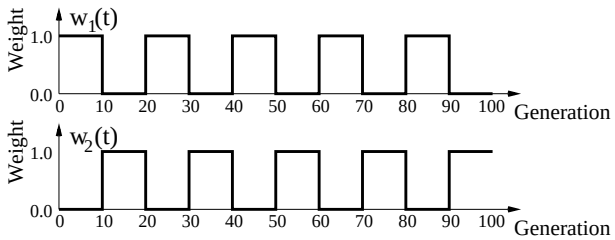

Figure 5: History of the weights in DWA.

The result is shown in Figure 6. We show all evaluated candidates in order to see the explored fitness region. All solutions are shown by black points. The circle means the original design.

In Figure 6, some designs have lower pressure drop than the original design. A closer look reveals that most of these solutions are based on the same shape like Figure 7, denote

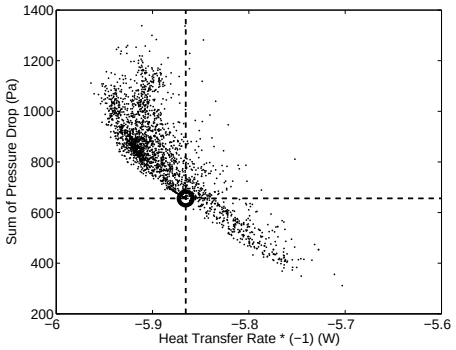

Figure 6: Final result by DWA (after 2520 evaluations).

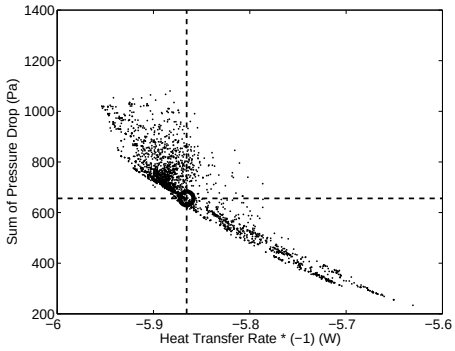

Figure 8: Final result by NSGA-II (after 2520 evaluations).

as *sine curve*. If all individuals in the population are occupied by this design, diversity will be lost. In particular, for small population size, this can occur, however increasing the size in our experiments is not possible due to the high computational cost.

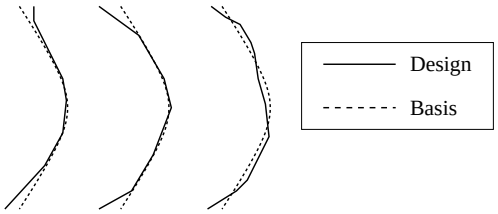

Figure 7: Schematic explanation of the designs based on the same shape.

5.2 Pareto Front by NSGA-II

We use NSGA-II with string alleles [Deb00, Deb02]. The parameters in NSGA-II are shown in Table 3.

Table 3: Parameters in NSGA-II.

Number of individuals	100
Number of bits per one floating value	20
Crossover	One Point Crossover
Crossover Rate	0.9
Mutation	Bit flip
Mutation Rate	0.05

The result is shown in Figure 8. We also show all evaluated solutions. The tendency of solutions is very similar to the result of DWA. Although NSGA-II uses 100 individuals, most of solutions in NSGA-II are also based on the sine curve like DWA. We will discuss this problem later.

5.3 Comparison of Results

Generally, several runs are necessary to compare MOO methods due to the influence of random variables [Oka03]. Since the computational costs of optimisations including CFD simulations are very expensive, it was not possible to execute several runs. Therefore, all results presented here are the results from one single optimisation run. In the following, the histories of the PIs of DWA and NSGA-II are given. All PIs are calculated for the non-dominated solution set found.

The absolute values of the two axes (Figure 6, 8) are different. The range of f_1 is about $[-6.0, -5.6]$ but one of f_2 is about $[200, 1400]$. In order to avoid the influence caused by the big difference of the absolute values, we normalise both objective functions.

The result of H index [Zit98] is shown in Figure 9 as a function of the number of evaluations. As the origin O' in Figure 1, we use $(-5.6, 1400)$. In the early stage of the optimisation NSGA-II shows a faster convergence to the Pareto front. However, at the end of the optimisation, both results become very similar.

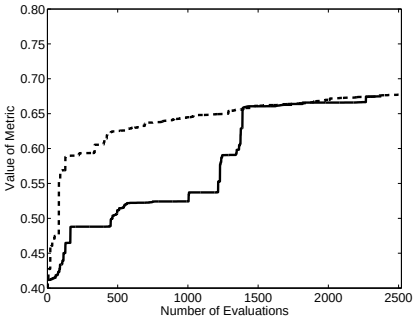

Figure 9: The history of H index. The solid line is the result of DWA and the dotted line is one of NSGA-II.

The result of Δ' index [Deb00] is shown in Figure 10. In the early stage, the Δ' index of NSGA-II shows high values. This indicates that solutions are not uniformly distributed along the Pareto front. But DWA shows well-distributed solution set.

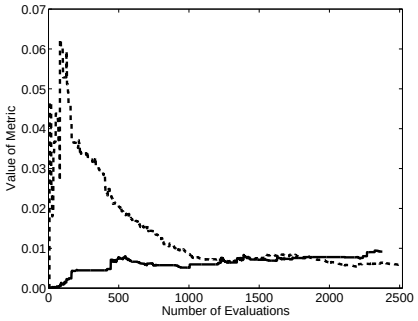

Figure 10: The history of Δ' index. The solid line is the result of DWA and the dotted line is one of NSGA-II.

The result of $\mathcal{M}_3^*$ index [Zit00] is shown in Figure 11. During the whole optimisation, NSGA-II shows higher values than the DWA method. It indicates that the part of the Pareto front which is identified from the DWA method is limited compared to the NSGA-II method.

Whereas NSGA-II searches a large region from the beginning, DWA seems to focus on some parts. This consideration corresponds to Figure 9 and 10 because if DWA concentrates on some parts, new solutions tend to cover a similar area that is dominated by old solutions. This means that the change of H index becomes smaller. Since most of solutions locate in a small region, the deviation of the distance to the neighbours (Δ') becomes small.

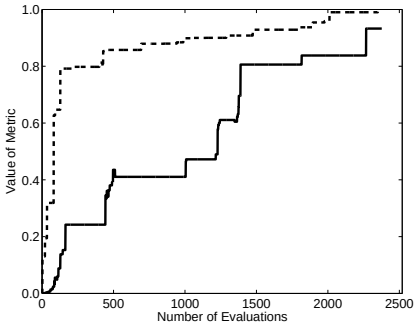

Figure 11: The history of $\mathcal{M}_3^*$ index. The solid line is the result of DWA and the dotted line is one of NSGA-II.

NSGA-II seems to focus on the whole Pareto front from the beginning in opposite to DWA which may search locally in the beginning. However, the most interesting thing is that the final results are very similar.

In the first half of the evaluations the improvement by NSGA-II is fast, but in the last half it becomes slower. On the other hand, DWA can find out new solutions continuously.

From these results, we may conclude the following:

1. NSGA-II based on GA searches a wider region from the beginning.
2. DWA based on ES searches a smaller region in the beginning.
3. NSGA-II finds most solutions in the first half of the optimisation run; the improvement in the second half is slower.
4. DWA can find out new solutions continuously.

6 Discussions

In this paper, we used 10 control points to express the shape of the boundary with NURBS [Pie97]. Although there are some differences, most of solutions on Pareto front are based on the same half of a sine curve. This means that it is very difficult to change the frequency by control points. Generally, the 10 control points should be nearly able to represent a sine curve with period 5. However, this is not seen during the optimisation. The reasons may be the difficulty of changing the frequency by the control points. Let's think about two sets of control points that represent half of the sine curve and a full sine curve. We can easily understand that there is big difference among them because the shape is completely different. Thus, in order to change the shape from half to a full sine curve, most of the control points should change considerably and adjust correctly. However, this task is very difficult and may be impossible for the optimiser. Thus, if the population achieves the same sine curve, most of them will keep the same sine curves. To overcome this difficulty, the easiest solution is to represent the frequency into alleles directly.

We also try to optimise the model whose boundaries can be expressed as:

$$y = A \times \sin\left(\frac{1}{H} B z \pi\right). \tag{15}$$

Here, y, H and z are described in Figure 2. The variables A and B are the design parameters.

The result of NSGA-II [Deb00, Deb02] is shown in Figure 12. The result of DWA [Jin01, Jin01b] is not shown because the tendency is very similar with the one of NSGA-II.

By comparison of Figure 12 and 8, we can easily understand that this solution set can dominate some of solutions in Figure 8. This means that some of the obtained solution set by NURBS are local optimal. Thus, DWA and NSGA-II also are trapped by some local optimal solutions. This trial indicates again that the representation strongly influences the solution set. By several trial-and-error, we should select the most important design parameters carefully. This should be done in the near future.

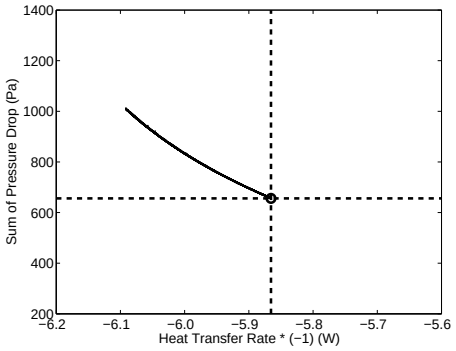

Figure 12: Result by NSGA-II.

7 Conclusion

Comparative studies of DWA (Dynamically Weighted Aggregation) and NSGA-II (Non-dominated Sorting Genetic Algorithm) on the micro heat exchanger optimisation were carried out. At the beginning DWA searches more locally, whereas NSGA-II explores a wider region right from the start. In the end both algorithms perform very similarly both with respect to visual inspection of the Pareto surfaces as well as to the different performance indices we used. Besides the comparison, we have seen that the choice of the representation might actually be more important than the choice of the optimisation algorithm. Although the initial NURBS representation can in principle describe sine curves with higher frequency, these are difficult to identify for the algorithm. A representation directly based on the mathematical description of sine curves showed partially better results, however, at the expense that *only* sine curves can be represented. This indicates that a trial-and-error approach might have to be realized to find the best representation which of course is not very desirable. Additionally, in this paper, we also built up the optimisation flow with the commercial multi-physics solver and pointed out the necessary functionalities of the commercial solver to be used in the field of EC.

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